UNIVERSITÀ
DEGLI STUDI
DI BERGAMO

PHD Thesis:

Technical and Fundamental Features' analysis for Stock Market Prediction with Data Mining Methods

Sasan Barak

Supervised by

Prof. Sergio Ortobeli Lozza

Prof. Tomas Tichy

September 2018
Bergamo, Italy

Contents

1. Introduction

Of the most important concerns of market practitioners is future information of the companies which offer stocks. A reliable prediction of the company's financial status provides a situation for the investor to more confident investments and gaining more profits(Huang, 2012b). Accurately prediction of stocks' prices has a positive affects into the organizations financial stability (Asadi et al., 2012). Since financial market is complex and has non-linear dynamic systems, its prediction is really challenging (Huang and Tsai, 2009).

The steady and amazing progress of computer hardware technology in the past decades has led to large supplies of powerful and affordable computers, data collection equipment, and storage media. This technology provides a great boost to the database and information industry and makes a huge number of databases and information repositories available for transaction management, information retrieval, and data analysis.

Data mining are defined as group of algorithms and methods designed to analyze data or to extract patterns in specific categories from data contributing greatly to business strategies, engineering, medical research, and financial areas (Klosgen and Zytkow, 1996). Prediction of stock prices, credit scores, and even bankruptcy potentials are examples of significant applicability of data mining in the field of finance.

In this research we are using the potential tools of data mining area for the forecasting the stocks and shares' prices and future trends. However, there are different approaches in financial forecasting in general and stock market price forecasting in particular including using fundamental analysis, technical analysis, and news via econometric or machine learning algorithms (Atsalakis et al., 2011; Kar et al., 2014), while in the this thesis we will go through all of these methodologies. The structure of the thesis is consist of three papers of the Author, published in the ISI journals about using technical and fundamental features for stock market prediction with different algorithms in the data mining as chapter 3 until chapter 5. The thesis exploits different types of financial data set and established three aspects of stock market forecasting via different combination of feature engineering in the finance dataset and machine learning models.

In the second chapter, a background and preliminary tools in the data mining area are described based on the generic CRISP-DM reference model. Chapter three is devoted for using fundamental features to predict the stocks' return and risk and proposed a novel hybrid feature selection approach to enhance the efficiency of prediction results. Chapter four focuses on the forecasting with the features captured from technical analysis concept with a hybrid algorithm of ICA (an optimization algorithm) and ANFIS (a forecasting model) for stock trend prediction. Chapter five is proposed a developed hybrid machine learning approach to solve the same problem in the chapter three for the risk and return prediction. Finally in the last chapter, all the chapters are combined and a general conclusion are presented.

2. Background: The Generic CRISP-DM Reference Model

The CRISP-DM reference model for data mining provides an overview of the life cycle of a data mining project (Shearer, 2000). It contains the phases of a project, their respective tasks, and their outputs. The life cycle of a data-mining project is broken down in six phases which are shown in Fig. 1. The sequence of the phases is not strict. The arrows indicate only the most important and frequent dependencies between phases, but in a particular project, it depends on the outcome of each phase which phase, or which particular task of a phase, has to be performed next.

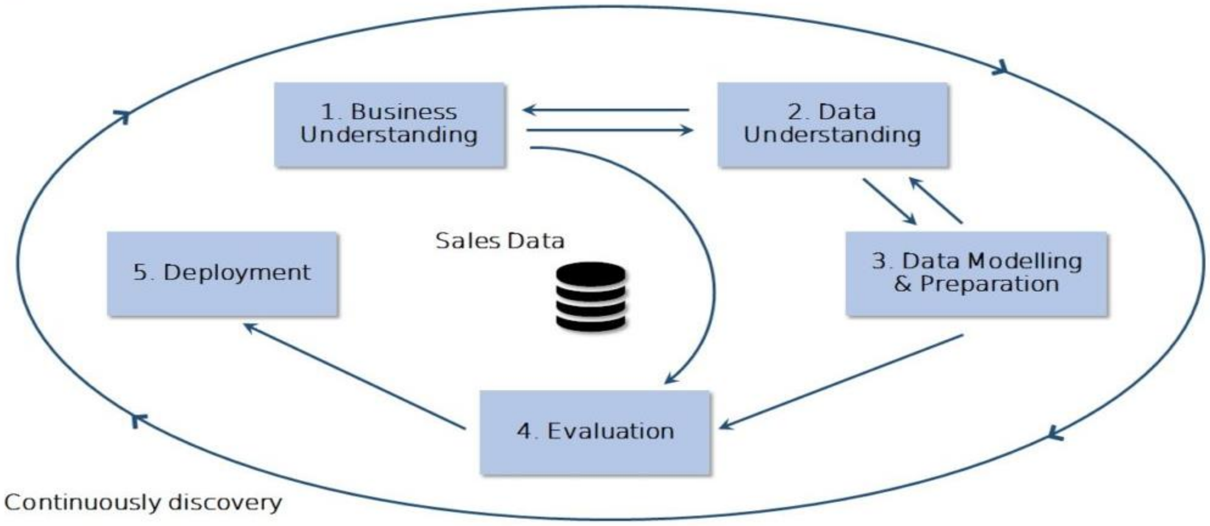


Fig 1. The phases of the current CRISP-DM process model for data mining

As it is displayed in Fig 1, the current CRISP-DM process model for data mining includes following phases:

2.1. Business Understanding

This initial phase focuses on understanding the project objectives and requirements from a business perspective, and then converting this knowledge into a data mining problem definition, and a preliminary project plan designed to achieve the objectives.

2.2. Data Understanding

The data-understanding phase starts with an initial data collection and proceeds with activities in order to get familiar with the data, to identify data quality problems, to discover first insights into the data, or to detect interesting subsets to form hypotheses for hidden information.
There is a close link between Business Understanding and Data Understanding. The formulation of the data mining problem and the project plan require at least some understanding of the available data.

2.3. Data Preparation

The data preparation phase covers all activities to construct the final dataset from the initial raw data. Data preparation includes basic operations such as removal of noise if appropriate, collecting the necessary information to model or account for noise, deciding on strategies for handling missing data fields, accounting for time sequence information and known changes (Ye, 2003).

Data preparation tasks are likely to be performed multiple times, and not in any prescribed order. Tasks include table, record, and attribute selection, data cleaning, construction of new attributes, and transformation of data for modeling tools (Kantardzic, 2003).

It is widely recognized that around 80% of the resources in data mining applications are spent on data cleaning and preprocessing. The actual mining or extraction of patterns from the data requires the data to be clean since input data are the primary, if not the only, source of knowledge in these systems. Cleaning and preprocessing data involves several steps including procedures for handling incomplete, noisy, or missing data; sampling of appropriate data; feature selection; feature construction; and also formatting the data as per the representational requirements of methods (e.g., decision trees, neural networks) used to extract knowledge from these data (Han and Kamber, 2006).

To achieve an accurate data mining process, the identification of the effective features (variables) is a crucial task. In other words, recognition of the most important representative features plays a key role in the accuracy and speed of the data mining process. Feature selection is the problem of choosing a small subset of features that ideally is necessary to describe the target concept (Yu and Liu, 2003). Therefore, in the following the feature selection concept and existing algorithms have been presented.

2.4. Feature Selection

Feature selection is of paramount importance for any learning algorithm which when poorly done (i.e., a poor set of features is selected) may lead to problems associated with incomplete information, noisy or irrelevant features, not the best set/mix of features, among others. The ultimate objective of feature selection is to obtain a feature space with (1) low dimensionality, (2) retention of sufficient information, (3) enhancement of separability in feature space for example in different categories by removing effects due to noisy features, and (4) comparability of features among examples in same category (Piramuthu, 2004). The optimality of a feature subset is measured by an evaluation criterion.

Feature selection algorithms designed with different evaluation criteria broadly fall into three categories:: 1. Filter methods, 2. Wrapper Methods, and 3. Hybrid methods (Chen and Cheng, 2012; Huang and Tsai, 2009).

2.4.1. *Filter algorithm*

The filter model relies on general characteristics of the data to evaluate and select feature subsets without involving any mining algorithm. For a given data set D, the algorithm starts the search from a given subset S0 (an empty set, a full set, or any randomly selected subset) and searches through the feature space by a particular search strategy. Each generated subset S is evaluated by an independent measure M and compared with the previous best one.

If it is found to be better, it is regarded as the current best subset. The search iterates until a predefined stopping criterion δ is reached. The algorithm outputs the last current best subset S_{best} as the final result. Compared to the wrapper and hybrid models, algorithms of the filter model are independent of any learning model, therefore do not have bias associated with any learning models. Another advantage of the filter model is that it allows the algorithms to have very simple structure, which usually employs a straightforward search strategy, such as backward elimination or forward selection, and a feature evaluation criterion designed according to certain criterion. The benefit of the simple structure is two-folds. First, it is easy to design, and after it is implemented, it is easy to understand for other researchers. This actually explains why most feature selection algorithms are of the filter model. In addition, in real world applications, many most frequently used feature selection algorithms are also filters. Second, since the structure of the algorithms is simple, they are usually very fast.

2.4.2. *Wrapper algorithm*

Feature selection algorithms of Wrapper model require a predetermined learning algorithm and use its performance on the provided features in the evaluation step to identify relevant feature. In the wrapper method the goal is to find a subset of size r from n variables (r <n) that maximizes the predictor performance (Maldonado and Weber, 2009b). The method utilizes the learning mechanism as the fitness function and seeks the best subset of the features while standard optimization techniques with learning mechanisms for ranking of the subsets are possible. (Kohavi and John, 1997a) have a leading role in popularization of the wrapper approach that is really powerful in feature selection, but it has its computational complexities and it is more time consuming than Filter method (Huang, 2012b). For a given dataset of G with N features, the Wrapper approach starts from a subset of F0 (an empty set, a full set, or any randomly selected set) and with a particular strategy searches the features space. It evaluates each generated subset of Fi by applying a learning model that considers Fi as an input and if the learning model performance improves with F_i; F_i is regarded as the best current subset. Then the wrapper modifies Fi by adding or eliminating features and performing the search until coming to the predefined stopping criterion (Kabir et al.). The above mentioned feature searching problem is NP-hard and the number of local minima can be quite large and naturally a wide range of heuristic search strategies including forward selection, backward elimination, hill-climbing,

branch and bound algorithms, and metaheuristics algorithms like simulated annealing and genetic algorithms (GAs) have been used (Huang, 2012a).

2.4.3. *Hybrid algorithm*

The hybrid model attempts to take advantage of the two models by exploiting their different evaluation criteria in different search stages. The hybrid model is recently proposed to handle large data sets. It makes use of both an independent measure and a mining algorithm to evaluate feature subsets: it uses the independent measure to decide the best subsets for a given cardinality and uses the mining algorithm to select the final best subset among the best subsets across different cardinalities. Comparing with the wrapper model, hybrid algorithms are usually more efficient, since they look into the structure of the involved learning model and use its properties to guide feature evaluation and search. In recent years, the embedded model is gaining increasing interests in feature selection research due to its superior performance. Currently, most embedded feature selection algorithms are designed by applying L_0 norm (Guyon and Elisseeff, 2003; Huang et al., 2008b; Liu and Setiono, 1996) or L_1 norm (Liu et al.; Zhu and Shasha, 2003) as a constraint to existing learning models to achieve a sparse solution. Generally, compared to the filter model, feature selection algorithms of the wrapper and embedded models can usually select features that result in higher learning performance for a particular learning model, which is used in the feature selection process.

2.5. Modeling

Having the data mining model and task defined, next would be the data mining methods to build the approach based on discipline involved. There is a close link between Data Preparation and Modeling. The methods used for data mining are classification, clustering and forecasting. Here a brief description of these three techniques is described as follows.

2.5.1. *Classification and forecasting methods*

Classification is one form of data analysis that can be used to extract models describing important data, which predicts categorical (discrete, unordered) labels. Data classification is a two-step process, in the first step, a classifier is built describing a predetermined set of data classes or concepts. This is the learning step (or training phase), where a classification algorithm builds the classifier by analyzing or “learning from” a training set made up of database tuples and their associated class labels. Initially, training data are analyzed by a classification algorithm, then the test data are used to estimate the accuracy of the classification rules. If the accuracy is considered acceptable, the rules can be applied to the classification of new data tuples.
Classification is one form of prediction, where the value to be predicted is a label. In another word, predicting class labels is classification, while if we have to predict the values of output, then the problem changes to the

forecasting problem. In numerical prediction (often called regression) one wish to predict a numerical value, such as a company's profits or a share price. Classification and forecasting have numerous applications, including fraud detection, target marketing, performance prediction, manufacturing, medical diagnosis and stocks return or stock risks and many other applications. For example, one can build a classification model to categorize the stock return as either high, average or low.

Classification methods: common tools used for classification are Artificial neural networks, Decision Trees, Nearest Neighbor Matching, Association Rules, Bayesian Classification.

- ***Artificial neural networks***

Artificial neural networks are used to map an input to a desired output like a mathematical function. It is inspired by the behavior of neurons located in the brain (Priddy and Keller, 2005). Neural networks are non-parametric estimators that can be used for several kind of tasks such as forecasting, clustering, function approximation and optimization (Mehrotra et al., 1997).

The inputs of a neural network are vectors of variables corresponding to an observation. These vectors are weighted and combined by linear filters and become the inputs of hidden layers where non-linear computation is done on inputs. Network output will be calculated by a function called activation function that receives output of hidden layers and calculate the output of the network (Gershenfeld, 1999).

In the following the mathematical explanation of multilayer perception (Zhang et al., 1998) which is one of the most favorite models of ANN has been presented (see Eq. (1)):

$$F_t = \beta_0 + \sum_{n=1}^{N} \beta_n W(\theta_{0i} + \sum_{j=1}^{m} \theta_{nj} x_j\ ) \tag{1}$$

Where m is the number of inputs (x_j) and N is the number of nodes in the hidden layer. θ_{nj} is the weight for output layer and β_n is the weight for the hidden layers. Here the zeroth indices in the weights refer to the bias nodes in each layer. One can use either sigmoid or hyperbolic tangent functions as the transfer function W. The whole process of learning is achieved by adjusting the weight parameters and the network is updated each time it has been feed by new data. After the parameters are updated the desired outcome will be the classification of the data. More on optimization methods can be found in (Ragg et al., 1998) .

- ***Decision Tree***

Decision tree algorithm is a non-parametric and non-linear machine learning technique. This technique takes advantage of a hierarchical structure for recursively segmenting training data and therefore it has a great flexibility and interpretability in data analysis. The most common strategy to induct a decision tree is greedy top-down construction which recursively partitions the data into subsets until the stopping criterion has met.

The stopping criterion is crucial so that it can prevent growing branches that does not affect the tree quality (Murthy, 1998).

Some of these stopping rules are:

1- The number of observation in a node is less than a pre-specified threshold.
2- All observation assigned to a node belongs to the same class.
3- Depth of the node is more than some pre-specified limit.
4- Nodes purity are more than a specified threshold (Esposito et al., 1997).

Decision trees are often prone to over-fitting according to high variance, hence methods are proposed to find right sized tree. The most famous method is pruning trees (Rizzo et al., 2017), so in order to have a high quality tree, first the complete tree is built and then inefficient sub-trees, that do not influence cost function significantly, are removed.

The evaluation function used for splitting in classification trees in CART (classification and regression tree)method is Gini index, which describes the chance of coming up with a false node for the data if the node was chosen randomly from the nodes' distribution. The Gini index can be stated as Eq. (2).

$$Gini(t) = 1 - \sum [P(K|t)]^2 \tag{2}$$

Where $P(K|t)$ is the proportion of finding the data class K in node t (node purity). The aim is to minimize Gini index. From the formula it can be inferred that if the classification is done in a perfect way, the Gini index would be zero (Friedman et al., 2001), (Kumar, 2013).

- ***Nearest Neighbor Matching***

This method relies on identifying (say) the five examples that are ʹclosest in some sense to an unclassified one. If the five ʹnearest neighbors' have grades Second, First, Second, Second and Second, one might reasonably conclude that the new instance should be classified as ʹSecond (Han and Kamber, 2006).

- ***Association Rules***

Sometimes researchers wish to use a training set to find any relationship that exists amongst the values of variables, generally in the form of rules known as association rules. There are many possible association rules derivable from any given dataset, most of them are little or with no value. Therefore, it is usual for association rules to be stated with some additional information indicating how reliable they are, for example: the following is an association rule mined from a data set shown with its confidence and support (Han and Kamber, 2006), Where "^" represents a logical "*and*"

$$Age = (youth \wedge credit = OK)\, buys\ computer = yes\ [support = 20\%, confidence = 93\%]$$

- ***Bayesian Classification***

Bayesian classifiers are statistical classifiers. They can predict class membership probabilities, such as the probability that a given tuple belongs to a particular class. Bayesian classification is based on Bayes' theorem (Han and Kamber, 2006).

2.5.2. *Clustering*

Clustering is the task of segmenting a heterogeneous population into a number of more homogenous clusters (Khan and Ahmad, 2004; Linoff and Berry). It is different to classification in that clusters are unknown at the time the algorithm starts. In other words, there are no predefined clusters. A cluster is a collection of data objects that are similar to one another within the same cluster and are dissimilar to the objects in other clusters. A cluster of data objects can be treated collectively as one group and so may be considered as a form of data compression. Common tools for clustering include Partitioning methods, Hierarchical methods, Density-based methods, Grid-based methods and Model-based methods.

- ***Hierarchical methods***

A hierarchical method creates a hierarchical decomposition of the given set of data objects. A hierarchical method can be classified as being either agglomerative or divisive, based on how the hierarchical decomposition is formed. The agglomerative approach, also called the bottom-up approach, starts with each object forming a separate group. It successively merges the objects or groups that are close to one another, until all of the groups are merged into one (the topmost level of the hierarchy), or until a termination condition holds. The divisive approach, also called the top-down approach, starts with all of the objects in the same cluster. In each successive iteration, a cluster is split up into smaller clusters, until eventually each object is in one cluster, or until a termination condition holds.

2.6. Evaluation

At this stage in the project you have built one or more models that appear to have high quality, from a data analysis perspective. Before proceeding to final deployment of the model, it is important to more thoroughly evaluate the model, and review the steps executed to construct the model, to be certain it properly achieves the business objectives. A key objective is to determine if there is some important business issue that has not been sufficiently considered. At the end of this phase, a decision on the use of the data mining results should be reached. In other words, in this step we will choose the appropriate forecasting model to be employed. To do so, we compare the result of a specific error measure on different candidate models and select the model with lowest error. There are different kinds of error measures. The error measurements have been joined in the seven groups: absolute forecasting errors, measures based on percentage errors, symmetric errors, measures based on relative errors, scaled errors, relative measures and other error measures.

2.7. Data mining in finance

According to the efficient market theory, it is impossible to predict prices based on historical stock data. This theory also states that the prediction of the classical criteria of risk and return cannot bring advantages to shareholders. There is abundant evidence in the literature, however, that argues against the efficient nature of the market (Cervelló-Royo et al., 2015). A precise prediction of companies' future values enhances investors confidence to make a profitable investment.

One of the useful approaches to predict future information of the companies is data mining as a new growing interdisciplinary branch of science that combines various fields like statistics, machine learning and parallel processing to extract knowledge from data flooding around organizations, governments and individuals. To achieve an accurate stock market prediction, the identification of the effective features is crucial. In other words, the representative features of the factors play a key role in prediction efficiency. Technical and fundamental analyses are two essential tools in financial market evaluation. A brief presentation about the technical and fundamental analyses are presented below:

Technical analysis (TA): evaluates securities by means of statistics such as past price and volume that are generated by market activities (Barak et al., 2015). The major criticism of TA is that it only considers the price movement and ignores the fundamental factors related to the company. Moreover, TA takes a comparatively short-term approach to analyse the market.

Fundamental analysis: can be used to evaluate a firm's performance and financial status over a period of time by carefully analysing the institute's financial statement (Huang, 2012a). Fundamental analysis seeks to find the essential features of stock and market movements. In fact, the logic behind fundamental analysis is that if a company has a proper fundamental strength, then long term stock investment in the company will be more secure and stable. Thus, the stocks of these fundamentally strong companies, which are making money, gaining profit and growing their businesses, represent an opportunity for a successful investment.

After this brief presentation about the technical and fundamental analyses, three recent papers of the author are presented to explain the usefulness of using different features for stock market analyzing in the following chapter 3, 4, and 5.

3. Developing an approach to evaluate stocks by forecasting effective features with data mining methods

Summary of the third chapter

In this research, a novel approach is developed to predict stocks return and risks. In this three stage method, through a comprehensive investigation all possible features which can be effective on stocks risk and return are identified. Then, in the next stage risk and return are predicted by applying data mining techniques for the given features. Finally, we develop a hybrid algorithm, on the basis of filter and function-based clustering; the important features in risk and return prediction are selected then risk and return re-predicted. The results show that the proposed hybrid model is a proper tool for effective feature selection and these features are good indicators for the prediction of risk and return. To illustrate the approach as well as to train data and test, we apply it to Tehran Stock Exchange (TSE) data from 2002 to 2011.

3.1. Introduction

Of the most important concerns of market practitioners is future information of the companies which offer stocks. A reliable prediction of the company’s financial status provides a situation for the investor to more confident investments and gaining more profits (Huang, 2012b). One can refer to different studies about share gaining and return prediction, for example, time series stock price prediction model (Araújo and Ferreira, 2013), Buy-hold-sell prediction model (Wu et al., 2014; Zhang et al., 2014b) , Index prediction model with Anfis (Svalina et al., 2013) or MARS and SVR (Kao et al., 2013), Profit gaining (Ng et al., 2014). However, unlike the return, risk has been rarely considered for prediction, while customers usually balance their return for a proper level of risk, then clearly both risk and return are important factors in financial decision making (Barak et al., 2013; Tsai et al., 2011). Without risk evaluation the portfolio efficient frontier does not make sense. Thus, this paper implements the forecasting of both risk and return of stocks which has tremendous effect on price setting. Also, up-down prediction of stock movement such as (Patel et al., 2014; Yu et al., 2014; Zhang et al., 2014a) cannot result in precision view of stock future and investors gaining. While classifying the amount of risk and return to different categories like our method gives more specific and clear knowledge.

Therefore, in this study, the simultaneous prediction of risk and return classes with different classification algorithms is investigated.

To predict risk and return variables accurately, the effective factors need to be identified. In fact, one of the key issues of stock prediction design lies on how to select representative features for prediction(Zhang et al., 2014a).

Most studies in this area focus on technical features, financial ratios or macroeconomic indicators. For example, Tsai and Hsiao (2010) studied 8 financial ratios and 16 macroeconomic indicators as the main features to predict stock return by Back Propagation in Taiwan stock market. Cheng et al. (2010a) conducted a comprehensive study on macroeconomic and technical features and studied 8 financial ratios and 10 macroeconomic indicators to investigate their effect on return variation in Taiwan stock market. By applying probabilistic Back Propagation algorithm, Rough set and C4.5 Tree, they achieved 76% accuracy. de Oliveira et al. (2013) use 15 technical indicators and 11 fundamental indexes to prediction of stocks movement in Petrobras with artificial neural networks and obtain 87.50% for direct prediction. Tsai et al. (2011) considered 19 financial ratios and 11 macroeconomic indicators in Taiwan stock market by combining logistic regression Algorithm, MLP Back Propagation and CART Tree to investigate their effect urn (negative or positive) on the stock return and achieved 66.67% accuracy based on Bagging and Voting algorithms. In majority of studies, as mentioned, the focus is mostly on financial ratios, macroeconomic indicators, and technical indicators based on experts' ideas to predict returns. However, this paper presents a systematic and efficient methodology for comprehensive searching the potential representative features on stock market in 3 categories of financial ratio, profit & loss reports, and Stock pricing models and not arbitrarily choosing likely effective features.

Furthermore, many studies have claimed and verified that feature selection (FS) is the key process in stock prediction modeling (Tsai and Hsiao, 2010). Zhang et al. (2014a) use a causal feature selection (CFS) algorithm to find effective features in Shanghai Stock Exchanges. The idea in their model is about Causalities based feature selection algorithm. They assert that CFS represents direct influences between various stock features, while correlation based algorithms cannot distinguish direct influences from indirect ones. Wu et al. (2014) use textual and technical features to improve prediction accuracy of stock market. They use SVR algorithm and trend segmentation method to forecast trends and generate trading signals, respectively. Their feature selection algorithm is stepwise regression analysis. Although there are a variety of studies in the area of feature selection, almost all of them use a single feature selection model.

In this research, a novel hybrid feature selection algorithm on the basis of filter and function-based clustering method is applied to select the important features. What makes our proposed approach different from the previous ones is that we consider the combination of 9 different feature selection algorithms with function-based clustering algorithm. Hybrid model of our paper enjoys the power and advantage of correlation based algorithms like Chi-Square, One-R in addition to the power of classified errors based, interval based, and information based algorithms like SVM, Relief-f, and Gini index/ gain ration algorithms respectively. The effectiveness of our model is illustrated with the prediction of both risk and return of stocks and then analyzing the results with and without implementing of our hybrid feature selection algorithms.

To sum up, in the first stage of paper, a complete list of likely effective features on the stocks risks and returns are identified. After developing an appropriate database in the second stage, different classification algorithms are used to predict the risk and return. We also scrutinize on the effect of their results to our data base based on feature-oriented view point. Finally, in the third stage, a novel hybrid feature selection algorithm on the basis of filter and function-based clustering method is applied to select the important features which affect the prediction of risk and return.

The contribution of the paper is summarized as follow:

- A comprehensive and systematic study to identify the likely effective features in risk and return prediction.
- Stock risks as well as return prediction with different classification methods.
- Designing a hybrid feature selection algorithm on the basis of filter and function-based clustering.
- Finally, each algorithm with a feature-oriented view point is analyzed. The results indicate the factors which cause strength and weakness of that algorithm. As a result the nature of each feature is provided according to the amount of interference variable in their prediction.

The rest of the article is organized as follows. In Section 2, the proposed model is presented which has three stages. In Section 3, to illustrate the approach, we implement it with some real data from Tehran Stock Exchange (TSE). The results are analyzed in which the predictions with and without considering important effective features are also compared. Then in Section 4, a discussion on real return and risk prediction with important features has been represented. Finally, some conclusion and future research directions are provided in Section 5.

3.2. Proposed model

Our proposed algorithm which consists of three stages is shown in Figure 3.1. In the first stage a database is developed and data is pre-processed. Non-systematic risk as well as real return is predicted with classification algorithms in the next stage. A hybrid feature selection algorithm is also presented in the third stage and risk and return are re-predicted based on selected features.

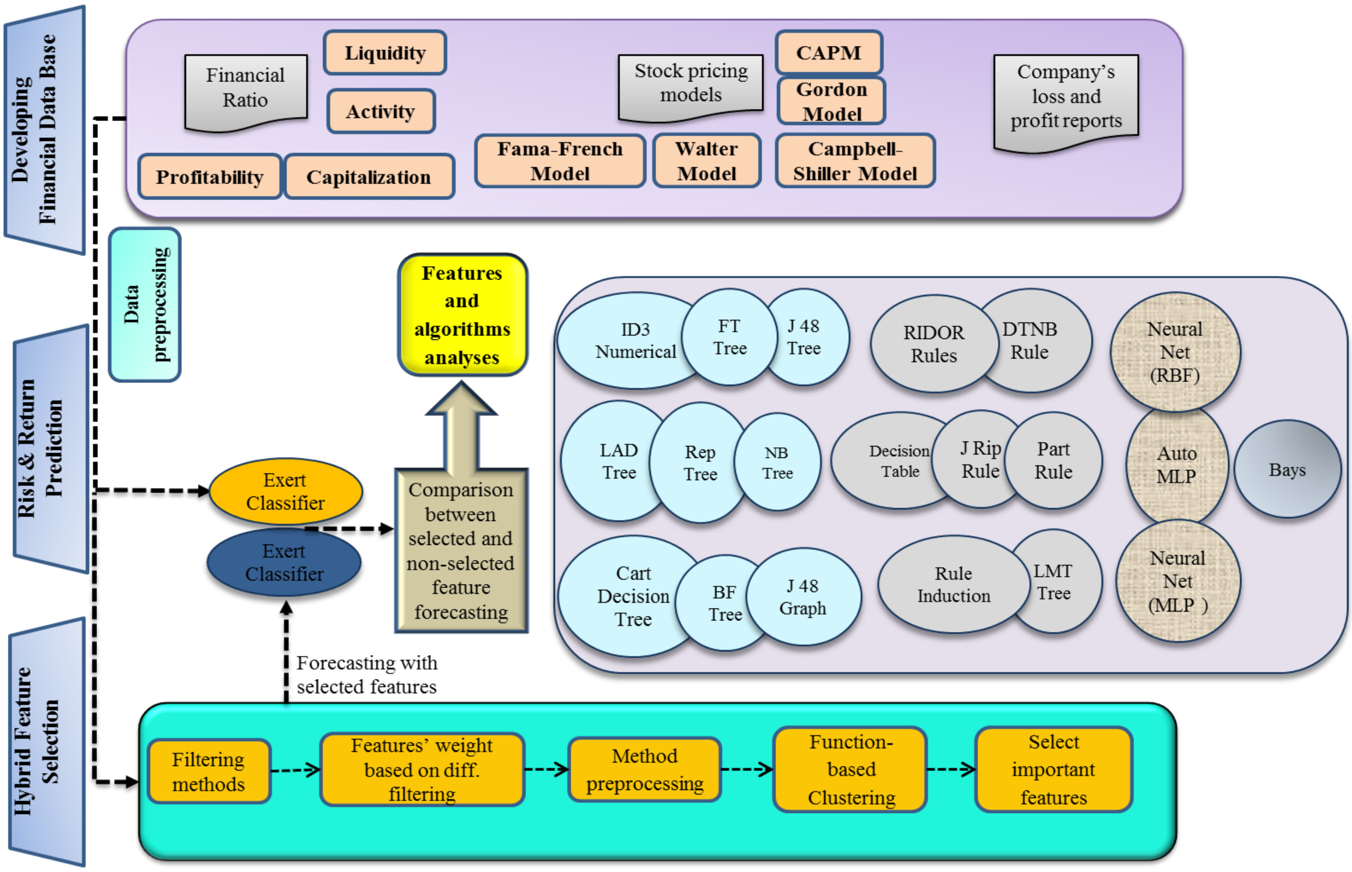


Figure 3.1. Conceptual design of the proposed model

3.2.1.First stage: Developing financial database

This stage we utilize the concepts and techniques of input features, response variables, and preprocessing models.

- **Input features**

First we analyze and gather important features from the company's financial ratios and the profit & loss reports, as well as stock pricing models (Table 3.1).

- Financial Ratio: To have a complete list of effective features we gather 4 general groups of financial ratio as a part of input variables of companies' database. The importance of these features is discussed in many studies [see(Bauer et al., 2004; Bernstein and Wild, 1999; Carnes and College, 2006; Huang, 2012a; Omran and Ragab, 2004; Sadka and Sadka, 2009; Soliman, 2008)], also see financial ratio's part of Table 3.1.
- Stock pricing models: We review different stock pricing models (Capital Asset Pricing Model (CAPM), Gordon, Walter, Campbell-Shiller, and Fama-French) and obtain other important factors which effective on the risk and return prediction of stocks, see Table 3.2[(Kaplan and Ruback,

1995)(Brealey et al., 2007; Fama and French, 1993, 2012; Gordon, 1982; Hjalmarsson, 2010; Lee et al., 2009; Lewellen, 2004; Mukherji et al., 1997)]

- Company's profit and loss reports: By using the profit and loss reports of companies, the other added factors are extracted. In Table 3.1, all input variables of financial model are provided.

Table 3.1. Stock pricing models

CAPM	$R = r_f + \beta(r_m - r_f),(1)$	This model explains the connection between expected return and risk and it is used for bonds pricing with risk.(Kaplan and Ruback, 1995) R: expected Return, r_f : rate of return without risk, β: systematic risk, r_m: market expected return. A brief description about this formula can be found in Appendix A. On the basis of this model, r_m ,r_f , β are added to database.
Gordon Model	$P = \frac{DPS}{k-g},(2)$ $DPS = EPS \times DPR$	Gordon has suggested this model using the investment of retained earnings to stock pricing(Gordon, 1982). g: stock profit increase, K: shareholder's expected return ratio. From this model two important factors EPS and DPS are achieved. ROE feature have been mentioned also in financial ration before. In addition to this, four other features that were obtained from EPS have been regarded and inserted into the model as follows: EPS prediction of companies in fiscal year, EPS coverage, prediction difference percentage of EPS with the real amount, and EPS growth ration in compare to the previous fiscal year(Hjalmarsson, 2010). Gordon Model is used in different capital market discussions like(Lee et al., 2009).
Walter Model	$P = \frac{DPS + (EPS - DPS)r/k}{k}$, (3)	P: stock market price of each stock, r: internal rate of return, EPS-DPS: cumulative profit per share, K: capitalrate cost(Brealey et al., 2007). According to this model, cumulative profit per share is known as a criterionin the database.
Campbell - Shiller Model	P/E , P/S ratio	This model calculatesthe stock P/E average by using Market data (Brealey et al., 2007). From the literature, it was clarified that P/E parameter is very important for analyzing and predicting the stock price, and it is inserted to database(Hjalmarsson, 2010; Lewellen, 2004). In addition to this, P/S ratio that is result of Stock pricedivided to each stock sale is also inserted to database(Mukherji et al., 1997).
Fama-French Model	$r_i = \alpha + \beta\,(r_m) + \beta_{size}\,(Size)$ $+ \beta_{\frac{\beta}{M}}\,(\frac{\beta}{M}),(4)$	Fama- French offer β, size and book value to market value's Model with the help of CAPM Model as a multivariate regression to study the Factors affecting portfolio returns(Fama and French, 1993, 2012) The first part of the model is similar to Sharp model. The second part shows the company size which is a factor showing the company's capital and third part indicates the book value to market value. By using this model, company's capital, stock Book value and stock Market value are inserted to the database as 3 important factors. The other models like Glassman-Host and kernel are derived from the introduced methods and they do not help this research in finding new features.

- Company's profit and loss reports: By using the profit and loss reports of companies, the other added factors are extracted. In Table 3.2, all input variables of financial model are provided.

Table3.2. Financial input features

Category		**Features**
Financial ratio	Liquidity ratios	current ratio , quick ratio, current assets ratio, Net working capital, Liquidity ratios
	Activity ratio	Average payment period, current assets turn over, Fixed asset turnover, Total asset turnover
	Capitalization ratio	Equity ratio, Debt coverage ratio, debt to total assets ratio, debt to equity ratio, long-term debt to equity ratio, current debt to equity ratio.
	profitability ratio	Percentage of net profit to sale, Percentage of Operating profit to sale, Percentage of Gross profit to sale, Percentage of net profit to Gross profit, Return on asset (after tax) ROA, Return on equity (after tax) ROE, working capital return percentage, fixed assets return percentage, assess theloan usefulness
Stock pricing models	Capital Asset Pricing Model	r=return ration without riskβ= stock beta coefficient (systematic risk) r_m =expected return from market

	Gordon Model	EPS, DPS, EPS prediction, EPS cover, prediction difference percentage of EPS with the real amount, EPS growth ration in compare to the previous fiscal year.
	Campbell - Shiller Model	P/E, P/S
	Walter model	Stock cumulative profit
	Fama- French Model	Company's capital(investment), stock book value, stock market value
Company's loss and profit reports	Total predicted income (last income prediction in the current fiscal year),Total income growth % (total real income / (total real income - total predicted income)), predicted Profit margins (last profit ratio / company's income in the current fiscal year), profit margin growth rate (real profit margin / (real profit margin – predicted profit margin)) and Efficiency (Precent of daily trading volume / company's daily value in the before period).	

- **Response variables**

The most important response variables in our model are real return and Non-systematic risk, as follows:

$$R = \sqrt[n]{(1+\frac{r_1}{100})(1+\frac{r_2}{100})...(1+\frac{r_n}{100})} \ ,(5)$$

Where $r_1 \ldots r_n$ = real return of $1 \ldots n^{th}$ periods

Non-systematic risk is defined as the standard deviation of the stock return, as follows.

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=0}^{n}(r_i - E(r)^2)},(6)$$

- **Data pre-processing**

Data preparing stage is an important part of the approach. Furthermore, it is time consuming in data mining process, described as follows.

- Removing high correlation features: Features with higher than a predefined correlations percent on the basis of Pearson test are removed.
- Missing data: Defected records caused by incomplete information of company or the company's negligence in reporting are also deleted from the database. Some decision tree algorithms and K nearest neighbor techniques do not need to replace the missing data.
- Finding outlier data: To find outlier data in database, we use the distance-based approach which is based on data intervals(Knorr and Ng, 1999), density approach(Breunig, Kriegel, Ng, & Sande, 2000)in which a parameter named Local Outlier Factor (LOF) is specialized to each sample based on K-Nearest neighbor density. Samples with high LOF are known as Outlier points, clustering approach(Hong and Wu, 2011)within the use of k means clustering algorithm, and deviation method(Hong and Wu, 2011).

3.2.2. *Second stage: Risk and return prediction with classification methods*

Generally, researchers and scholars are seeking to achieve a more scientific model, ranging from Portfolio Theory by Markowitz in 1952 and Sharp assets pricing models in 1964, to Fama- French in 1992. However, they cannot solely evaluate price, risk, and return well. Bartholdy and Peare (2005) compared CAPM and

Fama-French Model while it appears that the latter can better explain the return deviation and can give better evidences. But regarding the real data, none of them can explain return well. Cao et al. (2005) concluded that the neural network is much more powerful than Fama- French Model in stock return prediction. Dastgir and Afshari (2004) compared Walter, Gordon and current value of future cash flow stock pricing models in Tehran Stock Exchange and observed that real prices and prices obtained by models were not equal. As these studies show the traditional methods cannot necessarily estimate properly. Thus, it is necessary to apply some methods to be able to determine the complexity of the data. Some researchers have used different methods like neural networks and statistical methods. Among these results, the conclusion gained by machine learning algorithm and data mining are prominent(Patel et al., 2014).

Ou and Wang (2009b) and Lai et al. (2009) concluded that decision tree methods have outstanding performance in stock return prediction. In addition, what is important is the rules obtained from the rule based algorithms and trees, since these rules conduct investors to buy and select the portfolio.

On the other hand, the output of the methods that are applied in this area (like SVM and NN) which do not use rules for prediction is not appropriate for practitioners. Decision tree structure is more comprehensive, transparent and rational. On the basis of what was discussed, our study focuses on tree and rule based algorithms in order to be more appropriate for investors and analysts. Levin and Zahavi (2001) concluded that data correlation problem in tree algorithms is more transparent than statistical algorithms, and it can be solved by Pruning algorithms. Chang (2011) compared CART, Back Propagation, and CART-Back Propagation hybrid method from the point of view of stock price prediction based on fundamental data and concluded that Back Propagation and Decision Tree accuracy perform better than the Hybrid methods.

In this study, by using different classification methods, risk and return are predicted on the basis of the given features and database. A comparison between different methods is performed. Actually, this section is done for two times. In the first time the prediction is done with all features but in the second time, the best selected features from hybrid feature selection algorithm are predicted. A comprehensive comparison between these two predictions is also done. In other words, in this paper we compare the accuracy of risk and return forecasts with and without feature selection, based on different classification methods and explain the effect of feature selection on classification methods. The classification algorithms are shown in Figure1.

Testing Strategy

In order to get robustness prediction, we perform 10- fold cross-validation model on the predictors (duda et al., 2001). This method has been proved to be statistically good enough in evaluating the performance of the predictive model(Mitchell, 1997a). In 10-fold cross-validation, the training set is equally divided into 10 different subsets. Nine out of 10 of the subsets are used to train the classifier and the tenth subset is used as the test set. The procedure is repeated 10 times, with a different subset being used as the test set and the best result has been chosen.

In order to reliably evaluate the predictors, we consider not only prediction accuracy but sensitivity and specificity. The accuracy of a predictor on a given test set is the percentage of test set tuples that are correctly predicted by the predictor. Prediction accuracy for five classes can be measured by a confusion matrix shown in Table 3.3 with formula (1).

Table3.3. Confusion matrix for five classes

		Predicted class				
		Very low	low	normal	high	very high
Actual class	Very low	a_1	b_1	c_1	d_1	e_1
	Low	a_2	b_2	c_2	d_2	e_2
	Normal	a_3	b_3	c_3	d_3	e_3
	High	a_4	b_4	c_4	d_4	e_4
	Very high	a_5	b_5	c_5	d_5	e_5

$$Accuracy = \frac{a_1 + b_2 + c_3 + d_4 + e_5}{\sum_{i=1}^{5} a_i + b_i + c_i + d_i + e_i} \qquad (7)$$

Sensitivity is also referred to the proportion of positive tuples that are correctly identified while specificity is the proportion of negative tuples that are correctly identified(Han and Kamber, 2006).

3.2.3. Third stage: Hybrid feature selection

Based on special conditions in stock exchange, occasionally we encounter with many attributes whereas some of them no longer have useful information and just complicate the condition. For this reason feature selection is one of the very crucial aspect that has a highly regarded recommendation (Huang, 2012a; Huang et al., 2008a; Tsai and Hsiao, 2010).

In this section to investigate the features which have greater effect on risk and return and better analysis of algorithms results a novel feature selecting method in 2 levels is established. It should be noted that feature selecting in capital markets issues has double importance. The reason is that we encounter with so many features that are either useless or have low information value. Thus, dealing with these features is time wasting without any gain. Feature selection methods are generally divided into three categories: 1. Filter methods, 2. Wrapper Methods, and 3. Hybrid methods(Chen and Cheng, 2012). In this approach we use a hybrid model based on combination of filter and function-based clustering method to extract a set of efficient features as a follow:

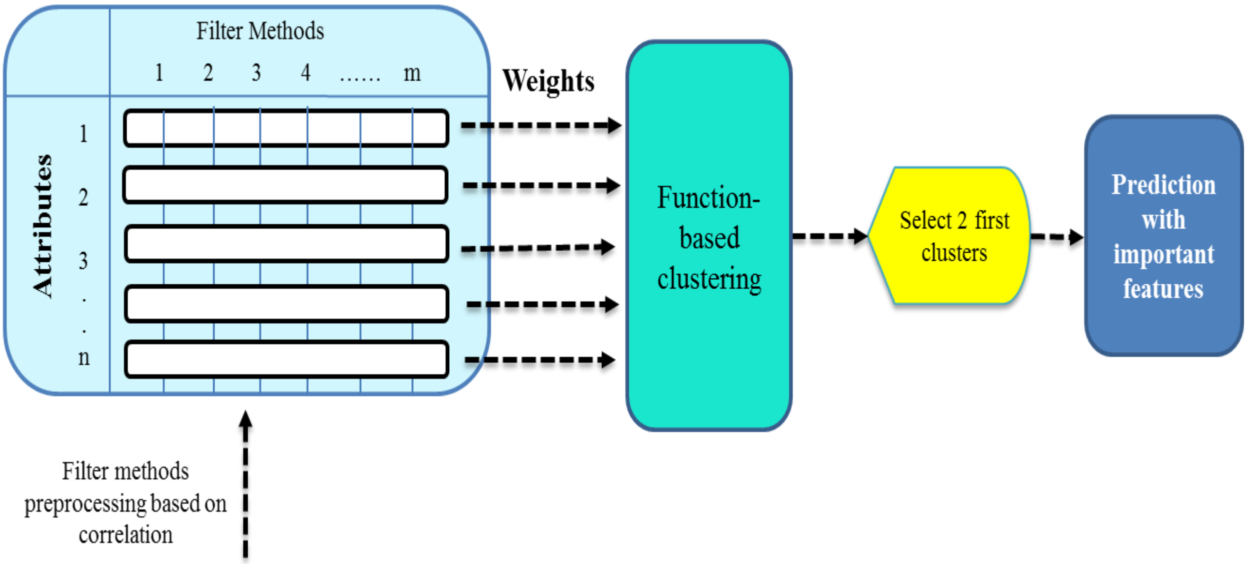

Filter Methods
1 2 3 4 …… m
Attributes
1
2
3
.
.
n
Weights
Function-based clustering
Select 2 first clusters
Prediction with important features
Filter methods preprocessing based on correlation

Figure3.2. Hybrid feature selection

- **Filter methods**

According to Witten and Frank (2011) seven algorithms were defined as Filter method: Chi square (Kononenko, 1994), info gain (Dumais et al., 1998), Gain Ratio(duda et al., 2001), Relief-f (Kononenko, 1994), Consistency(Liu and Setiono, 1996), One R (Holte, 1993) and CFS(Hall, 1998). In addition, Symmetrical Uncertainty and SVM algorithm are also used for weighting the features(Chen and Cheng, 2012). In this section, to compare the importance of each feature using mentioned methods, a comprehensive analysis was conducted on the features and eventually the weightings of features are presented.

- **Function-based clustering method**

After attaining the features weights by different filter based algorithms we have n attributes with m attributes' weight and then we need a model to determine the important features' clustering between these weighted attributes. In this section we develop Li (2006a) function-based clustering method. This model is based on hierarchical divisive clustering method which begins with one cluster including all objects, ($\mathbf{X}_{n\times m}$). For the object $\mathbf{x}_1,\ldots,\mathbf{x}_n$, we denote the vector of group membership of objects as $\mathbf{z}=(z_1, \ldots, z_n)^T$, where $\mathbf{z}\in\mathbf{Z}$, and $\mathbf{Z}$ is the space of sign vectors defined to be

$$\mathbf{Z}=\left\{\mathbf{z}=(z_1, \ldots, z_n)^T \mid z_i=\pm 1\right\} \quad (8)$$

All objects that are associated with an entry of 1 in $\mathbf{z}$ are classified into one group, whereas the others with an entry of −1 are classified into the other group.

Then by using the model of multivariate analysis of variance defined to be

$$\mathbf{x}_i=\boldsymbol{\mu}+z_i\boldsymbol{\gamma}+\boldsymbol{\varepsilon}_i, \qquad i=1,2,\ldots,n \qquad (9)$$

where the error vectors εi are assumed to be normally distributed with a zero mean and a common covariance matrix V, i.e. N(0,V). In addition ε_i and ε_j (i ≠j) are assumed to be independent. Then by maximum likelihood, the clustering problem is formulated as a least squares optimization problem.

$$\min_{\alpha,\boldsymbol{\beta},\mathbf{z}\in\mathbf{Z}}\{(\mathbf{z}-\alpha\mathbf{1}-\mathbf{X}\boldsymbol{\beta})^T(\mathbf{z}-\alpha\mathbf{1}-\mathbf{X}\boldsymbol{\beta})\} \qquad (10)$$

Simultaneously the unknown vector of cluster membership and the coefficients of the linear clustering function are estimated. The computation of the clustering-function-based method will be converted to that of sign analysis(Li, 2006b), and by problem solving two clusters is achieved.

Next, one of these groups based on higher within-group dispersion matrix is further divided into two dissimilar subgroups. The process continues until some stopping criterion has been satisfied. Most of the stopping criteria are based on within-group dispersion and/or between-group dispersion matrices.

By this approach we use the advantages of different filter methods and use these weighting attributes by function-based clustering method to make more accurate decision of effective feature.

3.3. Experimental results and analysis

In this study a database including 44 input features and 2 goal features are gathered from TSE data from 2003 to 2012. The resulting database has 1963 records for 400 companies.

According to a group of experts, 5 intervals were introduced for the real return: very high with a range higher than 9.3 , high with the range of 4 to 9.3 , average with a range of 1.14 to 4, low with the range of -1.3 to 1.14 and very low that lower than -1.3 . Risk is also classified in 3 intervals: high in range of higher than 15.5, average in range of 6.3 to 15.5 and low in rage of lower than 6.3. According to literature, it is found out that to predict return, negative and positive return (Tsai et al., 2011; Wang and Chan, 2006) and negative and positive return trend (Enke and Thawornwong, 2005)are used [see also (Patel et al., 2014; Yu et al., 2014; Zhang et al., 2014a)]. For more accuracy, we increased the prediction intervals. These intervals give more information to investors and they can develop a balance between the share price and the future gained return. In fact, the information which is limited to the company's profitability or losses does not help them very much. Beside this, risk has been rarely mentioned in prediction field of stock exchange. We can conclude whether the proposed return range is optimal or not just by knowing the risk amount. The previous studies of the field have just focused on return prediction while these 2 features together show the Portfolio Efficient Frontier and investors can use it to select the best optimal portfolio. The process is illustrated in figure 3.3.

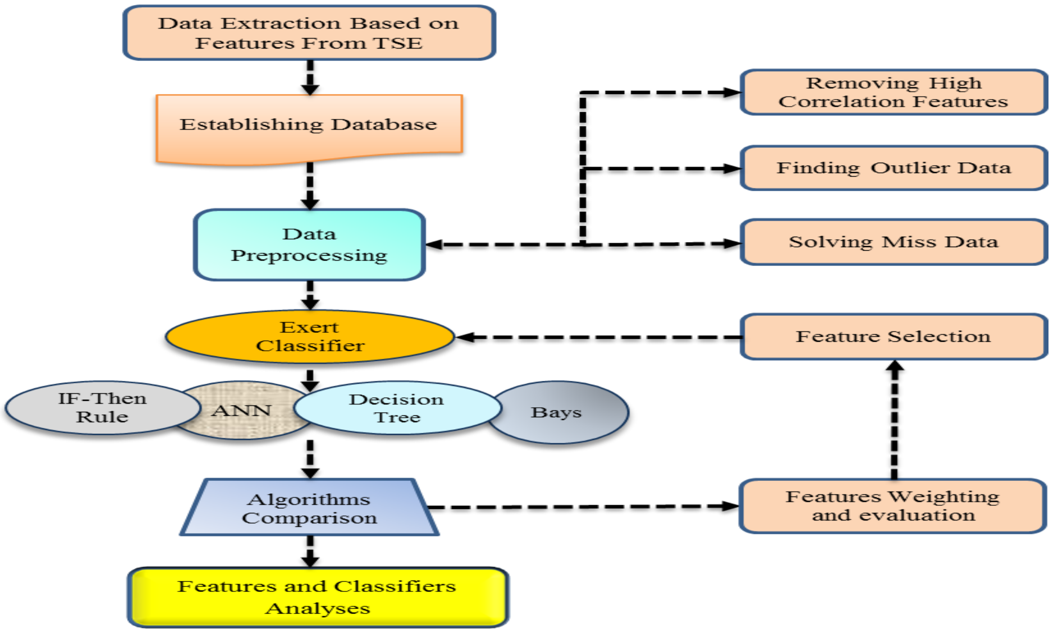


Figure3.3. Experimental results process

3.3.1. Data pre-processing

- **Removing high correlation features:** features with higher than 0.95% correlations on the basis of Pearson test were removed. Therefore, features including: gross profit to sale percentage, assess the loan usefulness, stock cumulative profit, fixed assets return percentage, debt to equity ratio, and current debt to equity ratio are removed. Their correlation with return and risk variables is higher than 95% in comparison with the other features. The correlation between real return and risk with other features has been illustrated in table 3.4 and 3.5 respectively.

Table3.4. Correlation between real return and other features

debt to total assets ratio	net profit to sale	Operating profit to sale	net profit to Gross profit	ROA	ROE	current assets turn over	Fixed asset turnover	current ratio	quick ratio
0.0023	0.017	0.0488	-0.0131	-0.1494	-0.0113	0.0005	-0.0019	-0.0304	0.0103
return from market	Net working capital	Average payment period	current assets ratio	working capital return	Total asset turnover	Equity ratio	predicted Profit margins	long-term debt to equity ratio	Debt coverage ratio
0.0218	0.0251	-0.0113	0.0128	-0.0021	-0.0937	0.0977	0.0066	0.0011	0.0246
Efficiency	DPS	EPS	capital	EPS prediction	EPS difference with real EPS	return ratio without risk	EPS growth	Total predicted income	
0.0135	-0.1168	-0.1402	0.0059	-0.1211	0.0037	-0.0384	0.0194	-0.0547	
Total income growth	profit margin growth rate	EPS cover	Liquidity ratios	P/E	stock book value	P/S	stock market value	beta coefficient	
-0.0231	0.0135	0.0171	-0.0378	0.0058	-0.0377	0.0109	0.0651	0.0153	

Table3.5. Correlation between Risk and other features

debt to total assets ratio	net profit to sale	Operating profit to sale	net profit to Gross profit	ROA	ROE	current assets turn over	Fixed asset turnover	current ratio	quick ratio
0.0203	-0.0301	0.0444	0.0148	-0.0307	-0.0176	-0.0055	-0.0062	0.05	-0.0015
return from market	Net working capital	Average payment period	current assets ratio	working capital return	Total asset turnover	Equity ratio	predicted Profit margins	long-term debt to equity ratio	Debt coverage ratio
0.0414	0.0056	0.0099	-0.0057	-0.0021	-0.0195	-0.0112	0.0296	0.0212	-0.0126
Efficiency	DPS	EPS	capital	EPS prediction	EPS difference with real EPS	return ratio without risk	EPS growth	Total predicted income	
0.0135	0.0099	0.0222	-0.0317	0.02251	-0.0156	-0.0935	0.0159	-0.0247	
Total income growth	profit margin growth rate	EPS cover	Liquidity ratios	P/E	stock book value	P/S	stock market value	beta coefficient	
-0.0369	-0.0031	-0.0313	-0.0238	-0.0114	-0.0089	-0.0149	0.0251	-0.0283	

- **Finding outlier data and miss data:** To find outlier data in database, at first we used the distance-based approach and by analyzing remote records we concluded that some are very large governmental companies that are not applicable in our study and in fact they are not outlier data. Other outliers were also deleted. By using the densityapproach12 records were known as Outlier points, in which 7 of them were large companies. Thus they remained in the database. However, others were omitted, mostly because they did not provide accurate information. With clustering approach we determined some outlier data that were in none of the clusters. As a result 6 samples were identified as outlier data. By analyzing input feature of the company, no suspected case was found and no company was omitted. Finally, by using the techniques based on the deviation, 5 records were known as outlier points. Analyzing records clarified that input feature of these records were pertained to the previous fiscal year and then were removed. Also, among 1963 records, 12 records because of miss value derived from lack of information are deleted.

3.3.2. Comparison of algorithms

Table 3.6 shows the results of decision trees, rule base algorithms, and neural networks accuracy for real return prediction. As it is clear (from table 3.6), LAD Tree algorithm has achieved a higher accuracy in the prediction of return. The other algorithms, like SVM and K-Nearest neighbor, had accuracy of close to 60%. Thus, due to their low accuracy, we did not apply them for analysis. Low accuracy of SVM algorithm can be because of its high sensitivity to the missed data. In fact, it is generally an algorithm to predict 2 class outputs, while we are dealing with multi-class data and many missed data.

Table 3.6. Algorithms Comparison for real return variable

Algorithm	Accuracy	Sensitivity	Specificity	Number of Rules	Tree size	Number of leaves
LAD Tree[1](Hall et al., 2009)	78.00	77.15	75.29	-	31	15
Cart Decision Tree[2]	76.50	74..27	74.3	-	13	7
DTNB Rule[3](Hall and Frank, 2008)	76.00	75.08	73.55	998	-	-
Decision Table[4]	75.50	75.14	72.44	56	-	-
Rep Tree[5]	75.00	74.09	71.64	-	33	17
RIDOR Rules (Witten &Eibe, 2011)	75.00	75.3	73.07	208	-	-
J Rip Rule[36]	74.90	73.18	74.02	9	-	-
BF Tree[6](Shi, 2007)	74.50	78.49	74.28	-	9	5
Part Rule[7](Frank and Witten, 1998)	72.60	67.84	69.15	104	-	-
J 48 Graph	71.50	69.68	66.38	-	1619	810
NB Tree(Witten &Eibe, 2011)	71.00	70.2	69.5	-	97	49
LMT Tree(Witten &Eibe, 2011)	70.50			-	30	20
Neural Net (RBF)	70.00	67.3	66.4	-	-	-
Neural Net (MLP[8])	69.00	66.3	67.1	-	-	-
Auto MLP[9]	70.00	67.01	66.02	-	-	-
Rule Induction[10]	68.50	69.27	66.76	56	-	-
FT Tree	68.50	66.3	64.8	-	45	28
J 48 Tree	67.39	66.2	65.6	-	303	152
ID3 Numerical	61.50	58.42	57.47	-	1905	979
Bays	60.00	58	62.28	-	-	-

From investigating the results it can be stated that generally denser trees have shown better accuracy than big ones. This is clear in the cases of ID3 Numerical, J48 Graph, and J48 Tree. Due to the importance of pruning after tree construction, since these models have no pruning stage or their pruning algorithm is not efficient, their accuracy is not acceptable.

Trees with the size of less than 33 for real returns have an accuracy of higher than 70%. Despite the medium accuracy of these trees compared to larger trees, they have higher accuracy in test data.

DTNB Rule algorithm has the highest accuracy in comparison with the other “If-Then Rules” algorithms on test data. On average, the accuracy of “If- Then Rules” algorithms is better than trees, however the best

[1] It uses AD Tree with boosting for prediction and cross validation to select training data and class label decisions are done on the basis of this algorithm most votes.

[2] The used tree’s split has been done by Gini index algorithm and the Pruning is done based on cost – complexity after constructing the tree.

[3] At first, these models determined the important variables by using Naive Bays algorithm (18 attribute achieve) and then offer classification prediction rules are provided by decision tree.

[4] Algorithm first uses the Forward election algorithm to determine the input variables. After 375 implementing the algorithm, ROE, Net working capital, EPS prediction and return are known as effective features and then based on best first (BF) algorithm the model is constructed.

[5] This algorithm is based on information gain and its Pruning is based on prediction error minimization.

[6] BF Tree uses binary Pruning to construct a tree based on selecting the first important feature as nodes point. Based on this, the model has found the feature that best predicts the output variable among other input variables. Then a binary tree based on this variable is constructed. Best-First (BF) Decision Tree just use return variable to prediction real return. (Just this input is considered in this method’s tree).

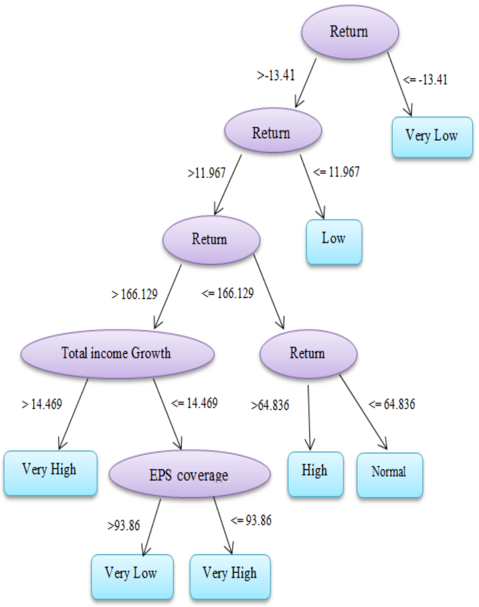
[7] This method has used C4.5 algorithm in every implantation and has used the best of them as a new rule in the model rules.

[8] Feed Forward Multi Layout Perceptron based on Levenberg- Marquat algorithm with 12 Neuron in hidden layer.

[9] Number of neurons and hidden layers are optimized.

[10] This algorithm gains the rules based on the information gain and first gained rule is:
If return without risk ≤ 11.967 and return without risk > -12.164 and EPS > 51.447 and EPS coverage percent > 164.500 then Low
This algorithm, gains the rule based on the information gain and based on decrease amount in model accuracy while constructing the rules we prune them. And will construct the model till there is no other variable to be added to the model or the error amount is more than 0.5.

prediction is obtained by LAD Tree. Some algorithms of tree types are shown in Figures 3.4 to 3.7 (Returns in all figures' nodes are return ration without considering risk).



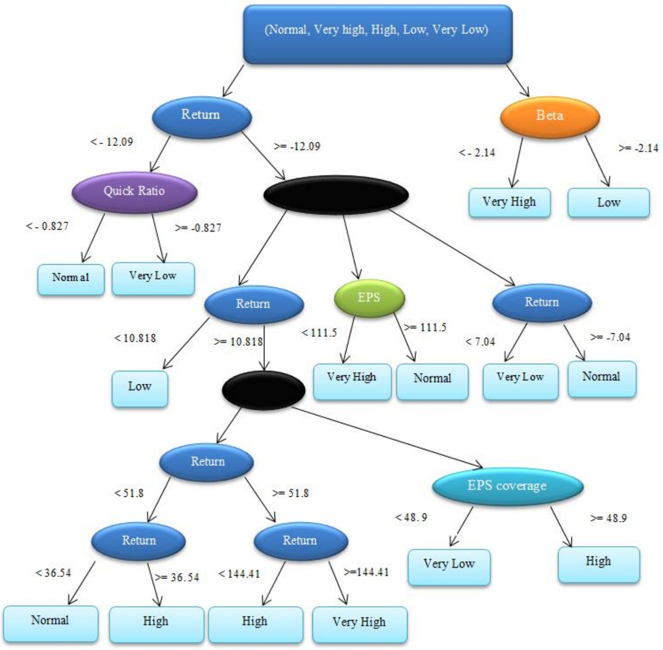


Figure3.4. Real return prediction - Cart Decision Tree

Figure3.5. Real return prediction - LAD Tree

Figure3.6. Best-First Decision Tree

0 Return< -13.10281: very low (365.0/62.0)
0 Return >= -13.10281
1 Return < 10.81819: Low (392.0/96.0)
1 Return >= 10.81819
2 Return < 53.97851: normal (326.0/126.0)
2 Return >= 53.97851
3 Return < 136.66997: high (184.0/63.0)
3 Return >= 136.66997: Very high (72.0/27.0)

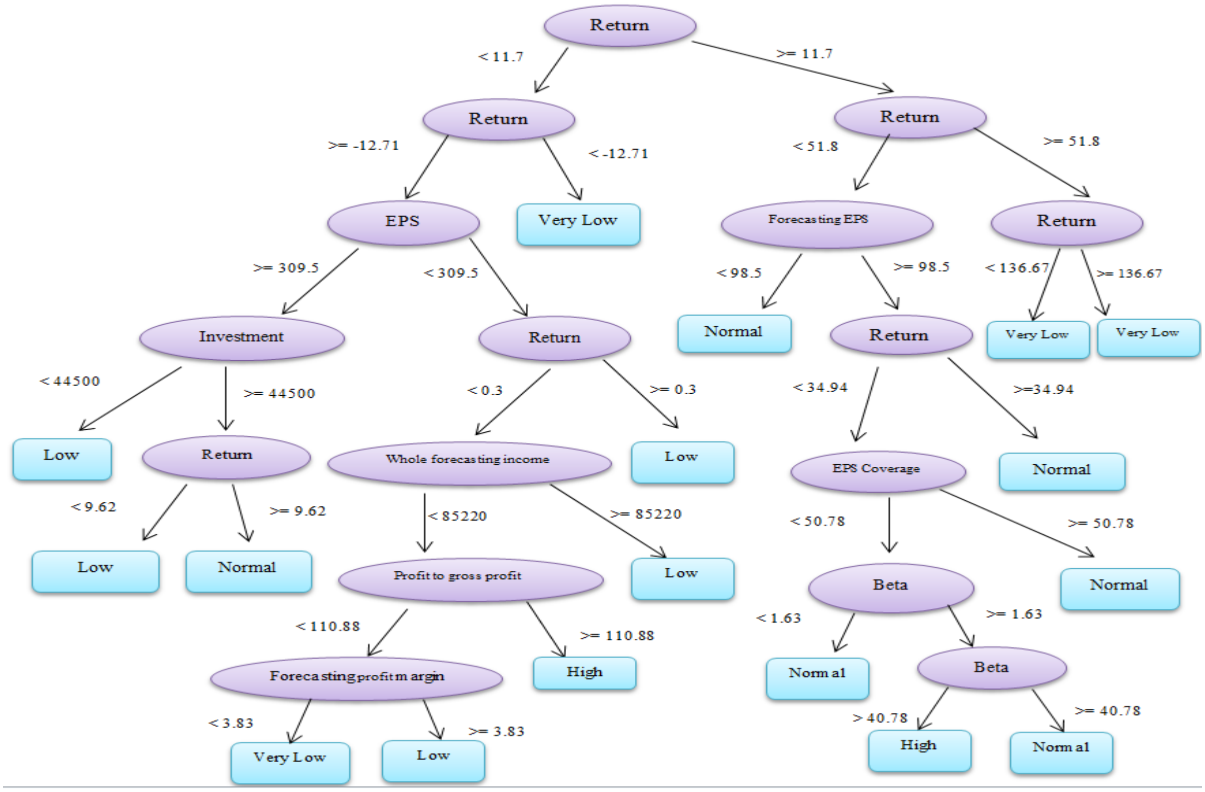


Figure3.7. Real return prediction - Rep Tree

Similarly, risk is predicted as shown in table 3.7.

Table3.7. Algorithm comparison for risk variable

Algorithm[11]	Accuracy	Sensitivity	Specificity	Number of Rules	Tree size	Number of leaves
LAD Tree	78.24	69.62	80.24	-	31	20
DTNB Rule	77.41	69.44	78.51	426	-	-
Decision Table	76.57	65.38	81.32	297	-	-
BF Tree[12]	76.15	67.41	74.71	-	109	55
J Rip Rule	74.90	73.7	74.3	9	-	-
J 48 Graph	73.64	64.68	71.66	-	721	361
Part Rule	73.64	65.36	71.64	55	-	-
Rep tree	72.80	67.13	69.39	-	77	39
Rule Induction	71.55	64.45	70.25	59	-	-
J 48 Tree	71.55	70.9	72.5	-	313	157
FT Tree	67.78	65.6	64.8	-	63	32
NB Tree	66.95	66.3	64.7	-	7	4
Neural Net (MLP)	59.00	61.2	59.22	-	-	-
ID3 Numerical	57.00	55.1	54.2	-	553	403
Bays	55.65	57.3	50.2	-	-	-

It can be stated that generally larger trees (for example higher than 300) and smaller trees have no prominent results in comparison to medium sized trees. In comparison to “If- Then Rules” algorithms, the highest prediction accuracy for test data is gained from DTNB, similar to real return prediction. For risk prediction

[11] Some algorithms that used in real return prediction have low prediction accuracy in risk prediction and we don’t report their results.

[12] The beta coefficient is known as the first leaf.

also “If- Then Rules” algorithms accuracy is also better than those gained by tree, but the best prediction is gain by LAD Tree. To predict risk, neural network results have lower accuracy in comparison with the prediction of return. In Figure 3.8 LAD tree for risk prediction is depicted.

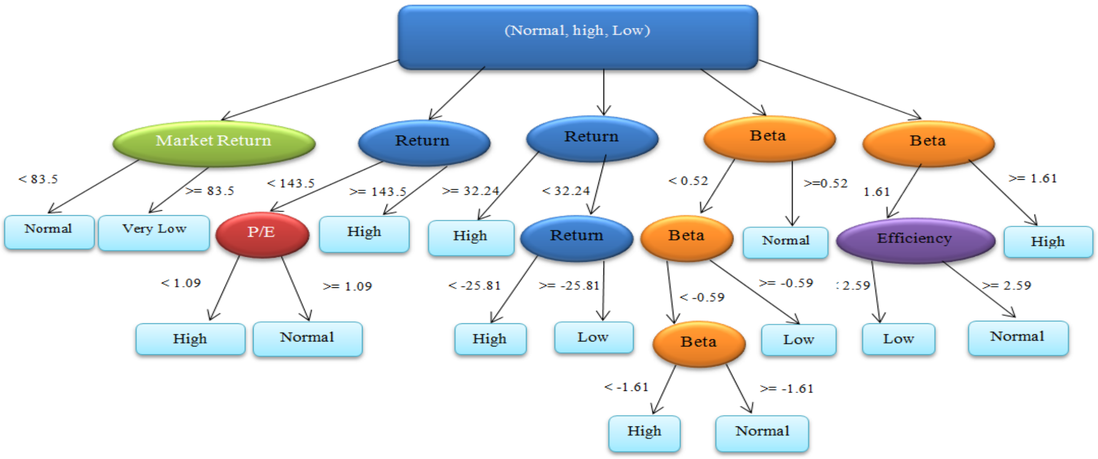


Figure3.8. Risk prediction- LAD Tree

3.3.3.   Prediction after hybrid Feature selection

In this section, we develop a hybrid feature selection to evaluate each feature. In the first stage by using the above mentioned filter methods, a comprehensive analysis of the features is conducted to assign suitable weights for features. (All features even high correlation features are considered.)

Depending on the evaluation function, we applied the following filter methods:

- Based on interval method: Relief-f method.
- Based on information: Gini index, Information gain ratio, Information gain, Symmetrical Uncertainty methods.
- Based on correlation: Chi square, one R methods.
- Based on consistency: Consistency method.
- Based on classified errors: SVM method.

The CFS method did not have any acceptable result because of dependence and was eliminated in method pre-processing step.

We have applied Rapid Miner and Weka software to implement the algorithms (Hofmann and Klinkenberg, 2013). Furthermore, the algorithm which is used by Weka is mentioned, like Weka IG, Weka Chi-2….

The resulting weights for features of risk parameter and real return parameter are shown in Tables 3.8 and 3.9, respectively.

Table3.8. Weighting for risk parameter

Attributes	Chi-2	IG Ratio	Info Gain	R-f	SVM	Con Sistency	Weka IG	Weka chi-2	Weka con	Weka IGR	Weka R-f	Gini Index	Weka oneR
Return	1	0.69	0.61	1	0.024	0.87	0.513	0.437	0.513	0.63	0.9	0.725	0.759
Beta	0.188	0	0.062	0.397	0.079	0.163	0.097	0.073	0.097	0.132	0.519	0.061	0.124
Efficiency	0.091	0.707	0.076	0.071	0.083	0.099	0.056	0.044	0.056	0.112	0.093	0.093	0.127
Market return	0.058	0.67	0.072	0.019	0.023	0.058	0.106	0.092	0.106	0.157	0.021	0.064	0.117
EPS prediction%	0.008	0.615	0.099	0	0.076	0.005	0.05	0.039	0.05	0.17	0.002	0.112	0.111
long-term debt to equity	0.032	0.487	0.076	0.011	0.029	0.039	0.085	0.078	0.085	0.136	0.015	0.077	0.118
Total income growth %	0.021	0.707	0.055	0.005	0.045	0.016	0.03	0.025	0.03	0.16	0.002	0.075	0.095
EPS growth%	0.025	0.707	0.046	0.005	0.061	0.016	0.026	0.021	0.026	0.136	0.002	0.061	0.095
ROE	0.058	0.328	0.074	0.054	0.07	0.073	0.039	0.031	0.039	0.135	0.046	0.092	0.089
DPS	0.046	0.328	0.078	0.047	0.025	0.063	0.041	0.033	0.041	0.15	0.045	0.089	0.123
Debt to total assets ratio	0.07	0.338	0.057	0.035	0.065	0.086	0.03	0.024	0.03	0.141	0.034	0.057	0.1
profit margin growth rate	0.01	0.615	0.036	0.005	0.084	0.008	0.021	0.017	0.021	0.136	0.009	0.045	0.055
EPS	0.046	0.421	0.024	0.063	0.088	0.045	0.016	0.013	0.016	0.056	0.131	0.033	0.093
P/E	0.027	0.328	0.064	0.013	0.108	0.041	0.032	0.025	0.032	0.102	0.002	0.075	0.127
Predicted profit margin	0.053	0.319	0.067	0.071	0.023	0.07	0.036	0.028	0.036	0.11	0.037	0.063	0.047
Stock market value	0.029	0.615	0.023	0.013	0.043	0.029	0.016	0.012	0.016	0.065	0.011	0.027	0.049
ROA	0.033	0.422	0.038	0.01	0.038	0.046	0.023	0.019	0.023	0.152	0	0.056	0.049
current debt to equity ratio	0.039	0.381	0.046	0.003	0.043	0.049	0.026	0.018	0.026	0.121	0.002	0.039	0.092
debt to equity	0.036	0.419	0.047	0	0.012	0.05	0.041	0.039	0.041	0.114	0.005	0.026	0.043
Book value	0.015	0.615	0.013	0.004	0.131	0.016	0	0	0	0	0.001	0.021	0.048
assess the loan usefulness	0.039	0.421	0.026	0.01	0.031	0.052	0.018	0.016	0.018	0.122	0.006	0.018	0.075
Equity ratio	0.018	0.615	0.003	0.001	0.099	0.019	0	0	0	0	0	0.011	0.04
Gross profit to sale	0.021	0.107	0.055	0.005	0.034	0.016	0.03	0.025	0.03	0.134	0.002	0.074	0.059
Current ratio	0.016	0.615	0.008	0.002	0.073	0.018	0	0	0	0	0	0.013	0.032
Operating profit to sale	0.017	0.615	0	0.001	0.09	0.02	0	0	0	0	0.004	0.002	0.023
P/S	0.014	0.615	0.01	0.002	0.06	0.015	0	0	0	0	0	0.018	0.037
Fixed asset turnover	0.032	0.421	0.006	0.027	0.059	0.024	0	0	0	0	0.128	0.011	0.061
fixed assets return	0.016	0.615	0.008	0.002	0.058	0.018	0	0	0	0	0	0.013	0.032
Debt coverage ratio	0.005	0.366	0.041	0.002	0.045	0.008	0.024	0.019	0.024	0.073	0	0.052	0.088
Liquidity ratio	0.015	0.421	0.028	0.011	0.018	0.022	0.033	0.027	0.033	0.083	0.006	0.025	0
Net profit to sale	0.023	0.377	0.021	0.004	0	0.04	0.015	0.012	0.015	0.046	0.001	0.03	0.068
working capital return percentage	0.002	0.319	0.027	0.012	0.094	0.003	0.017	0.015	0.017	0.064	0.001	0.02	0.049
EPS deviation	0	0.338	0.026	0.006	0.033	0	0.017	0.014	0.017	0.06	0	0.038	0.067
Capital	0.034	0.371	0.016	0.01	0.04	0.036	0	0	0	0	0.025	0.022	0.052
current assets ratio	0.034	0.371	0.016	0.009	0.024	0.037	0	0	0	0	0.025	0.022	0.041
Total predicted income	0.009	0.347	0.024	0.003	0.026	0.015	0.016	0.013	0.016	0.051	0	0.034	0.019
Net profit to gross profit	0.016	0.338	0.009	0.03	0.068	0.019	0	0	0	0	0.027	0.015	0.013
EPS coverage percent	0.008	0.328	0.016	0.014	0.061	0.016	0	0	0	0	0.003	0.024	0.063
Net working capital	0.015	0.358	0.009	0.019	0.011	0.025	0	0	0	0	0.001	0.013	0.064
Average payment	0.018	0.319	0.011	0.034	0.024	0.034	0	0	0	0	0.013	0.007	0.053
Total asset turnover	0.015	0.358	0.008	0.019	0.011	0.025	0	0	0	0	0.001	0.013	0.054
Quick ratio	0.027	0.328	0.009	0.001	0.043	0.038	0	0	0	0	0.01	0.015	0.027
Stock cumulative profit	0.012	0.338	0.004	0.005	0.016	0.018	0	0	0	0	0.001	0.008	0.033
Current assets turnover	0.012	0	0	0.01	0.073	0.019	0	0	0	0	0.007	0	0.051

Table3.9. Weighting for real return parameter

Attributes	Chi-2	IGR	IG	R-f	SVM	Con sistency	Weka IG	Weka chi-2	Weka con	Weka IGR	Weka R-f	Gini Index	Weka oneR
Return	1	0.69	0.61	1	0.024	0.87	0.513	0.437	0.513	0.63	0.9	0.725	0.759
Market return	0.188	0	0.062	0.397	0.079	0.163	0.097	0.073	0.097	0.132	0.519	0.061	0.124
ROA	0.091	0.707	0.076	0.071	0.083	0.099	0.056	0.044	0.056	0.112	0.093	0.093	0.127
Beta	0.058	0.67	0.072	0.019	0.023	0.058	0.106	0.092	0.106	0.157	0.021	0.064	0.117
ROE	0.008	0.615	0.099	0	0.076	0.005	0.05	0.039	0.05	0.17	0.002	0.112	0.111
EPS growth %	0.032	0.487	0.076	0.011	0.029	0.039	0.085	0.078	0.085	0.136	0.015	0.077	0.118
Profit margin growth rate	0.021	0.707	0.055	0.005	0.045	0.016	0.03	0.025	0.03	0.16	0.002	0.075	0.095
Operating profit to sale	0.025	0.707	0.046	0.005	0.061	0.016	0.026	0.021	0.026	0.136	0.002	0.061	0.095
EPS	0.058	0.328	0.074	0.054	0.07	0.073	0.039	0.031	0.039	0.135	0.046	0.092	0.089
DPS	0.046	0.328	0.078	0.047	0.025	0.063	0.041	0.033	0.041	0.15	0.045	0.089	0.123
EPS prediction%	0.07	0.338	0.057	0.035	0.065	0.086	0.03	0.024	0.03	0.141	0.034	0.057	0.1
Predicted profit margin	0.01	0.615	0.036	0.005	0.084	0.008	0.021	0.017	0.021	0.136	0.009	0.045	0.055
Net profit to sale	0.046	0.421	0.024	0.063	0.088	0.045	0.016	0.013	0.016	0.056	0.131	0.033	0.093
EPS deviation	0.027	0.328	0.064	0.013	0.108	0.041	0.032	0.025	0.032	0.102	0.002	0.075	0.127
Efficiency	0.053	0.319	0.067	0.071	0.023	0.07	0.036	0.028	0.036	0.11	0.037	0.063	0.047
P/S	0.029	0.615	0.023	0.013	0.043	0.029	0.016	0.012	0.016	0.065	0.011	0.027	0.049
Net profit to Gross profit	0.033	0.422	0.038	0.01	0.038	0.046	0.023	0.019	0.023	0.152	0	0.056	0.049
Quick ratio	0.039	0.381	0.046	0.003	0.043	0.049	0.026	0.018	0.026	0.121	0.002	0.039	0.092
Equity ratio	0.036	0.419	0.047	0	0.012	0.05	0.041	0.039	0.041	0.114	0.005	0.026	0.043
stock market value	0.015	0.615	0.013	0.004	0.131	0.016	0	0	0	0	0.001	0.021	0.048
Book value	0.039	0.421	0.026	0.01	0.031	0.052	0.018	0.016	0.018	0.122	0.006	0.018	0.075
Long-term debt to equity	0.018	0.615	0.003	0.001	0.099	0.019	0	0	0	0	0	0.011	0.04
Gross profit to sale	0.021	0.107	0.055	0.005	0.034	0.016	0.03	0.025	0.03	0.134	0.002	0.074	0.059
Debt to equity ratio	0.016	0.615	0.008	0.002	0.073	0.018	0	0	0	0	0	0.013	0.032
Debt coverage ratio	0.017	0.615	0	0.001	0.09	0.02	0	0	0	0	0.004	0.002	0.023
Current debt to equity	0.014	0.615	0.01	0.002	0.06	0.015	0	0	0	0	0	0.018	0.037
Net working capital	0.032	0.421	0.006	0.027	0.059	0.024	0	0	0	0	0.128	0.011	0.061
Assess the loan usefulness	0.016	0.615	0.008	0.002	0.058	0.018	0	0	0	0	0	0.013	0.032
Stock cumulative profit	0.005	0.366	0.041	0.002	0.045	0.008	0.024	0.019	0.024	0.073	0	0.052	0.088
P/E	0.015	0.421	0.028	0.011	0.018	0.022	0.033	0.027	0.033	0.083	0.006	0.025	0
Liquidity ratio	0	0.615	0.007	0.007	0.025	0	0	0	0	0	0.001	0.012	0.02
working capital return percentage	0.023	0.377	0.021	0.004	0	0.04	0.015	0.012	0.015	0.046	0.001	0.03	0.068
Total income growth%	0.002	0.319	0.027	0.012	0.094	0.003	0.017	0.015	0.017	0.064	0.001	0.02	0.049
current ratio	0	0.338	0.026	0.006	0.033	0	0.017	0.014	0.017	0.06	0	0.038	0.067
Current assets ratio	0.034	0.371	0.016	0.01	0.04	0.036	0	0	0	0	0.025	0.022	0.052
Debt to total assets ratio	0.034	0.371	0.016	0.009	0.024	0.037	0	0	0	0	0.025	0.022	0.041
Current assets turn over	0.009	0.347	0.024	0.003	0.026	0.015	0.016	0.013	0.016	0.051	0	0.034	0.019
Total asset turn over	0.016	0.338	0.009	0.03	0.068	0.019	0	0	0	0	0.027	0.015	0.013
EPS coverage percent	0.008	0.328	0.016	0.014	0.061	0.016	0	0	0	0	0.003	0.024	0.063
fixed assets turn over	0.015	0.358	0.009	0.019	0.011	0.025	0	0	0	0	0.001	0.013	0.064
Total predicted income	0.018	0.319	0.011	0.034	0.024	0.034	0	0	0	0	0.013	0.007	0.053
Fixed assets return	0.015	0.358	0.008	0.019	0.011	0.025	0	0	0	0	0.001	0.013	0.054
Average payment	0.012	0.338	0.004	0.005	0.016	0.018	0	0	0	0	0.001	0.008	0.033
capital	0.012	0	0	0.01	0.073	0.019	0	0	0	0	0.007	0	0.051

After attaining the features weights by different filter based algorithms we have 13 columns (m) with 44 attributes' weight (n) and then because of obtain accurate clusters, we use preprocessing on this data set. Therefore, the seventh column (Weka IG) of the Tables 4 and 5 is put aside from the analysis, because of its correlation with other ones. This way we do the grouping for 12 columns and 44 features.

Then, we use the clustering-function-based method for clustering attributes to predict the most important features. Usually the first and second clusters are the effective ones and we choose them(Li, 2006b).

For real return,in the first step of clustering, return and market return is separated from the other attributes. In other words, they are more important with higher weights compared with other attributes. In the second step, 6 features out of 43 remaining ones are separated. Finally, eight features in the first and second clusters are considered as important features. Similarly, for risk parameter in the first step, three features, return, beta coefficient and efficiency of 44 features can be separated. In the second step, 12 features out of the 42 remaining ones can be separated. Finally 15 features from 44 features are selected as important ones. The results for risk and real return parameters are presented in the Table 3.10.

Table 3.10. Selected features for risk and real return parameters

Selected features of the first and second cluster, based on function clustering method for real return parameter.	Return, Market return, Beta coefficient, Return on asset (ROA), Percent of growthEPS, EPS, Predicted profit margin, EPS coverage percent.
Selected features of the first and second cluster, based on function clustering method for risk parameter.	Return, Beta coefficient, Efficiency, Market return, EPS prediction, Percent of growth EPS, DPS, P/E, EPS, Equity ratio, Stock book value, Debt to total assets ratio, Predicted profit margin,P/S,Total incomes Growth

As can be seen, more features were selected for the risk variable than with real return. The classification results with selected features show in parenthesis at Table 3.11, in which "Deviation = Accuracy base on selected feature - Accuracy base on all feature". If deviation is positive, it means that, use of important feature will improve the prediction results and vice versa.

Table 3.11. Algorithms Deviation

Algorithm	Risk Accuracy Deviation	Return Accuracy Deviation
LAD Tree	%2 (80.24%)	1 (79%)%
Cart Decision Tree	%1.5(66.5%)	%-4.5 (72%)
DTNB Rule	%-0.9 (76.51%)	%-1 (75%)
Decision Table	%-1.2(75.37%)	%0.07 (76.20%)
BF Tree	%-2 (74.15%)	%1.5 (76%)
J Rip Rule	%0 (74.90%)	%-1.2 (73.7%)
J 48 Graph	%-1.83 (71.81%)	%-2 (69.50%)
Part Rule	%1.91 (75.55%)	%2 (74.6%)
Rep tree	%0.77 (73.52%)	%-2 (73%)
Rule Induction	%0.95 (72.50%)	%1. 5 (70 %)
J 48 Tree	%-1.5 (70. 05%)	%-0.50 (66.89%)
FT Tree	%2 (69.18%)	% 2 (70.5%)
NB Tree	%-4.20 (62.75%)	%-1 (70%)
Neural Net (MLP)	%2.00 (61.00%)	%2.5 (71.5%)
ID3 Numerical	%2.5 (59.5%)	%2 (63.5%)
Bays	%-1.40 (54.15%)	%-2.00 (58.00%)

As results show from Table 3.11, by this hybrid method we can get better prediction in some methods with fewer numbers of features.

3.4. Discussion

The real return results in prediction with selected features:

If for denser structure trees all effective features in first prediction are selected by the proposed hybrid model, results in better accuracy, such as “BF tree”, “LAD tree”, and “FT tree”. Otherwise, it is possible that accuracy drops, like “CART and Rep” trees. The selected features have different effect on the accuracy of forecasting. Some trees with large structure, such as J48 graph and J48 Tree are get lower accuracy, while some get a higher accuracy such as ID3 Numerical. Higher accuracy of all algorithms is due to the fact that the hybrid feature selection model, as a pruning algorithm, is used to reduce over training error. Bays algorithms for both real return and risk obtained weak prediction. Thus, DTNB and also NB Tree output for both real return and risk achieved lower accuracy. The results show that the rule base algorithms with average number of rules, such as Part Rule, Decision Table and Rule Induction, obtain better results. On the other hand, the accuracy of the algorithms with fewer rules like J Rip Rule has descended. The accuracy of the neural network for each output has increased, because of not getting stuck in local optimum points.

The risk results in prediction with selected features:

Due to the large number of features extracted from the hybrid feature selection algorithm for risk, the moderate size tree, such as Rep tree, FT Tree, and LAD tree have better accuracy than before. However, BF Tree accuracy has been decreased because of removing 2 effective attribute.

With this analysis it is also clear that the algorithms, such as LAD Tree, which use the features beta coefficient, market return, P/E, and the efficiencies, obtained the highest accuracy which has improved up to 80.24%. Large trees such as J 48 Tree and J 48 Graph get lower prediction accuracy but ID3 Numerical results are improved. As said before, the prediction result of bays based algorithms like DTNB and NB Tree have been decreased but the large drop in NB Tree prediction is because of its dense structure.

For other rule base algorithms the prediction result have been improved or remained stable, except decision table algorithm. This is derived from the average number of rules that are covered by the selected features.

Moreover, by using weight of features obtained from Chi-2 or IG Ratio or Info Gain algorithms (without using the hybrid model), the return and market returns features to predict real return get the highest weight (90% of cumulated weight). Maybe, the high percentages predicted by BF Tree and LAD Tree algorithms are due to these two features. Also to risk parameter, return, beta coefficient, and efficiency features get the highest weight (90% of cumulated weight). Thus the high accuracy of LAD Tree, FT Tree, Rep Tree, and Rule Induction algorithms could be due to these three features. Because these algorithms emphasize these high weight features more than others.

A comparison between our method and similar researches is illustrated in Table 3.12. Six hybrid methods which have a brilliant accuracy in return forecasting in different country stock exchange compared based on input data, base classifier, feature selection, hybrid prediction model and the best accuracy as follow:

Table 3.12. Comparison results with other studies

Author /Year	Stock Exchange	Input Data	Base Classifier	Feature selection	Hybrid Model	The Best Accuracy%
Tsai, et al. (2011)	Electronic Industry in Taiwan	19 Financial ratios and 11 Macroeconomic indicators	MLP- Cart - Logistic Regression	---	Bagging - Voting	66.67
C.-F. Huang (2012)	30 special companies in Taiwan	14 Financial ratios	SVR- GA	---	---	85- 76.71
Cheng, et al. (2010)	Taiwan	10 Technical Indexes and 8 Macroeconomic indicators	PNN- C4.5- Rough Set	---	Hybrid	76
Huang, et al. (2008)	South-Korea and Taiwan	23 Technical Indexes	SVM- K-NN- Cart- Logistic Regression- Back Propagation	Wrapper	Voting	76.06 80.28
Tsai and Hsiao (2010)	Taiwan	8 Fundamental Index and 11 Macroeconomic indicators	---	GA-PCA-Cart	Back Propagation	79
)Tsai, Lu, and Yen (2012((	Taiwan	61 intangible assets value variable	MLP	PCA- Stepwise Regression- decision trees- association rules- GA	MLP	75
Recent work	Return Forecasting in TSE-Iran	44 Financial ratios and Fundamental Index	Cart , Rep Tree, LAD Tree, …	Function based Clustering	Hybrid	80.24
Recent work	Risk Forecasting in TSE-Iran	44 Financial ratios and Fundamental Index	DTNB , BF Tree, LAD Tree,…	Function based clustering	Hybrid	79.01

We also exerted data dimension reduction methods including: Principle Component Analyses (PCA), Independent Component Analysis (ICA), Factor Analysis (FA), Discrete Wavelet Transform (DWT), and Discrete Fourier Transform (DFT) methods on data set. Our results on this methods show that despite of long runtime the accuracy of prediction algorithms highly decreased. As an instance, after the reduction of dimensionality from 44 to 11 with PCA algorithm, the LAD Tree prediction results get 52.7 % which is a very low accuracy.

Moreover, the data reduction process time in this data is very high and as an instance, based on Rapid miner Software it takes 11 hours and 32 minutes in DWT algorithms. Although by using MATLAB algorithm, the execution time is less than before, but the accuracy of the results will not differ much. Among these 5 algorithms, ICA results despite of long execution time (approximately 31 hours with Rapid miner software) obtain better prediction accuracy and the accuracy predicted based on LAD Tree is 71%.

3.5. Conclusions

In this study, an approach for simultaneous prediction of risk and real return were developed by applying data mining technique as well as fundamental data set. To do this, first through a comprehensive study, the features which can be potentially effective on risk and return were investigated. Then, after developing an appropriate database the preprocessing of database step was taken. To predict the real return and risk, 20 and 15 different prediction algorithms were applied respectively. Then, the strength and weakness of each one was investigated by analyzing the size and leaves of tree algorithms or/and "If- Then Rules" gains of rule based algorithms. In the next step, by using hybrid feature selection algorithm on the basis of 9 different filter algorithms and function-based clustering method, important features were selected and re-prediction with selected features was performed. The results show that for real return parameter, the number of effective features are usually less than the number of effective features on risk parameter. With the help of these features, the results in most algorithms were improved. In this way, this hybrid feature selection method is capable of identify effective features. The high accuracy of prediction results indicates that the extracted features explain the behavior of market very well and can be considered as a suitable database for the future research. Our findings can enable the investors to analyze the market and gain high accurate results with fewer features, and not getting confused in the market by many features which are not necessarily effective. This study is differed from the previous ones by considering the combination of 9 different feature selection algorithms with function-based clustering algorithm. This hybrid model can enjoy the advantages of all feature selection algorithms and make a robust and accurate decision. The effectiveness of our model is illustrated with the prediction of both risk and return of stocks and then analyzing the results with and without implementing of our hybrid feature selection algorithms. While almost none of the relevant studies in this field pay attentions to prediction of risk feature. Furthermore, we design a systematic and efficient methodology for comprehensive searching the potential representative features on stock market in 3 categories of financial ratio, profit & loss reports, and Stock pricing models and not arbitrary choosing likely effective features.

Finally, investigating each algorithm with a feature-oriented view point indicates the factors which cause strength and weakness of that algorithm. Therefore, by searching about property of data base, we can choose a proper algorithm without implementation of all methods. This idea can be further extended not only in quantitative investment, but also in other field of studies where expert systems and machine learning techniques are used.

The limitation of this method is that collecting all data and information may be difficult for some real cases. Future research directions of paper include but are not limited to

1. Combining prediction methods in the framework of fusion models or optimize the classification algorithms by applying some metaheuristics algorithms to improve the prediction results
2. Predicting the other important variable (in addition to risk and return) such as liquidity (Barak et al., 2013).
3. Using technical features and textual information, in addition to fundamentals features, in order to have a more comprehensive features and to be able to predict short term situation of stocks
4. Customizing the proposed approach for the prediction of risk and return in a particular industry or investigating the accuracy of the procedure by data from other popular stock markets, such as US stock market which may result in new dimensions in this procedure.
5. Applying different clustering models to our feature selection data set and compare results by considering new feature selection methods, such as CFS (Zhang et al., 2014a) or entropy-based clustering for feature selection (Lin, 2013)

Appendix A. CAPM Model

- β coefficient is the amount of changes in the stock return to market and accounted as follow.

*β = (Cov (Market return * stock return)) / Var (Market return).*(A1)

- Market expected return, shows the amount of market return in a definite time which is gained with this formula:

$$r_m = \frac{P_t - P_{t-1}}{P_{t-1}} \qquad (A_2)$$

In this p_t = the market indicator at the end of period (for example 2013/12/28) and P_{t-1} = the market indicator at the beginning of period (for example 2013/1/1).

- Return without risk also can be done through this formula.

$$r_{ft} = \frac{(p_t - p_{t-1}) + D_t}{p_{t-1}} \times 100 \qquad (A_3)$$

In this p_t is end of period stock price, P_{t-1} = beginning of period stock price and D_t =Benefits of stock ownership which has belonged to Shareholder in period t. if we have capital increase in period of investment from savings or receivables and cash income then the formula will change as a follow :

$$r_{ft} = \frac{D_t + p_t(1+\alpha+\beta) - (p_{t-1} + c\alpha)}{p_{t-1} + c\alpha} \times 100 \qquad (A_4)$$

In this α = the percent of capital increase of the receivables and cash income, β = the percent of capital increase of savings, *c*= Nominal amount paid by investor to increase the capital of the receivables and cash income. We use this formula for calculate the r_m , r_f and β .

4. Wrapper ANFIS-ICA method to do stock market timing and feature selection on the basis of Japanese Candlestick

Summary of the forth chapter

Predicting stock prices is an important objective in the financial world. This paper presents a novel forecasting model for stock markets on the basis of the wrapper ANFIS (Adaptive Neural Fuzzy Inference System) – ICA (Imperialist Competitive Algorithm) and technical analysis of Japanese Candlestick. Two approaches of Raw-based and Signal-based are devised to extract the model's input variables with 15 and 24 features, respectively. The correct predictions percentages for periods of 1- 6 days with the total number of buy and sell signals are considered as output variables. . In proposed model, the ANFIS prediction results are used as a cost function of wrapper model and ICA is used to select the most appropriate features. This novel combination of feature selection not only takes advantage of ICA optimization swiftness, but also the ANFIS prediction accuracy. The emitted buy and sell signals of the model revealed that Signal databases approach gets better results with 87% prediction accuracy and the wrapper features selection obtains 12 % improvement in predictive performance regarding to the base study. Additionally, since the wrapper-based feature selection models are considerably more time-consuming, our presented wrapper ANFIS-ICA algorithm's results have superiority in time decreasing as well as prediction accuracy increasing regarding to other algorithms such as wrapper Genetic algorithm (GA).

4.1. Introduction

A good prediction contributes to better decision-making and planning for the future while it allows the current variables to create a considerable value. Predictions accuracy affects the organizations financial stability (Asadi et al., 2012). In the industry of information processing, data mining is an ever growing technology and has been applied in engineering, business and management. Prediction of stock prices, credit scores, and even bankruptcy potentials are examples of significant applicability of data mining in the field of finance. Since financial markets are complex and non-linear dynamic systems, their predictions are really challenging (Huang and Tsai, 2009). There are different forecasting approaches such as statistical models, technical analysis (TA), and econometric methods (Atsalakis et al., 2011; Kar et al., 2014) while in this study the focus is on wrapper approach based on TA.

The most crucial points for trading are peaks and bottoms of the price trend in the way that a professional and lucky practitioner sells at peaks and buys at bottoms. In real world, TA gives a considerable assistance in such decisions (Lin et al., 2011) and its application has been well conceived by the financial market experts (Menkhoff, 2010). It should be noted that for short term period prediction, TA is the best tool although lately it has gone beyond the intention of short-term trading (Cervelló-Royo et al., 2015; Zhu and Zhou, 2009).

Due to the discussed importance, over the last two decades a lot of researches have focused on development of intelligent soft computing models (Bisoi and Dash, 2014; Hafezi et al., 2015; Majhi et al., 2009). Most of them combine soft computing techniques and TA with stock analysis such as (Chen et al., 2009; Patel et al., 2015b; Wen et al., 2010).

Since the end of the 1980s, some financial scholars applied artificial neural networks (ANNs) to predict the stock market (Lee and Jo, 1999). However, the ANNs have some shortcomings in patterns learning because stock market data are noisy and with complex dimensions (Huang et al., 2008a). Therefore, to deal with these challenges, scholars proposed combination of fuzzy theory and ANNs.

A Takagi–Sugeno–Kang-Type Neuro-fuzzy rule-based system to forecast Taiwan Stock Exchange price deviation is developed by Chang and Liu (Chang and Liu, 2008) with accuracy of 97.6% and 98.08% in TSE index and MediaTek respectively. A hybrid Neuro-fuzzy with ANFIS (Adaptive Neural Fuzzy Inference System) is developed by Yunos et al. (Yunos et al., 2008) to predict daily movements of the Kuala Lumpur Composite Index (KLCI) and the results show superiority of the ANFIS to ANN. In comparison with the others, ANFIS has high speed of training, the most effective learning algorithm, and is simple in terms of the structure (Sarkheyli et al., 2015). ANFIS provides better results when applied without any pre-training (Vairappan et al., 2009). (Bagheri et al., 2014) used an ANFIS with QPSO (Quantum-behaved Particle Swarm Optimization) hybrid method for financial forecasting. For the scholars from this field the review paper of Atsalakis and Valavanis (Atsalakis and Valavanis, 2009) and Kar et al. (2014) can be useful.

Technical knowledge usually is elicited by TAs and in this study a Japanese Candlestick chart analysis is used in order to elicit technical knowledge. Although the supporting literature on the Japanese Candlestick charting and its antiquity are important reasons for application of them in decision making but the two following points are the main points for its application in our new model:

1. Consideration of open, high, low and close prices unlike the other works that use only close prices.
2. Being more robust than the other technical trading rules from the perspective of data snooping (Jasemi et al., 2011).

Since there are many indices in stock exchange and more specifically in TA problems, feature selection becomes much more important. Number of studies have claimed and verified that feature selection (FS) is the key process in stock prediction (Barak and Modarres, 2015; Tsai and Hsiao, 2010). Feature selection decreases the calculation cost by decreasing the corresponding dimensionality, or improves the forecasting performance by elimination of extra and unrelated features (Crone and Kourentzes, 2010). Generally there are 2 types of feature selection methods which are: (i) Wrapper methods, and (ii) Filter methods (Barak and Modarres, 2015; Chen and Cheng, 2012) while wrapper algorithms are more successful in most cases

(Chiang et al., 1996; Kohavi and John, 1997b; Lawrence et al., 1997; Maldonado and Weber, 2009a; Min and Lee, 2005; Wang et al., 2015).

To sum up, in this research, a novel hybrid feature selection algorithm on the basis of wrapper ICA-ANFIS method is applied to select the important features. What makes our proposed approach different from the previous ones are that we proposed a new combination of Japanese Candlestick charts and wrapper ANFIS-ICA for forecasting.

Application of Japanese Candlestick charts as a technical analysis is a key advantage of this study and effectiveness of the selected features of this pattern is proved. Moreover the applied wrapper of this study is a new combination in the way that ANFIS is an analyzer to predict future of the stock market trend, and feature selection is done by ICA (Imperialist Competitive Algorithm). The model not only increases the prediction accuracy but also the process pace and finally it should be noted that the patterns of Japanese Candlestick is on the basis of Jasemi et al. (2011).

The contribution of the paper is summarized as follows:

- Gathering a comprehensive Japanese Candlestick database regarding to new adaptive technical analysis.
- Developing a hybrid feature selection algorithm on the basis of wrapper ICA-ANFIS model.
- Exploring how much efficient an ANFIS would be to infer the TA clues if it is provided with important indices of the TA (based on wrapper feature selection) and actual trends.

The rest of the paper is organized as follows: section 2 reviews the literature of wrapper, ANFIS, and ICA; section 3 introduces the model; section 4 presents the experimental results and finally section 5 focuses on the conclusions.

4.2. The background

4.2.1. Wrapper feature selection method

In the Wrapper method the goal is to find a subset of size r from n variables (r<n) that maximizes the predictor performance (Maldonado and Weber, 2009a). The method utilizes the learning mechanism as the fitness function and seeks the best subset of the features while standard optimization techniques with learning mechanisms for ranking of the subsets are possible. Kohavi and John (Kohavi and John, 1997b) have a leading role in popularization of the wrapper approach that is really powerful in feature selection, but it has its computational complexities and it is more time consuming than Filter method (Huang et al., 2007). Fig.4.1 shows the approach concept.

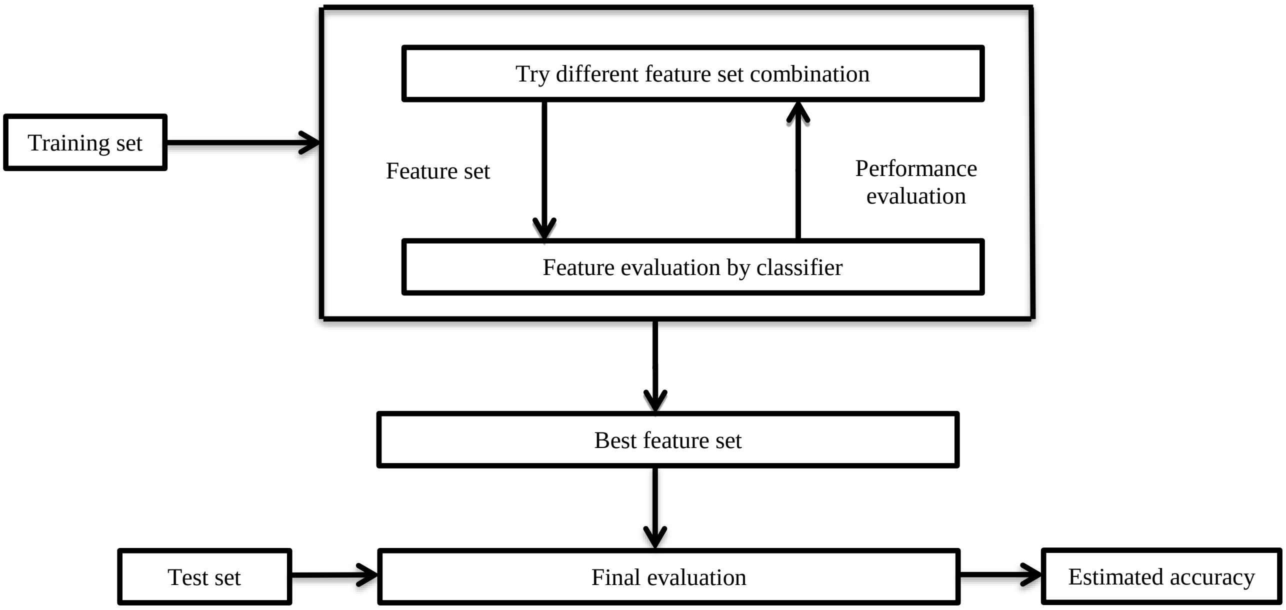


Fig4.1. The approach of Wrapper

For a given dataset of G with N features, the wrapper approach starts from a subset of F_0 (an empty set, a full set, or any randomly selected set) and with a particular strategy searches the features space. It evaluates each generated subset of F_i by applying a learning model that considers F_i as an input and if the learning model performance improves with F_i, F_i is regarded as the best current subset. Then the wrapper modifies F_i by adding or eliminating features and performing the search until coming to the predefined stopping criterion (Kabir and Islam, 2010). The above mentioned feature searching problem is NP-hard and the number of local minima can be quite large and naturally a wide range of heuristic search strategies including forward selection, backward elimination, hill-climbing, branch and bound algorithms, and metaheuristics algorithms like simulated annealing and genetic algorithms (GAs) have been used (Huang et al., 2007).

4.2.2. Adaptive Neural Fuzzy Inference System (ANFIS)

ANFIS is a multi-layer adaptive network-based fuzzy inference system proposed by Jang (Jang, 1993). An ANFIS consists of totally five layers to implement different node functions to learn and tune parameters in a Takagi–Sugeno fuzzy inference system (FIS) using a hybrid learning mode.

The first layer executes a fuzzification process, the second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the membership functions, the fourth layer executes the conclusion part of the fuzzy rules, and the last layer computes the output of the fuzzy system by summing up the outputs of the four layers. The feed forward equations of the ANFIS structure with two inputs and two labels for each input are presented as follow:

$$W_i = \mu_{A_i}(x) \times \mu_{B_i}(x) \quad i = 1,2 \qquad (1)$$

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \qquad i = 1, 2 \tag{2}$$

$$\begin{cases} f_1 = p_1 x + q_1 y + r_1 z \\ f_2 = p_2 x + q_2 y + r_2 z \end{cases} \quad \Rightarrow \; f = \frac{w_1\, f_1 + w_2\, f_2}{w_1 + w_2} = \bar{w}_1\, f_1 + \bar{w}_2\, f_2 \tag{3}$$

where *x* and *y* are inputs to node *i*, A_i and B_i are linguistic labels for inputs, w_i is the output of layer 3, and $\{p_i, q_i, r_i\}$ are the parameters setting.

ANFIS model design consists of two sections: constructing and training. In the construction section, the number and type of FIS structure are defined. Construction of the ANFIS model requires the division of the input/output data into rule patches. This can be achieved by using a number of methods such as grid partitioning, subtractive clustering method and fuzzy c-means (FCM).

When there is only one output, FCM can be applied for making a primary FIS to train the ANFIS (Bezdek, 1981). FCM is done with minimizing a goal function that represents the distance of each data point to data center that has been weighted by membership degree of the data point (Eq. 4).

$$\min\ J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} U_{ij}^{m} \left\| X_i - C_j \right\|^2 \ , \ 1 \le m \le \infty \tag{4}$$

where *m* is a real number greater than 1 and each of U_{ij}, X_i and C_j shows the degree of membership of X_i in the *j-th* cluster, the *i-th* p-dimensional data and the p-dimensional center of the cluster respectively, and ||*|| is any norm that shows the similarity between each measured data and the center. With iterative optimization of the above objective function, fuzzy partitioning is done, by updating membership U_{ij} and cluster centers C_j as follow:

$$U_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| X_i - X_j \right\|}{\left\| X_i - C_j \right\|} \right)^{\frac{2}{m-1}}} \ , \ C_j = \frac{\sum_{i=1}^{N} U_{ij}^{m} X_i}{\sum_{i=1}^{N} U_{ij}^{m}} \tag{5}$$

when $\max_{i,j} \left\{ \left| U_{ij}^{(K+1)} - U_{ij}^{(K)} \right| \right\} \prec \varepsilon$ is satisfied, iteration will stop, where ε is a number between 0 and 1, and *k* is the step's number of iteration (Esfahanipour and Aghamiri, 2010) (Sarkheyli et al., 2015).

4.2.3. Imperialist Competitive Algorithm (ICA)

ICA is a new socio-politically motivated global search strategy that has been introduced for dealing with different optimization tasks (Atashpaz-Gargari and Lucas, 2007). This evolutionary optimization strategy has shown great performance in both convergence rate and better global optima achievement (Atashpaz-Gargari and Lucas, 2007; Biabangard-Oskouyi et al., 2008; Gargari et al., 2008; Khoshnevisan et al., 2015;

Rajabioun et al., 2008; Sepehri Rad and Lucas, 2008). Nevertheless, its effectiveness, limitations and applicability in various domains are currently being extensively investigated.

Fig.4.2 (Atashpaz-Gargari and Lucas, 2007) shows the flowchart of the ICA. Similar to other evolutionary algorithms, this algorithm starts with an initial population. Each individual of the population is called a country. Some of the best countries (in optimization terminology, countries with the least cost) are selected to be the imperialist states and the rest form the colonies of these imperialists. All the colonies of initial countries are divided among the mentioned imperialists based on their power. The power of each country, the counterpart of fitness value in the GA, is inversely proportional to its cost. Then an imperialist with its colonies can found an empire. Fig.4.3 shows the primary empires while the most powerful imperialist 1 has more countries than the others.

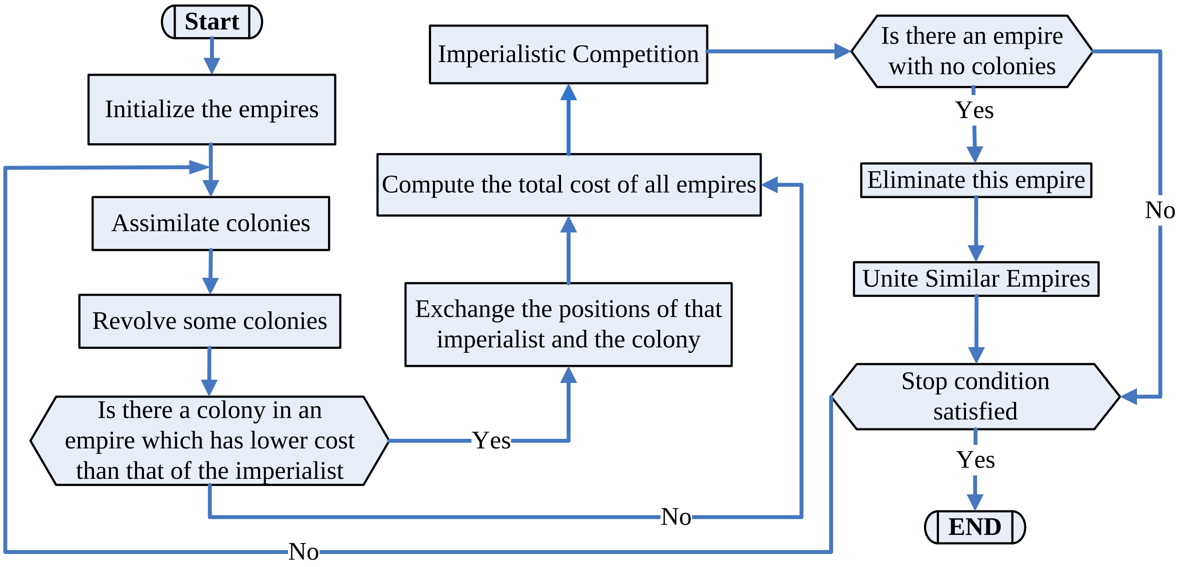

Start
Initialize the empires
Assimilate colonies
Revolve some colonies
Is there a colony in an empire which has lower cost than that of the imperialist
Yes
No
No
Exchange the positions of that imperialist and the colony
Compute the total cost of all empires
Imperialistic Competition
Is there an empire with no colonies
Yes
No
Eliminate this empire
Unite Similar Empires
Stop condition satisfied
Yes
END

Fig 4.2: Flowchart of the Imperialist Competitive Algorithm

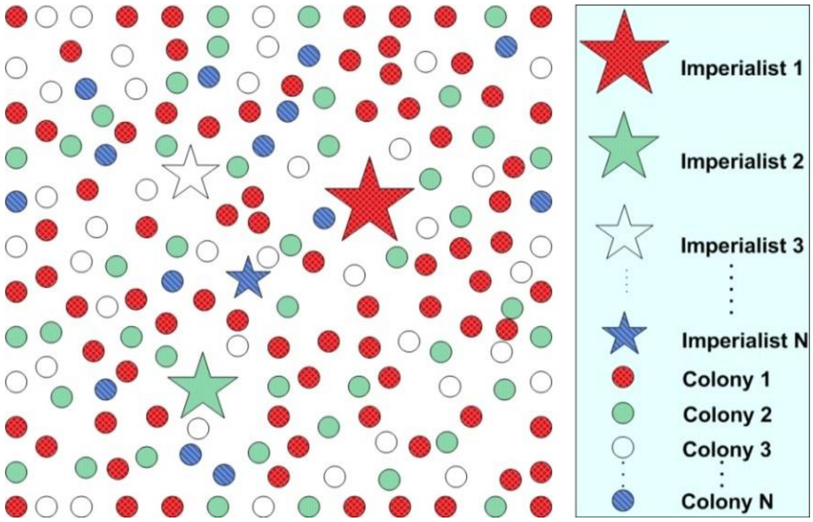


Fig 4.3: Making the primary empires

After forming initial empires, the colonies in each of them start moving toward their relevant imperialist country. This movement is a simple model of assimilation policy which was pursued by some of the imperialist states. The Assimilation makes the colonies of each empire in searching space, closer to the imperialist position while the revolution covers random changes in position of some of the countries. During Assimilation and revolution a colony may advance to a better position and has the probability of controlling the entire empire and replace the imperialist.

If after this move, one of the colonies has more power than the imperialist, they will be replaced. To initiate the competition among the empires, the objective function of each empire is calculated. This function depends on the imperialist objective function and its colonies. Then the competition starts and the weakest empire lose its assets and the powerful empire tries to achieve them. The empire that loses all of its colonies will vanish. Finally the most powerful empire possesses the other empires assets and wins the competition. From optimization point of view this leads to finding the optimal solution of the problem, i.e. solution with least cost value.

4.3. The proposed model

4.3.1. Adaptive TAs and ANFIS

Technical analysis normally has two general approaches to evaluate the stock prices while the first uses technical indicators and oscillators, and the second uses charts (Chavarnakul and Enke, 2008). Whether mathematical or pattern charts, the mechanism of a typical TA is based on signs and (their associated) signals, while signs are generated by the stock price alteration and signals are restricted to three states of ascending, descending and neutral (Lu, 2014).

The concept of Adaptive TAs is not much different from the old one. The new generation of TA models is again categorized into two categories of mathematical and pattern charts and it is again a system of signs and signals but unlike the static old one, it is dynamic.

In traditional combination, target data are results of applying the input data to some pre-determined rules of the selected TA. That is the rules are constant and the concern of model developer is to better educate the network. In traditional combination the target data is determined according to the input data and the predetermined rules. In statistic words the independent and dependent variables are input and target data, respectively. The following rules (Rule 1-6) are some of predetermined rules in TA which are illustrated in Fig 4.4 (Lu et al., 2012). The focus is on open (O_i), high (H_i), low (L_i) and close (C_i) prices of the stock in the *i*th day due to the Japanese Candlestick (do Prado et al., 2013).

1. The Piercing: $O_1 > C_1$, $O_2 < C_2$, $O_2 \leq C_1$, $C_2 < O_1$, and $C_2 > C_1 + 0.5\,(O_1 - C_1)$.

2. The Bullish Engulfing: $O_1 > C_1$, $O_2 < C_2$, $O_2 \leq C_1$, and $C_2 \geq O_1$.

3. The Bullish Harami: $O_1 > C_1$, $O_2 < C_2$, $O_2 > C_1$, and $C_2 < O_1$.

4. The Dark-cloud Cover: $O_1 < C_1$, $O_2 > C_2$, $O_2 \geq C_1$, and $C_2 < C_1 - 0.5\,(C_1 - O_1)$.

5. The Bearish Engulfing: $O_1 < C_1$, $O_2 > C_2$, $O_2 \geq C_1$, and $C_2 \leq O_1$.

6. The Bearish Harami: $O_1 < C_1$, $O_2 > C_2$, $O_2 < C_1$, and $C_2 > O_1$.

As we can see in the upper rules, they are some predetermined rules; however in this present paper, our approach are completely dependent on input and target data in the way that they may be completely different for two distinct periods of time. In other words there is no pre-determined rule in the proposed synthetic model but only some inputs and their associated target data on the basis of which, new rules are extracted. The most important task in the new model is with the analyzer that confirms the old rules or extracts the new ones. Fig. 4.5 shows how the analyzer relates input data, target data and the new technical rules together. In addition the new approach inserts some kind of continuity to the selected rules.

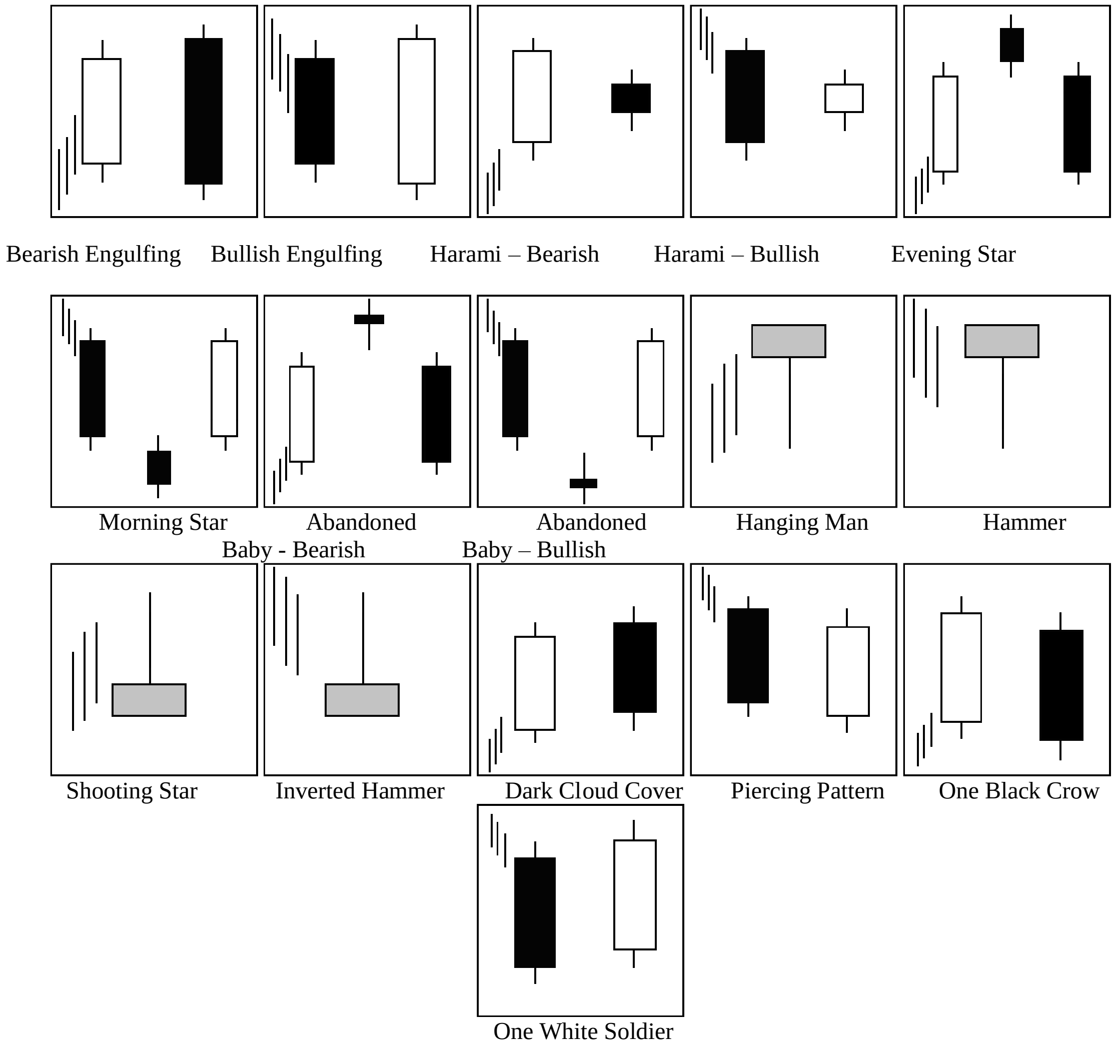


Fig4.4: Traditional 2-days patterns

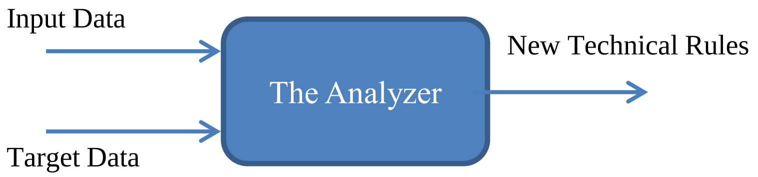


Fig4.5: The new relation of input data and technical analysis rules

In this study an ANFIS like in many similar works in the literature plays the analyzer role. But unlike the previous works, in the new model the ANFIS knowledge changes over time according to new training data.

Therefore in this study a modern combination of Japanese Candlestick charting and ANFIS is presented. In fact it is explored how much efficient an ANFIS would be to infer the TA clues if it is provided with important indices of the TA (based on wrapper feature selection) and actual trends. This model created for presented research, if successful, could be beneficial for stock traders, much in allowing them to make better decision making using the most up-to-date investment techniques.

4.3.2. Model

The model proposes an adaptive TA based novel methodology for signal prediction and feature selection with a wrapper approach called ANFIS-ICA, which results from the combination of ANFIS as a signal analyzer and ICA, as feature finder and subset evaluator. In the other words, this model uses ANFIS as a signal analyzer tool while a novel wrapper feature selection algorithm selects important Candlestick based features to feed the model. Fig 4.6 shows the general structure of the model while it will be discussed in details in the following parts.

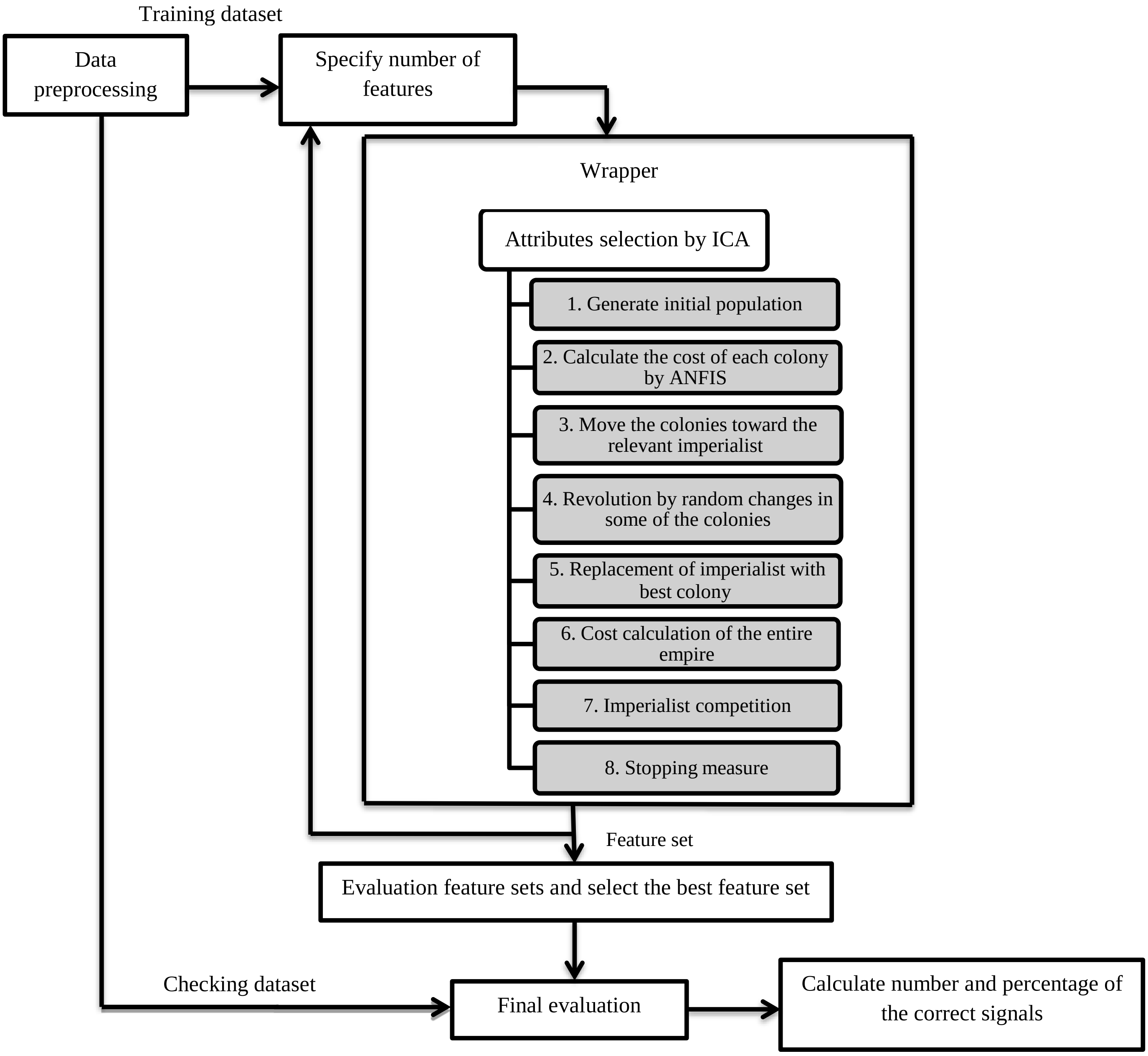

Training dataset
Data preprocessing
Specify number of features
Wrapper
Attributes selection by ICA
1. Generate initial population
2. Calculate the cost of each colony by ANFIS
3. Move the colonies toward the relevant imperialist
4. Revolution by random changes in some of the colonies
5. Replacement of imperialist with best colony
6. Cost calculation of the entire empire
7. Imperialist competition
8. Stopping measure
Feature set
Evaluation feature sets and select the best feature set
Checking dataset
Final evaluation
Calculate number and percentage of the correct signals

Fig 4.6: The general structure of the presented model

The following parameters are used throughout the study:

Nattrib: Number of features

NPop: Number of initial population

Nimp: Number of imperialists

Zeta: The effect coefficient of the colonies cost on the empire cost

Prevolution: Probability of revolution

Imp Colonies Costs (i): Colonies costs of i^{th} imperialist

Imp costs (i): Cost of i^{th} imperialist

Imp fitness (i) : Fitness of i^{th} imperialist

Max Decades: Maximum periods as stopping criterion in the ICA

Num MFs: Number of membership functions for FCM

Epoach_n: Number of train epochs in the FCM

- **Development of the initial population in ICA**

To generate the initial population, *NPop* random permutation of integers from 1 to *Nattrib* in a matrix structure (*Npop* × *Nattrib*) as it is shown in Fig 4.7 is developed.

	1	·	·	·	*Nattrib*	
1	2	7	5	9…	14	→ Country
·	3	13	2	10…	5	
·	11	6	2	1…	8	
·	8	6	1	13…	15	
Npop	7	14	9	2…	6	

Fig 4.7: Making the primary population

The colonies are organized on the basis of the initial population. The *i*th population with a position that includes *Nattrib* features makes the *i*th colony, while *j*th number in the colony is the number of the feature. Then cost of each colony is calculated and the colonies are sorted on the basis of their cost ascend and the most powerful colonies are selected as imperialists and the others (*Npop* - *Nimp*) are colonies of these imperialists [see (Atashpaz-Gargari and Lucas, 2007)].

- **Cost function**

ANFIS model is applied to calculate the cost function in ICA. Firstly the FCM function is applied for appointing the number of rules and membership functions. FCM uses Gaussian and Linear functions for input and output membership functions respectively. After making the initial FIS structure, ANFIS function is applied to train the system by the initial FIS structure that is made by FCM and training data. Then training *RMSE* of fuzzy output is calculated by Eq. (6).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} \left(y'_t - y_t\right)^2}{n}} \qquad (6)$$

while, y'_t is the result of prediction and y_t is the real amount of t^{th} data.

After the training phase, checking dataset is used to check the ANFIS. Furthermore, the checking *RMSE* is calculated. The check *RMSE* is used as the performance measure and cost function in ICA.

- **Assimilation policy**

To draw the colony closer to the imperialist (Assimilation), 2 random numbers from 1 to *Nattrib* are selected as R_1 and R_2, and then C_1 and C_2 are considered as minimum and maximum of them respectively. Then from 1 to C_1-*1* features of the imperialist are considered as 1 to C_1-*1* features of the child country; from C_1 to C_2 features of colony are considered as C_1 to C_2 features of the child country; from C_2+*1* to *n* features of the imperialist are considered as C_2+*1* to *n* features of the child country and so the features of the child country is achieved. Fig.4.8 shows an example of Assimilation with R_1=3 and R_2=6; C_1=3 and C_2=6.

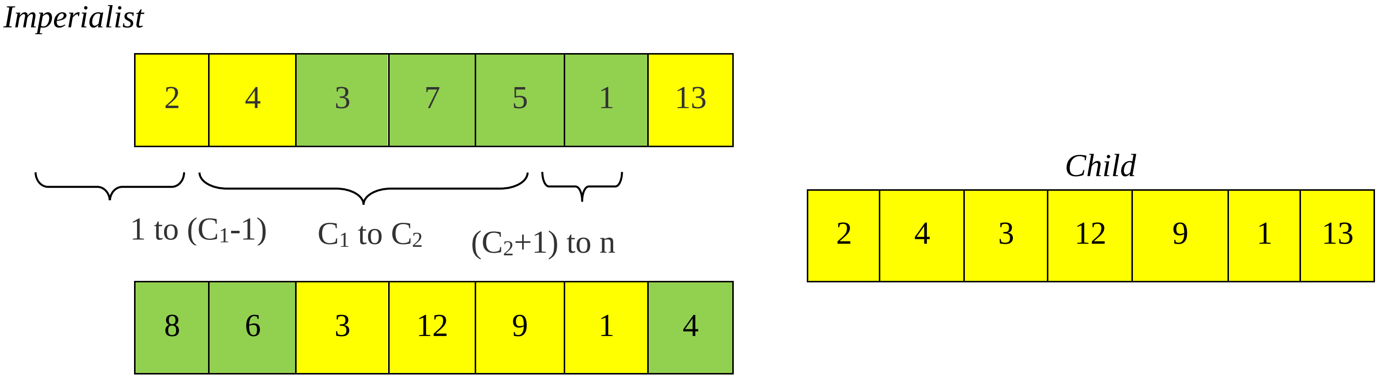


Fig4.8: Assimilation policy

The new country (child) is a combination of the previous colony that converges to the imperialist country.

- **Revolution**

For the j^{th} colony of the i^{th} imperialist if revolution chance (random number) is smaller than *P*, revolution is done by random changes in some of the colonies. In this regard two random numbers of k_1 and k_2 from 1 to *Nattrib* are selected and then feature k_1 from the j^{th} colony and the i^{th} empire is replaced with feature k_2 from that exact colony and so the revolution function in some of the countries is done. Fig.4.9 shows an example of the revolution.

Before	8	6	3	12	9	1	4
After	8	6	9	12	3	1	4

Fig4.9: Revolution

- **Replacement of the imperialist with the best colony**

If one of the colonies possesses more power than its relevant imperialist, they will exchange their positions.

- **Cost calculation of the entire empire**

The cost of each empire depends on the costs of imperialist and colonies as follows:

$$Imp\ fitness\ (i) = Imp\ costs(i) + zeta * \frac{\sum_{t=1}^{n} Imp\ Colonies\ Costs\ (t)}{n} \qquad i = 1,2,\dots,Nimp \qquad (7)$$

where *n* is the number of colonies in i^{th} empire.

- **Imperialist competition**

In this regard, first of all the empire fitness is updated by Eq. (8) and then the intended probability is got by Eq. (9).

$$Update\ Imp\ fitness\ (i) = \max_1^{Nimp} Imp\ fitness\ (n) - Imp\ fitness\ (i) \qquad i=1,\dots,Nimp \qquad (8)$$

$$p_i = \frac{update\ Imp\ fitness\ (i)}{\sum_{n=1}^{Nimp}(Imp\ fitness\ (n))} \qquad i = 1,2,\dots,Nimp \qquad (9)$$

After calculating the probabilities, the vector of *P* is organized as follows:

$$\mathbf{P} = \left[p_1, p_2, p_3, \dots, p_{N_{imp}} \right] \qquad (10)$$

To distribute the colonies among the empires according to their possession probabilities, the approach of roulette is applied. The Empire with more fitness is has higher probability to be selected. After this stage it should be checked that if the weakest empire does not have any colony, and then it must be allocated as a colony to other empires on the basis of fitness probability of the empires and roulette wheel.

- **Stopping measure**

The algorithm is repeated until it comes to a pre-determined number of repetitions and finally the best answer is selected from them.

To sum up these steps, the semi-codes of the model are as follows:

```
(1) Set up ICA Settings:
    – Max Decades; Npop; Nimp; Prevolution; zeta;
    – Ncol = Npop - Nimp;
(2) Set up training and checking data and epoch_n
(3) $\theta$=1
(4) Generate the initial population
(5) Calculate the cost of each colony:
    1. Develop the FIS structure by FCM.
    2. Train the ANFIS by the initial FIS structure.
    3. Validate the model by RMSE and compute the train RMSE.
    4. Validate the model by the checking data.
    5. Compute the check RMSE and set as cost function.
(6) Select the most powerful colonies as imperialists.
(7) Allocate rest of the colonies to the imperialist on the basis of the imperialist power.
(8) Generate empires by imperialists and their colonies.
(9) Move the colonies toward the relevant imperialist.
(10) Revolve in some of the colonies.
```

(11) Exchange the position of a colony and the imperialist if its cost is lower.

(12) Compute the objective function (the total cost) of all empires.

(13) Pick the weakest colony and give it to the best empire.

(14) Eliminate the powerless empires.

(15) If the stop condition is satisfied stop, and if not go to step 10.

(16) Select the optimum subset of the features with the minimum check error (Check RMSE).

(17) If $\theta = Max\ decades$ then stop, and if not $\theta = \theta + 1$ and go to step5.

4.4. Empirical results

4.4.1. Input data

In this study the training data are based on the two applied approaches of Jasemi et al.(Jasemi et al., 2011). The first approach (Raw database) is based on Raw input features including 15 items and 1 output. In this approach the focus is on open (O_i), high (H_i), low (L_i) and close (C_i) prices of the stock in the *i*th day due to the Japanese Candlestick during last 3 days while to cover the stock price trend the close prices of the stock during the last 7 days are also included. Totally this approach comes to 15 normalized indices of $\frac{C_i}{C_1}$ i=2,3,4; $\frac{O_i}{C_1}$, $\frac{H_i}{C_1}$, $\frac{L_i}{C_1}$ and $\frac{C_i}{C_1}$ i=5,6,7.

The 15 indices of this approach are shown in Table 4.1.

Table 4.1: Raw approach

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
C_2/C_1	C_3/C_1	C_4/C_1	C_5/C_1	C_6/C_1	C_7/C_1	O_5/C_1	H_5/C_1	L_5/C_1	O_6/C_1	H_6/C_1	L_6/C_1	O_7/C_1	H_7/C_1	O_7/C_1

The second approach (Signal database) is based on the reverse signals of Japanese Candlestick technique including 24 input features and 1 output. This package covers the important factors of decision making in the technique. In this approach the focus is on the reversal signals of Japanese Candlestick like Morning star, Inverted hammer, Harami and many others. In fact this set of inputs is more advanced than the previous and covers important pattern charts' clues of the TA which are defined as shown by Table 4.2.

Table 4.2: Signal approach

1	2	3	4	5	6	7	8	9	10	11	12
$\frac{\boldsymbol{C_2}}{\boldsymbol{c_1}}$	$\frac{C_3}{c_1}$	$\frac{C_4}{c_1}$	$\frac{C_5}{c_1}$	$\frac{C_6}{c_1}$	$\frac{C_7}{c_1}$	$\frac{O_5}{c_5}$	$\frac{O_6}{c_6}$	$\frac{O_7}{c_7}$	$\frac{H_7}{Max\,(O_7\,,c_7)}$	$\frac{Min\,(O_7\,,c_7)}{L_7}$	$\frac{Max\,(O_7\,,c_7)}{Max\,(O_6\,,c_6)}$
13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
$\frac{\boldsymbol{Min\,(O_7\,,c_7)}}{\boldsymbol{Min\,(O_6\,,c_6)}}$	$\frac{O_7}{H_6}$	$\frac{L_6}{O_7}$	$\frac{C_7}{O_6}$	$\frac{Max\,(O_6\,,c_6)}{\boldsymbol{Min}\,(O_5\,,c_5)}$	$\frac{Max\,(O_7\,,c_7)}{Max\,(O_5\,,c_5)}$	$\frac{Min\,(O_7\,,c_7)}{Min\,(O_5\,,c_5)}$	$\frac{Min\,(O_6\,,c_6)}{\boldsymbol{Max}\,(O_5\,,c_5)}$	$\frac{H_7}{H_6}$	$\frac{H_7}{H_5}$	$\frac{L_6}{L_5}$	$\frac{L_7}{L_5}$

These approaches in 48 data sets, according to Table 4.3, are applied to train and test the introduced ANFIS model. This structure gains the advantage of adaptive TA in which the input data and the target data are dependent and change over the time. Also, this structure is enjoyed from sliding window function in time series prediction (Mozaffari et al.).

Table 4.3: Details of the applied data sets

NO.	Period of training data(year)	Period of testing data(year)	NO.	Period of training data(year)	Period of testing data(year)	NO.	Period of training data(year)	Period of testing data(year)	NO.	Period of training data(year)	Period of testing data(year)
1	2000	2001	**13**	2000-2001	2006	**25**	2000-2003	2007	**37**	2001-2002	2006
2		2002	**14**		2007	**26**		2008	**38**		2007
3		2003	**15**		2008	**27**	2001	2002	**39**		2008
4		2004	**16**	2000-2002	2003	**28**		2003	**40**	2001-2003	2004
5		2005	**17**		2004	**29**		2004	**41**		2005
6		2006	**18**		2005	**30**		2005	**42**		2006
7		2007	**19**		2006	**31**		2006	**43**		2007
8		2008	**20**		2007	**32**		2007	**44**		2008
9	2000-2001	2002	**21**		2008	**33**		2008	**45**	2001-2004	2005
10		2003	**22**	2000-2003	2004	**34**	2001-2002	2003	**46**		2006
11		2004	**23**		2005	**35**		2004	**47**		2007
12		2005	**24**		2006	**36**		2005	**48**		2008

4.4.2. Results

The input data of our experiment belong to daily stock prices of General Motors Company at New York Stock Exchange from 2000 to 2009. 48 data sets according to Table 3 are applied for learning and checking.

After the experiments is it examined that the proposed model is efficient? And which approach has a better performance? Does the quality of forecasting increase when the training data covers a longer period? Does the quality of forecasting decline when the distance between the training and testing data increases?

To optimize the ANFIS parameters, the pre-assumed hybrid method of pre-propagation and least squares is applied. After different evaluation, 20 membership functions were selected as optimal number of FCM rules. In ICA on the basis of different runs, the total number of colonies, number of empires, rate of colonies revolution (P), effect coefficient of colonies power on empire power (*zeta*) and maximum number of repetition as the stop condition are respectively 20, 5, 0.5, 0.1 and 30.

The following 4 figures show the outputs of the wrapper ANFIS-ICA model with the Raw input data of 2000-2001 for train and 2003 for checking. Fig 4.10.a shows the features attitudes of the data approach. The upper trend shows the features trend and the bottom represents the outputs for one sample of normalized data. Fig 4.10.b shows the empires costs and the stages of imperials elimination in ICA in the way that the weak imperials are eliminated and the strong ones remain. Fig 4.10.c shows the decrease of *RMSE* (cost) in repetition of the algorithm and represents two charts of the costs mean and the minimum cost in each repetition. Fig 4.10.d shows checking output and ANFIS output with root of mean square error for best position on top of the figure.

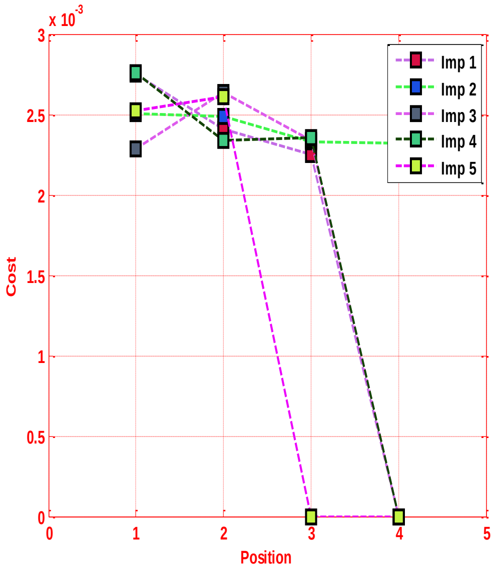


Fig 4.10.a: Trend of the input data of the system

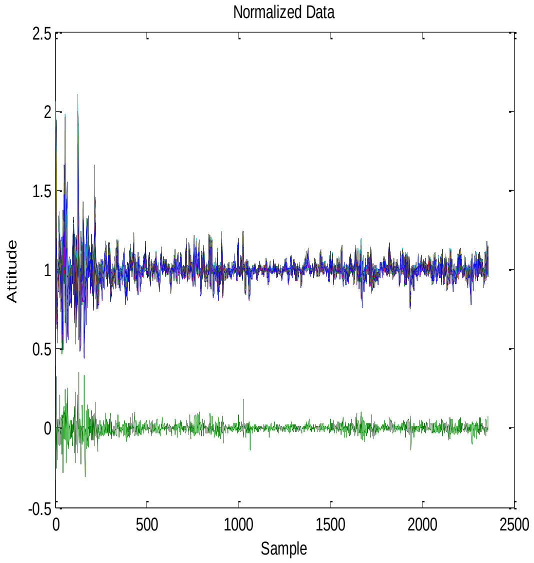


Fig 4.10.b: Imperialist competition

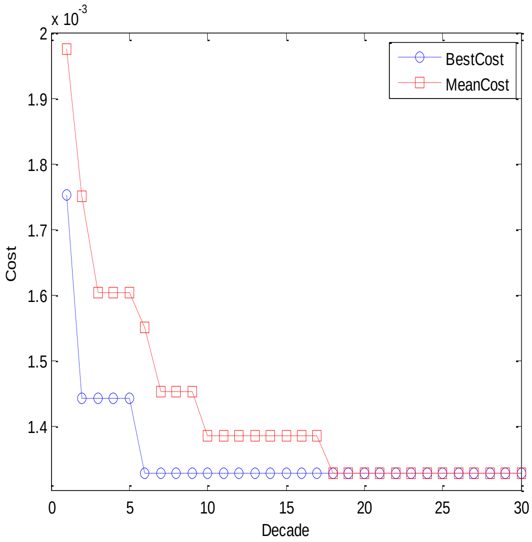


Fig 4.10.c: The costs trend in the algorithm stages

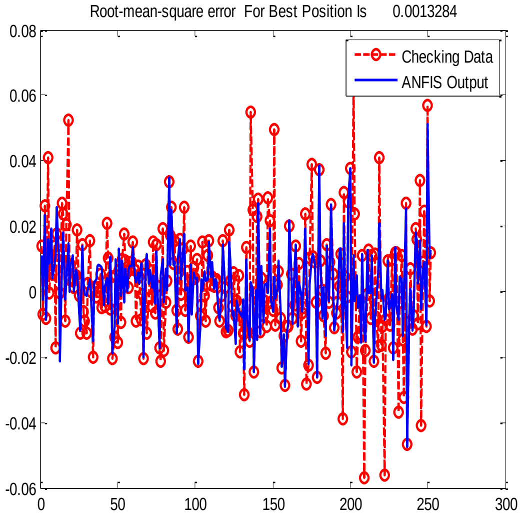


Fig 4.10.d: The real and fuzzy output

Lee and Jo (Lee and Jo, 1999) believe that if the hit ratio defined by $\frac{\text{Number of successes}}{\text{Total number of signals}}$ is above 51%, the model is regarded useful. The hit ratios of the new model for the first and second approaches are %85 and %87 respectively while the second approach gives more number of buy and sell signals.

In the base study of Jasemi et al. (Jasemi et al., 2011) the hit ratio for the first and second approaches are %75 and %74. Unlike the base study our results show the superiority of the second approach.

The percentages of correct signals for 1-day period are 40% and 43% for the first and second approaches respectively. It is to be noted that increasing the learning period's length does not have a sensible effect on the results.

Table 4.4 shows the prediction results for 1-day and 6-day periods and also the total number of buy and sell signals. The correct signals are achieved from comparing the predictions with real happenings of the stock market.

Table 4.4: The correct prediction percentage for 1 and 6 day periods with total number of buy and sell signals

Raw Database								**Signal Database**							
No	1d (%)	6d (%)	Sig. No	No	1d (%)	6d (%)	Sig. No	No	1d (%)	6d (%)	Sig. No	No	1 d (%)	6d (%)	Sig. No
1	0.33	0.93	175	25	0.35	0.84	146	1	0.27	0.94	177	25	0.33	0.87	124
2	0.32	0.93	147	26	0.35	0.8	148	2	0.33	0.92	123	26	0.28	0.83	168
3	0.36	0.9	205	27	0.29	0.91	171	3	0.55	0.9	168	27	0.34	0.95	122
4	0.35	0.93	205	28	0.34	0.9	191	4	0.4	0.93	161	28	0.55	0.92	184
5	0.21	0.63	166	29	0.35	0.9	194	5	0.28	0.65	167	29	0.4	0.96	164
6	0.33	0.85	132	30	0.3	0.87	191	6	0.44	0.87	124	30	0.28	0.67	186
7	0.33	0.84	141	31	0.4	0.87	130	7	0.34	0.88	163	31	0.37	0.69	183
8	0.33	0.93	147	32	0.32	0.84	184	8	0.24	0.82	182	32	0.3	0.81	207
9	0.29	0.92	167	33	0.31	0.74	180	9	0.55	0.9	145	33	0.23	0.82	187
10	0.34	0.93	164	34	0.32	0.92	184	10	0.61	0.96	165	34	0.58	0.97	175
11	0.36	0.93	192	35	0.37	0.94	173	11	0.43	0.94	150	35	0.57	0.95	211
12	0.33	0.69	168	36	0.2	0.65	131	12	0.21	0.9	154	36	0.43	0.93	174
13	0.32	0.89	145	37	0.37	0.89	142	13	0.41	0.87	143	37	0.51	0.91	211
14	0.35	0.81	156	38	0.37	0.83	139	14	0.34	0.84	149	38	0.36	0.81	170
15	0.33	0.87	151	39	0.35	0.83	145	15	0.27	0.8	184	39	0.29	0.85	181
16	0.29	0.9	185	40	0.37	0.92	186	16	0.61	0.94	123	40	0.36	0.94	176
17	0.34	0.92	186	41	0.18	0.68	158	17	0.54	0.96	171	41	0.49	0.91	143
18	0.16	0.63	124	42	0.43	0.9	150	18	0.2	0.64	166	42	0.4	0.96	172
19	0.4	0.89	144	43	0.37	0.84	131	19	0.29	0.85	142	43	0.35	0.83	164
20	0.69	0.9	155	44	0.39	0.82	140	20	0.28	0.87	177	44	0.25	0.83	184
21	0.42	0.71	149	45	0.18	0.64	107	21	0.21	0.75	181	45	0.42	0.92	136
22	0.33	0.91	199	46	0.4	0.89	149	22	0.35	0.94	137	46	0.36	0.85	154
23	0.18	0.57	152	47	0.38	0.83	136	23	0.33	0.89	168	47	0.37	0.82	154
24	0.38	0.87	133	48	0.35	0.84	146	24	0.44	0.94	133	48	0.26	0.84	172

Fig. 4.11 shows the *RMSE* changes for the datasets of 1, 2, 3 and 4 in the first approach for different number of features from 3 to 15. Figures 4.12 and 4.13 show the *RMSE* changes for different number of features and datasets. The first approach results show that all of the 15 features are important and have the best prediction; while by increasing the number of features in any of the 48 data sets, *RMSE* is decreased.

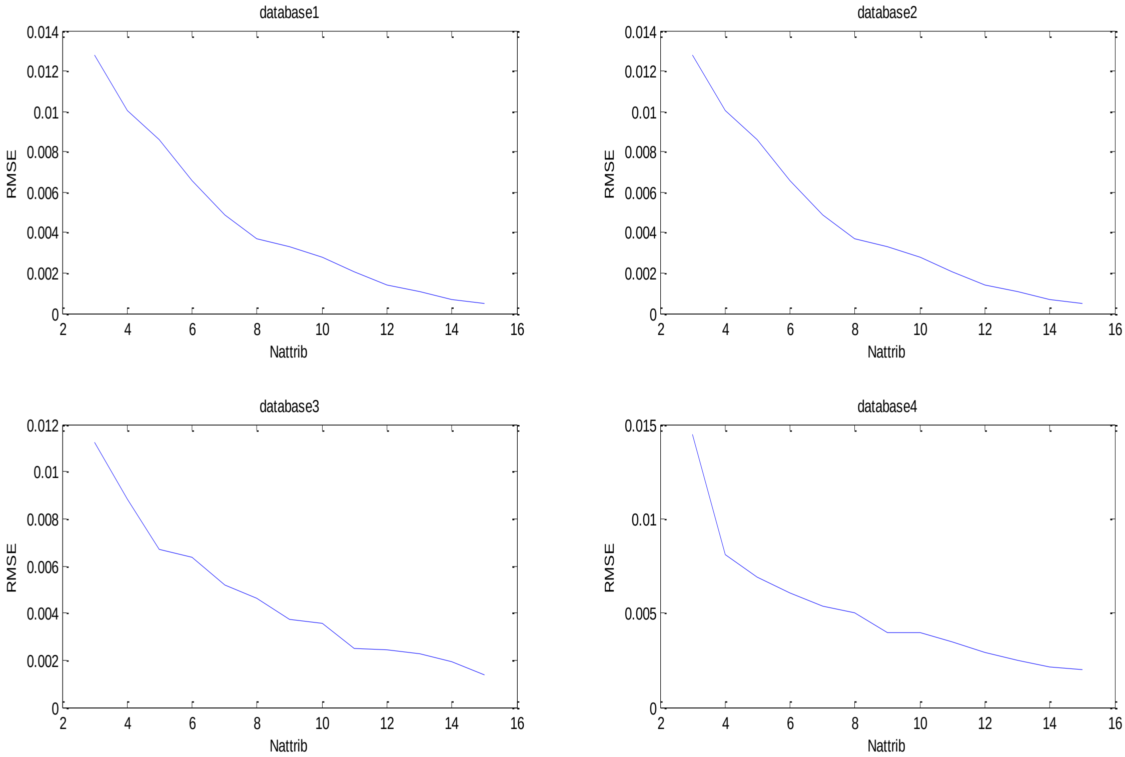


Fig 4.11: *RMSE* changing for the first approach in the first four datasets

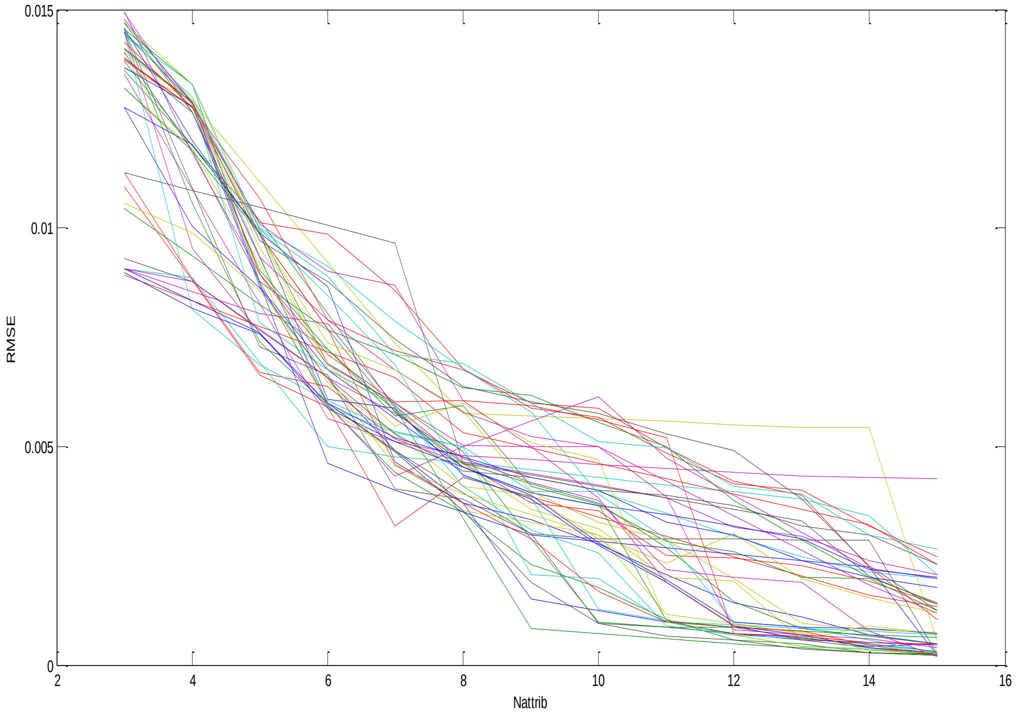


Fig 4.12: *RMSE* changing for the first approach in the 48 datasets

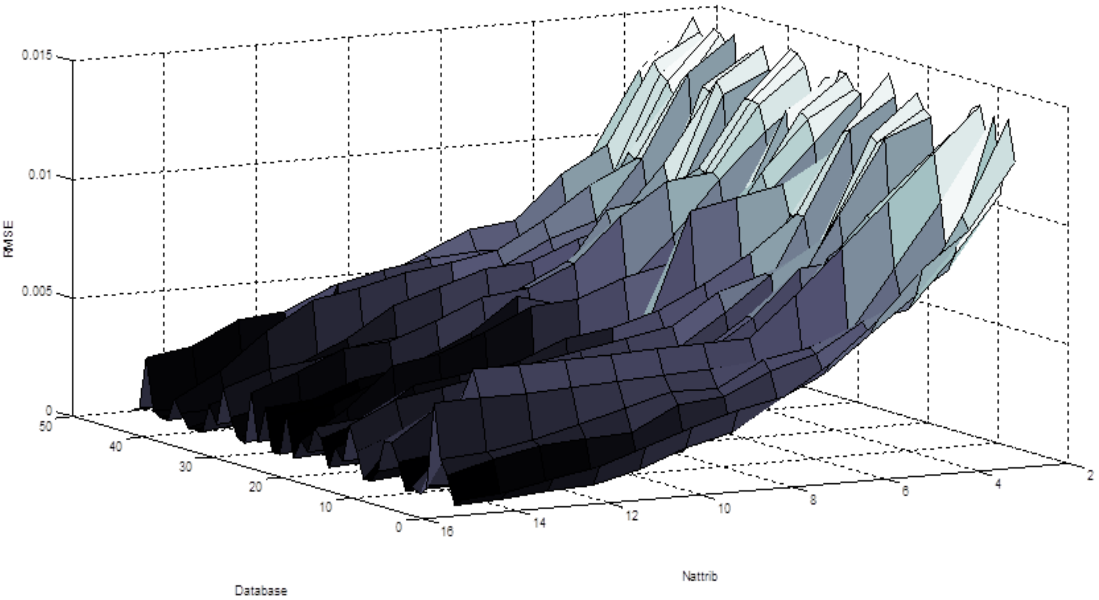


Fig 4.13: *RMSE* changing for the first approach with different number of features (*Nattrib*) for each dataset

Fig. 4.14 shows RMSEs in different numbers of features for the first four datasets in the second approach. In datasets 1, 2 and 4 respectively 15, 10 and 20 features have the minimum *RMSE*. The *RMSE* changes in all datasets are shown by Fig. 4.15. Also, Fig. 4.16 shows the *RMSE* changes with different number of features for all datasets. Results of this approach show that the feature selection is very important and affect the model efficiency considerably. In most of the second approach data sets, *RMSE* decreases by increasing the number of features and gets its minimum for a particular number of features and then increases. The best result in almost all of the data sets occurred in an interval from 15 to 20 features.

It should be noted that, the main aim of feature selection is to obtain fewer but more effective numbers of features and simultaneously minimizing the loss of the model's prediction accuracy. The results indicated that, by using 15 features, our obtaining accuracy is less than using the second approach with 24 features. However, in the second approach, we find the optimized number of features based on wrapper algorithm. Our results in finding the most effective features can enable the investors to analyze the market with fewer features, and not getting confused in the market by many features which are not necessarily effective.

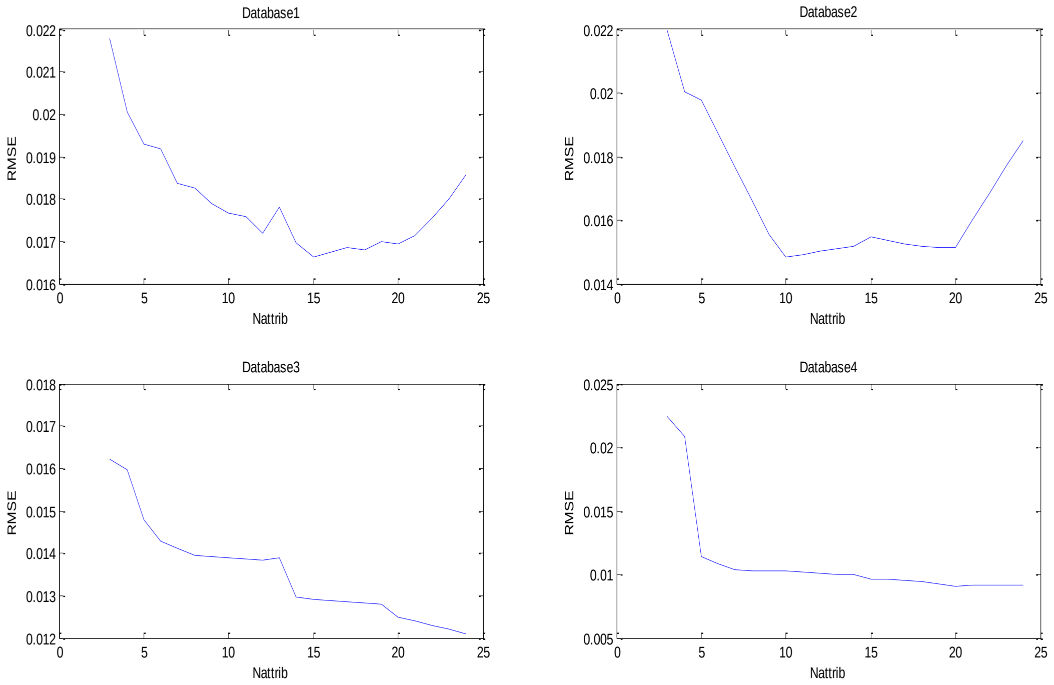


Fig 4.14: *RMSE* changing for the second approach in the first four datasets

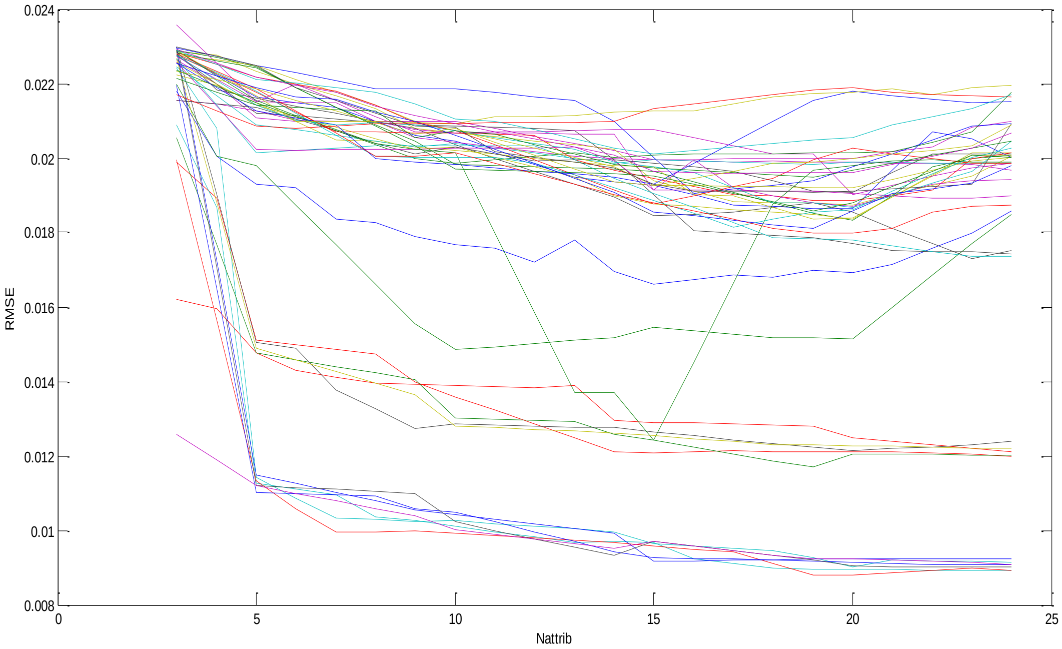


Fig 4.15: *RMSE* changing for the second approach in the 48 datasets

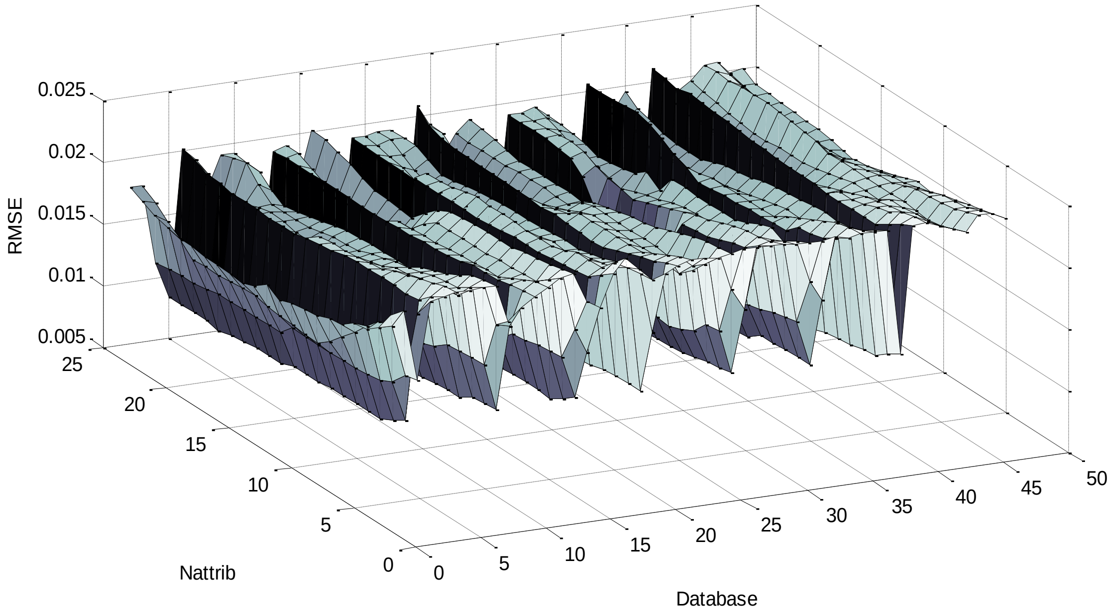


Fig 4.16: *RMSE* changing for the second approach with different number of features for each dataset

It is to be noted that the features are not the same in different datasets. Table 4.5 shows the optimum features and their best and mean costs for each dataset.

Table 4.5: Optimal features and their costs in second approach

Dataset	n-feature	Best sol-position	Best Cost(RMSE)	Mean Cost(RMSE)
1	15	[2 20 5 11 16 24 1 7 14 3 17 10 23 15 9]	0.016624	0.016624
2	10	[2 13 16 6 7 12 24 19 22 18]	0.0048508	0.0048508
3	24	[14 15 11 20 23 17 6 24 4 9 22 21 12 8 5 16 3 19 18 13 2 10 1 7]	0.012097	0.012097
4	20	[19 21 1 22 7 4 18 3 10 9 14 12 8 2 24 13 17 23 15 11]	0.0090231	0.0090231
5	15	[8 1 20 19 23 5 9 6 22 21 11 13 10 17 24]	0.019963	0.019963
6	20	[16 5 22 8 23 9 18 17 15 6 21 7 3 4 10 1 20 19 24 13]	0.018746	0.018746
7	23	[1 12 20 24 6 13 22 5 3 8 21 15 9 23 7 14 10 2 19 16 4 17 18]	0.017296	0.017296
8	20	[8 23 24 13 10 1 20 9 18 17 15 6 21 7 3 4 19 16 5 22]	0.018647	0.018647
9	20	[12 7 23 21 3 8 19 22 6 17 4 2 15 18 20 16 5 13 10 1]	0.018313	0.018313
10	24	[15 11 18 23 2 20 7 9 1 14 10 13 19 6 22 3 5 12 16 8 17 21 4 24]	0.012	0.012
11	24	[6 20 17 16 18 19 15 7 8 23 3 4 1 22 2 13 21 11 9 12 10 24 14 5]	0.008919	0.008919
12	24	[20 6 17 14 24 16 18 19 21 11 9 15 8 7 23 3 4 1 22 2 12 13 10 5]	0.019668	0.019668
13	20	[13 11 6 24 18 9 1 12 3 19 23 17 4 21 16 5 22 10 8 2]	0.018401	0.018401
14	24	[11 8 12 22 1 16 15 4 10 5 24 20 14 13 17 3 2 23 18 19 6 9 21 7]	0.017431	0.017431
15	20	[7 5 22 8 3 17 15 4 24 13 10 1 20 9 18 19 16 23 6 21]	0.019758	0.019758
16	24	[12 18 17 2 22 6 21 15 8 4 11 1 20 23 14 7 13 9 3 19 10 16 24 5]	0.01201	0.01201
17	20	[10 24 20 2 23 7 17 18 9 15 4 1 22 13 14 11 19 21 8 3]	0.008793	0.008793
18	24	[8 23 1 11 20 4 14 7 12 18 17 2 15 13 22 6 21 9 19 3 24 5 10 16]	0.019862	0.019862
19	20	[13 21 11 5 16 24 6 22 18 9 1 12 3 10 2 19 23 17 4 8]	0.019008	0.019008
20	20	[2 1 16 11 17 12 20 6 10 21 5 18 13 3 23 9 7 8 22 19]	0.018369	0.018369
21	21	[18 19 5 6 3 1 11 10 15 22 4 13 9 17 2 23 7 20 16 8]	0.019075	0.019075
22	24	[6 16 18 23 3 4 1 2 22 13 11 20 17 21 19 15 7 9 8 12 10 14 24 5]	0.009078	0.009078
23	10	[5 6 15 7 3 13 9 17 16 21]	0.01986	0.01986
24	20	[19 23 5 24 6 22 13 21 11 9 1 4 14 7 24 20 2 16 12 19]	0.018852	0.018852
25	23	[18 2 13 19 6 22 3 5 12 16 8 17 21 4 24 20 7 15 11 9 1 14 10]	0.017346	0.017346
26	23	[20 1 21 23 22 10 9 19 7 8 24 11 2 13 12 14 15 17 3 5 4 18 16 6]	0.01891	0.01891
27	20	[4 13 19 18 5 3 6 1 11 10 15 22 9 17 2 7 23 20 8 16]	0.019189	0.019189
28	20	[8 24 13 21 15 11 7 19 22 14 4 12 20 5 1 6 3 2 9 16]	0.012154	0.012154
29	15	[3 22 11 20 23 18 1 10 2 12 4 7 5 6 17]	0.0091685	0.0091685
30	20	[14 24 4 12 10 13 8 9 1 17 21 15 3 16 23 22 2 6 20 7]	0.020243	0.02043
31	17	[5 4 19 6 21 10 20 7 22 11 13 16 18 23 8 1 9]	0.018689	0.018689
32	20	[9 8 13 11 7 14 19 16 4 5 22 24 12 21 6 3 18 17 2 15]	0.018616	0.018616
33	20	[15 19 5 3 7 1 13 11 8 14 20 21 22 9 6 16 17 18 12 10]	0.019793	0.019793
34	24	[19 23 3 15 17 11 24 4 21 22 14 2 13 5 10 6 9 8 20 18 7 12 16 1]	0.012201	0.012201
35	24	[14 12 9 20 7 2 3 22 16 1 21 8 18 19 11 24 10 17 4 5 15 23 13 6]	0.0090162	0.0090162
36	14	[11 22 21 24 4 20 8 17 7 16 23 5 1 10]	0.019299	0.019299
37	20	[24 20 15 12 2 8 6 11 18 22 4 9 5 10 7 16 3 1 17 21]	0.018792	0.018792

Dataset	n-feature	Best sol-position	Best Cost(RMSE)	Mean Cost(RMSE)
38	20	[9 15 17 18 24 5 21 22 1 19 12 20 2 3 10 14 23 16 7 13]	0.017977	0.017977
39	20	[9 5 21 22 1 20 2 3 1019 12 15 17 18 24 16 7 14 23 13]	0.018675	0.018675
40	24	[23 22 10 20 1 13 12 14 15 17 3 4 5 21 9 19 7 8 24 11 2 18 6 16]	0.009077	0.009077
41	10	[11 7 14 19 16 12 20 24 13 21]	0.020924	0.020924
42	17	[16 1 20 7 8 17 2 10 14 19 23 5 15 4 22 9 6]	0.019094	0.019094
43	15	[18 19 2 17 13 1 22 4 15 9 24 23 6 10 3]	0.018561	0.018561
44	20	[15 17 9 5 12 18 24 22 1 20 16 21 2 3 1019 7 23 13 14]	0.019678	0.019678
45	4	[1 17 13 15 4 22]	0.020789	0.020789
46	15	[4 3 6 17 22 23 16 18 1 5 20 12 9 11 8]	0.020094	0.020094
47	20	[16 8 11 12 2 13 22 4 5 15 20 6 17 1 18 19 24 21 9 7]	0.019602	0.019602
48	15	[2 14 21 1 5 15 6 17 22 23 16 18 9 11 8]	0.019254	0.019254

The wrapper ANFIS-ICA output of this study shows that feature selection by ICA has a good impact on the accuracy of ANFIS for different datasets. We also compare our method with Jasemi et al (Jasemi et al., 2011) which uses a feed forward neural network (NN) optimized by a back propagate algorithm and ANFIS-GA wrapper model which used genetic algorithms (GA) instead of ICA for feature selection. The results accuracy shows that wrapper ICA-ANFIS algorithm dominates the NN and also wrapper ANFIS-GA algorithm. In more detail discussion, the ANFIS model has solely better results than NN algorithm. Forecasting accuracy of NN depends on learning data set and their adequacy. Moreover, NN methods sometimes get stuck in local minimum, so choosing proper dataset is too critical in neural network models. In the other side, the ANFIS has better result when it deals with noisy and inadequate data set. Based on the fact that, in stock exchange dataset we always encounter with noisy data, enjoying from ANFIS model is preferable than NN models. Also, the ICA can diversify the dataset for learning issues better than other models such as GA model.

Table 4.6: Comparison between algorithms

	Total Hit ratio	Hit ratio Approach 1	Hit ratio Approach 2	Hit ratio 1-day/ Approach 1	Hit ratio 1-day/ Approach 2	Mean Runtime (s)	Mean Cost (RMSE)
NN	74.2 %	74.8 %	73.6 %	45 %	43.4 %	20	0.0166
ANFIS-GA	77 %	76 %	78 %	35 %	38 %	110.9	0.0062
ANFIS-ICA	86 %	85 %	87 %	40 %	43 %	34.2	0.0048

It is considerable to mention that ICA algorithm gets the final response more quickly than GA and because of the fact that wrapper models are time-consuming and need a large amount of time to convergence, this algorithm proves its ability in other point of view.

4.5. Conclusion

The paper proposes a novel methodology for feature selection and time series estimation based on a wrapper approach called ANFIS-ICA, which results from the combination of ANFIS, a fuzzy logic based function estimator that adopts the adaptive systems framework to facilitate learning and adaptation, and ICA, an evolutionary algorithm used for subset evaluation. Additionally, the proposed model is applied on the basis of the technical analysis of Japanese Candlestick by two approaches of Signal and Raw database. In fact, the paper incorporates the technique of Japanese Candlestick charts for data transformation and attribute generation. Finally, daily stock prices for the General Motors Company at New York Stock Exchange from 2000 to 2009 are applied for benchmarking.

The root of mean square errors, the number and percentage of the signals that are predicted correctly are considered as the assessment measures while the results show a good reliability of the model that is even better than the base study and model of Jasemi et al. (Jasemi et al., 2011).

In the first approach, all the 15 features together have the best approximation but in the second approach, feature selection shows its effect on the results very well, while in different datasets almost 20 numbers of features are more appropriate. As a matter of fact it is believed that the analysis of different features or different subsets of them has significant influence on prediction accuracy. The second approach has a better performance than the first one. Also, it should be noted that the prediction accuracy of this model is better than some other time series models and shows great abilities for decision making about stock trading.

Future research directions of the paper include but are not limited to

1. Combining prediction methods in the framework of fusion models or optimize the classification algorithms by applying some metaheuristics algorithms to improve the prediction results
2. Predicting the other important variable (in addition to return) such as liquidity (Barak et al., 2013).
3. Using fundamental features and textual information, in addition to technical features, in order to have a more comprehensive features and to be able to predict long term situation of stocks
4. Prediction of stocks in other popular stock markets such as DAX or NASDAQ
5. Applying statistical feature selection models such as Filter methods and CFS (Zhang et al., 2014a), or using other wrapper models to compare the results

5. Fusion of Multiple Diverse Predictors in Stock Market

Summary of the fifth chapter

Forecasting stock returns and their risk represents one of the most important concerns of market decision makers. Although many studies have examined single classifiers of stock returns and risk methods, fusion methods, which have only recently emerged, require further study in this area. The main aim of this paper is to propose a fusion model based on the use of multiple diverse base classifiers that operate on a common input and a Meta classifier that learns from base classifiers' outputs to obtain more precise stock return and risk predictions. A set of diversity methods, including Bagging, Boosting and AdaBoost, is applied to create diversity in classifier combinations. Moreover, the number and procedure for selecting base classifiers for fusion schemes is determined using a methodology based on dataset clustering and candidate classifiers' accuracy. The results demonstrate that Bagging exhibited superior performance within the fusion scheme and could achieve a maximum of 83.6% accuracy with Decision Tree, LAD Tree and Rep Tree for return prediction and 88.2% accuracy with BF Tree, DTNB and LAD Tree in risk prediction. For feature selection part, a wrapper-GA algorithm is developed and compared with the fusion model. This paper seeks to help researcher select the best individual classifiers and fuse the proper scheme in stock market prediction. To illustrate the approach, we apply it to Tehran Stock Exchange (TSE) data for the period from 2002 to 2012.

5.1. Introduction

The future status of companies offering stocks is of great importance to stock market practitioners. According to the efficient market theory, it is impossible to predict prices based on historical stock data. This theory also states that the prediction of the classical criteria of risk and return cannot bring advantages to shareholders. There is abundant evidence in the literature, however, that argues against the efficient nature of the market (Cervelló-Royo et al., 2015). A precise prediction of companies' future financial status provides investors with the security to make a confident and profitable investment.

To achieve an accurate stock market prediction, the identification of the effective features is crucial. In other words, the representative features of the factors play a key role in prediction efficiency. Technical and fundamental analyses are two essential tools in financial market evaluation. Fundamental analysis can be used to evaluate a firm's performance and financial status over a period of time by carefully analysing the institute's financial statement (Huang, 2012a). Technical analysis (TA), conversely, evaluates securities by means of statistics such as past price and volume that are generated by market activities (Barak et al., 2015).

The major criticism of TA is that it only considers the price movement and ignores the fundamental factors related to the company. Moreover, TA takes a comparatively short-term approach to analysing the market.

Fundamental analysis seeks to find the essential features of stock and market movements. In fact, the logic behind fundamental analysis is that if a company has a proper fundamental strength, then long term stock investment in the company will be more secure and stable. Thus, the stocks of these fundamentally strong companies, which are making money, gaining profit and growing their businesses, represent an opportunity for a successful investment. For this reason, in this paper, fundamental analysis is applied in order to determine the fundamental features that decide which company is a good bet for a secure investment.

Stock return forecasting is a fascinating endeavour with a long history. From the standpoint of finance practitioners, asset allocation requires real-time forecasts of stock returns and an improved stock return forecast holds the promise of enhancing the investment performance (Rapach and Zhou, 2012). Many studies address the prediction of stock market returns (see, e.g., (Enke and Thawornwong, 2005; Hyup Roh, 2007; Tsai et al., 2011)). For an efficient investment, the return consideration is not sufficient. In fact, the risk and return must be considered simultaneously to create an accurate portfolio evaluation (Barak et al., 2013). In this paper, the prediction of stock return and risk are implied concurrently based on fundamental features in order to build a more comprehensive model for stock market analysis.

Although the statistical approaches such as logistic regression and regression analysis are widely applied to forecast the return and risk of stocks, the results of machine learning approaches are generally superior in comparison to statistical methods (Barak and Modarres, 2015; Cheng, 2014, 2015). The multiple classifier ensemble system (MCS), one type of machine learning technique, has recently become the focus of a new methodology for obtaining higher accuracy in predictions. The rationale is that the optimization of a combination of relatively simpler predictors appears more convenient than optimizing the design of a single complex predictor (Barak and Sadegh, 2016; Haghighi et al., 2011). In fact, three fundamental issues are effective for establishing a successful MCS model: accuracy of individual classifiers, diversity among classifiers, and the choice of the fusion methods that will be used. The aim of this combination scheme is to gain increased precision with proper single classifiers and eliminate the uncorrelated individual classifier errors, which are the errors made by individual classifiers on various parts of input space (Tsai et al., 2014).

In fusion methods, multiple dissimilar predictors are used and combined by a fusion algorithm that combines the outputs of the individual predictors. Fusion methods in MCS are generally categorized as linear, non-linear, statistical, and machine learning combination methods. Linear methods are known as the simplest fusion methods. For instance, the sum and average of the individual classifiers' outputs are examples of linear fusion methods (Kuncheva, 2004b). Non-linear methods include rank-based combiners such as Borda Count and majority voting strategies (Kuncheva, 2004b; Sharky and Sharky, 1997). In statistics-based fusion methods, statistical techniques such as regression or Bayesian combination methods are used to combine the outputs of individual classifiers (Pereira et al., 2009). Finally, different machine learning methods such as decision trees (DT) and support vector machines (SVM) can be used to fuse the base learner.

The second fundamental issue, diversity, refers to the differences existing among decisions made by various classifiers. In classifier combination design, it is believed that the success of combinations not only depends on the individual classifiers' suitability but also on diversity being inherent among them. In fact, classifiers that are strong in different areas are supposed to be diverse. The entire point of fusing multiple classifiers is to balance the weaknesses of the individual classifiers. This balancing requires classifiers that make errors in different areas of the decision space. Diversity creation methods are generally categorized as explicit and implicit methods (Haghighi et al., 2011). Explicit methods generally seek to optimize certain metrics during the diversity creation. Boosting and AdaBoost (Freund and Schapire, 1996) are examples of explicit diversity methods that directly manipulate the training data distributions in order to make some sort of diversity in the combination procedure. Implicit methods, unlike explicit methods, pay no special attention to diversity metrics. Bagging, as an implicit method, randomly samples from training data in order to train each individual classifier and these samples will be reused to produce diverse combination members (Breiman, 1996).

In the present paper, in which we aim to improve the accuracy of the risk and return prediction of stocks, we propose a fusion model framework that relies on the combination of multiple dissimilar and diverse classifiers operating on a common input. In the first phase, cross-validation is applied on the dataset and a specific (but optimum) number of different classifiers sets is learned from the dataset (creating a pool of classifiers). A classifier selection procedure is proposed in which the dataset is first clustered by the *k*-means method, after which the optimum number of clusters is chosen by Streamlined Silhouette Criterion Average (SSCA). The performance of the classifiers on the dataset is then evaluated and the best combinations are selected for the fusion phase. Finally, in the fusion phase, Bagging, Boosting and AdaBoost are applied to the classifiers of the selected combinations of the previous phase and one fusion algorithm as a Meta-classifier learns from their predictions to provide the final prediction of the initial input data.

The contribution of the paper is summarized as follows:

- Designing a fusion model for returns and risk prediction of stocks in financial market.
- Applying various diversity methods in order to achieve more precise predictions.
- Considering the simultaneous risk and return prediction of stocks.

- Developing a base classifier selection procedure from candidate procedures by dataset clustering and considering the accuracy of combined classifiers.
- Developing a wrapper-GA scheme for feature selection and prediction and comparing it with the fusion method.

This paper is divided into six sections and organized as follows: The backgrounds of multi-classifier systems and combination models, as well as diversity creation and fusion methods, are discussed in section 2. In Section 3, the proposed multi classifier ensemble system (MCS) is generally discussed. Next, in section 4, the experimental results are provided, and the discussion of real return and risk prediction with the proposed fusion model is presented in section 5. Moreover, in this section, a new selection scheme is also developed for feature selection part and compared with the hybrid method. Finally, this study's conclusions and future research directions are presented in section 6.

5.2. Literature Review

5.2.1. Stock prediction with classifier ensembles

The best way to design of MCS to achieve higher accuracy has become an important research topic in the field of pattern recognition, as stated in a number of related review articles (Finlay, 2011; Oza and Tumer, 2008; Rokach, 2009). The main idea behind using ensembles is that the combination of classifiers can improve the performance of a pattern recognition system in terms of better generalization with increased efficiency and clearer design (de Oliveira et al., 2009). Wolpert (2001) believes that every classifier has its own specific competencies over other competing algorithms, and MCS tries to take advantage of each of the available trained classifiers based on their competencies for different parts of the feature space.

Dasarathy and Sheela (1979) proposed combining a linear classifier and a *k*-nearest neighbour classifier in which the conflicting feature space regions were first identified by classifiers, after which one classifier works on the features of the conflicting region and the other works on the remaining features. This can be considered as the first study suggesting a classifier selection concept for MCS design. In 1981, Rastrigin and Erenstein (1981) further developed the idea by partitioning the feature space into several regions and assigning the individual classifiers with the best accuracy over each region. A survey of multiple classifier systems as hybrid systems can be found in (Woźniak et al., 2014).

In the stock exchange and financial research area, different machine learning methods such as artificial neural networks (ANN), decision trees (DT) and support vector machines (SVM) are widely applied to establish efficient ensemble systems. Neural network ensemble systems are found to be effective in achieving superior accuracy for stock price forecasting (Lahmiri, 2014; Tsai et al., 2011; Wang and Wu, 2012). In addition to neural networks, algorithms based on decision trees use a greedy search approach and tend to choose a search direction by means of a heuristic attribute evaluation function (Salzberg, 1994). This approach, however, does not guarantee finding an optimal solution. Thus, a combined algorithm starting from different initial points in the search space can improve the DT's performance in finding an optimal model. Qian and Rasheed (2007) combined several machine learning classifiers, including artificial neural networks, decision trees and *k*-nearest neighbour, to design a hybrid model for stock market prediction. The results show that accuracy of up to 65% is achieved. Tsai et al. (2014) combined three classifiers, including multi-layer perceptron (MLP) neural networks, SVM and DT based on a combination of the bagging and boosting methods. Their results showed that DT ensembles utilizing boosting techniques have the best performance, and this superiority is demonstrated by further studies on a Taiwan bankruptcy dataset.

5.2.2. Fusion in ensembles scheme

Fusion methods refer to the approaches used to obtain classifier ensembles. The motivation behind such methods is to combine predictions so that misclassification is less likely to occur. In other words, a proper fusion method is the one that can exploit the strength of individual classifiers and optimally combine their outputs to provide the final decision of the system (Woźniak et al., 2014). Among early studies regarding fusion techniques for MCS, the majority voting schemes application is widely known (Kuncheva et al., 2003).

In another category, aggregation methods such as supremum, average, mean or median value perform simple fusion operators and lack any learning procedures (Fumera and Roli, 2005; Kourentzes et al., 2014; Wozniak, 2008). The most essential advantage of these methods is that they balance the over-fitting of the individual classifiers. Tumer and Ghosh (1996) used a large number of unbiased and independent classifiers and reported the average of the outputs as the final results. These researchers claimed that their method returned the same results as applying the optimal Bayes classifier. Ho et al. (1994) used different methods based on decision ranks, such as Borda counts, for the combination function in order to achieve a useful representation for each classifier's decision. A Borda count is categorized as a support function in a fusion system that assigns a score for the decisions taken from each individual classifier.

Machine learning fusion methods are another group of fusers that use the accuracy of individual classifiers as training data and then apply a learner algorithm, e.g., DT, K-NN,…, as a high level classifier (meta classifier) that learns from the accuracy of individual classifiers to obtain higher accuracy (Ferreiro et al., 2011).

5.2.3. Diversity and accuracy creation

System diversity is highlighted as a crucial important aspect in MCS design (Kuncheva and Whitaker, 2003; Tang et al., 2006; Tsymbal et al., 2005). The main purpose of designing MCS is to integrate a set of mutually complementary individual classifiers in order to achieve outputs with higher accuracy and diversity and less correlation. Diversity can generally be achieved by inducing variations in classifier parameters (e.g., weights and topology of a neural network as initial parameters) (Windeatt, 2005), classifiers' training datasets (e.g., using the learning strategies, such as Bagging and Boosting) (Kuncheva, 2004a), and classifier types (e.g., using different types of classifiers as ensemble members).

Variation in classifiers' training dataset (data partitioning) is important for several reasons, such as data privacy or learning procedure requirements over distributed data partitions in different databases. In this category, cross-validation is a well-known approach that minimizes overlap among dataset partitions (Krogh and Vedelsby, 1995). Bagging (Breiman, 1996) and Boosting (Freund, 1995; Schapire, 2001) are both known as the most popular techniques in diversity creation and originate in bootstrapping. In this paper, diversity is achieved by making variations in the training dataset by means of the abovementioned techniques (e.g., cross-validation and Bagging, Boosting) and using different classifier types (e.g., neural network, decision trees, and SVM) as ensemble members.

5.3. Proposed Multi-Classifier Ensemble System (MCS)

The MCS is generally composed of three main phases: (1) generation, (2) selection, and (3) integration (see (Alceu S. Britto et al., 2014)). The generation phase focuses on creating a pool of base classifiers composed of the most appropriate candidates for the subsequent classifier selection and integration steps. In the second phase, the best classifiers from the pool are selected for building the MCS, and finally, in the integration phase, the predictions of the selected classifiers are combined in order to make a final decision.

In the generation phase, the aim is to create as many diverse classifiers as possible. Thus, several diversity methods are applied to build a pool of diverse base classifiers. In the second and third phases, a meta-learning approach is proposed (Giraud-Carrier, 2008). In other words, the selection of the most competent classifiers and final classifications are considered as another classification problem, termed the meta-problem. For a given instance, the base classifiers' outputs and the real class of the sample are passed down to a Meta classifier as its input data, and then the Meta classifier estimates the final class of the given sample.

In the following, three phases of the proposed MCS framework, including the generation of the base classifiers (pool of classifiers), selection of competent classifiers and final fusion phase are widely discussed.

5.3.1. Phase one: Base classifier generation

The main aim of MCS design is to effectively select competent classifiers and combine their predictions. In order to ease and increase the accuracy of the selection procedure, it is preferable to build an initial set of potentially competent base classifiers (pool of classifiers) first and then decide whether each candidate is sufficiently qualified to classify an input instance. A key factor here is to combine the prediction results of those classifiers in which the decision boundaries are widely different. To achieve this, the creation of diversity among classifiers is proposed. A diversification strategy aims to train the classifiers on different (disjoint) input subspaces in order to create a set of different but complementary classifiers. Several diversification approaches that are mainly used for generating diverse classifiers are discussed by (Mousavi and Eftekhari, 2015). Using unstable classifiers such as decision trees (DT) and neural networks (NN), applying different sets of classifiers including NN, DT, SVM, etc., and utilizing various datasets for training the base classifiers are the diversification methods used in this paper. To create variations in classifiers' training dataset, four methods are applied: Cross-validation, Bagging, Boosting and AdaBoost, each of which is discussed in detail below.

- ***Cross validation***

In order to generate variations in the training dataset, data partitioning approaches are used to create various partitions for classifier training. A common methodology in this category is cross-validation, which evaluates the robustness of the predictor and minimizes the overlapping of dataset partition. We utilize a 10-fold cross-validation model, which is proven to be sufficient in the predictor's performance evaluation (Mitchell, 1997b). In this model, the training dataset is divided equally into 10 subsets. The training procedure is repeated 10 times, and each time, nine out of 10 of the subsets are selected for classifier training while the tenth subset is used as the test set. When the procedure is complete, the best result will be selected.

- ***Bagging***

Bootstrap aggregation, simply known as Bagging, is an ensemble-based algorithm and one of the most intuitive and simple to implement methods with extremely good performance. In the Bagging approach, the classifier is trained on different training datasets that are generated by bootstrap method (Breiman, 1996). The Bootstrap method builds *k* training datasets by randomly re-sampling the original given dataset with replacement. Thus, there are *k* independent training datasets for the classifier training procedure. When classifier training is complete, the final results should be aggregated via an appropriate method, such as majority voting. Pseudo code for the Bagging method is given as follows:

```
Algorithm: Bagging
Input:
    Training data S with correct labels $\omega_i \in \Omega = \{\omega_1, ..., \omega_C\}$ representing C classes
    Weak learning algorithm WeakLearn
    Integer T specifying number of iterations
    Percent (of fraction) F to create bootstrapped training data
```

```
Do:    $t = 1,\ldots,T$
    1. Take a bootstrapped replica $S_t$ by randomly drawing percent of $S$.
    2. Call WeakLearn with $S_t$ and receive the hypothesis (classifier) $h_t$.
    3. Add $h_t$ to the ensemble, $E$.
End
Test: Simple Majority Voting - Given unlabeled instance $x$
    1. Evaluate the ensemble on $x$.
    2. Let $v_{t,j} = \begin{cases} 1, & \text{if } h_t \text{ picks class } \omega_j \\ 0, & \text{otherwise} \end{cases}$ be the vote given to class by classifier.
    3. Obtain total vote received by each class $V_j = \sum_{t=1}^{T} v_{t,j}$ ,   $j = 1, \ldots, C$
    4. Choose the class that receives the highest total vote as the final classification.
```

- ***Boosting***

In Boosting method, it is believed that finding many prediction rules can be much easier than building one rule with a high level of accuracy. In boosting, unlike bagging, each individual classifier is trained on different k training sets in a sequential and not a parallel and independent way. The algorithm creates an ensemble of classifiers through data resampling in order to provide the most informative training data for each consecutive classifier. Boosting creates three weak classifiers: the first classifier, C_1, is trained by a random sample of the training data. For the second classifier, C_2, the training set is selected as the most informative subset. In other words, half of the training data for C_2 is correctly classified by C_1 and the other half is misclassified by C_1. Finally, the third classifier C_3 is trained on samples that are misclassified by both C_1 and C_2. In fact, in each iteration, the classifier creates a new set of prediction rules and assigns new weights to data so that the classifier will pay more attention to misclassified tuples in subsequent iterations. Finally, after many repetitions, the boosting algorithm combines these rules into one single prediction rule that is expected to be much more accurate than any of the single rules.

Ultimately, boosting places heavier weights on the samples that are most often misclassified in every round. In other words, it forces the base learner (i.e., the individual classifier) to focus on the hardest samples that were mostly misclassified by the preceding rules. In order to combine the achieved prediction rules, using a (weighted) majority voting approach is suggested as an efficient method (Schapire, 2001). The pseudo code for the Boosting algorithm is given as follows:

```
Algorithm: Boosting
Input:
    Training data S of the size N with correct labels $\omega_i \in \Omega = \{\omega_1, ..., \omega_C\}$;
    Weak learning algorithm WeakLearn.
Training
    1. Select $N_1 < N$ patterns without replacement from S to create data subset $S_1$.
    2. Call WeakLearn and train with $S_1$ to create classifier $C_1$.
    3. Create dataset as the most informative dataset $S_2$, given $C_1$, such that half of $S_2$ is correctly
       classified by $C_2$, and the other half is misclassified. To do so:
        a. Flip a fair coin. If Heads, select samples from S, and present them to $C_1$ until the first instance
           is misclassified. Add this instance to $S_2$.
        b. If Tails, select samples from S and present them to $C_1$ until the first one is correctly classified.
           Add this instance to $S_2$.
        c. Continue flipping coins until no more patterns can be added to $S_2$.
    4. Train the second classifier $C_2$ with $S_2$.
    5. Create $S_3$ by selecting those instances for which $C_1$ and $C_2$ disagree. Train the third classifier $C_3$
       with $S_3$.
Test – Given a test instance x
    1. Classify x by $C_1$ and $C_2$. If they agree on the class, this class is the final classification.
    2. If they disagree, choose the class predicted by $C_3$ as the final classification
```

- ***AdaBoost***

In AdaBoost (Freund and Schapire, 1997), the most popular boosting algorithm, a series of models are combined; in each model, the dataset is re-sampled and weighted based on their difficulty to be learned and classified (Cao et al., 2012). AdaBoost takes the training set $s_n = [(x_1,y_1), \ldots, (x_m,y_m)]$ as input data and calls the base learning algorithm repeatedly for a series of iterations $t = 1, \ldots, T$. The $w_t = \{w_t^1, w_t^2, ..., w_t^n\}$ represents the weight distribution over samples in iteration t and is equally distributed in the first iteration. In each iteration t, AdaBoost maintains the weights on the training sample i denoted as w_t^i so that the weights of misclassified samples will increase and the learner algorithm will pay more attention to these difficult samples in the training set in subsequent iterations. Based on the given w_t in each round t, the base learning algorithm finds the most appropriate classifier h_t and assigns an importance measure α_t to it, set as:

$$\alpha_t = \frac{1}{2}\ln\left(\frac{1-e_t}{e_t}\right) \tag{1}$$

where e_t represents the mean squared error (MSE) for h_t. The final classifier H will be built by a weighted majority vote of the T base classifiers in which the parameter α_t is assigned as the weight of classifier h_t. The pseudo code of the presented AdaBoost is given as follows (Barak and Sadegh, 2016):

```
Algorithm: AdaBoost

Input:        Initial training set composed of n samples, denoted as $s_n = [(x_1,y_1), \ldots, (x_m,y_m)]$

Initialize:   $w_1^i = 1/n$, i.e., $w_1 = \{w_1^1, w_1^2, \ldots, w_1^n\} = \{1/n, 1/n, \ldots, 1/n\}$

                  For $t = 1,2, \ldots, T$

                  Take $R_t$ samples randomly from $s_n$

                  Determine the weight distribution $w_t$

                  Build a classifier $h_t$ using $R_t$ as the training set

                  Compute: $e_t$ = MSE for $h_t$ and $\alpha_t = \frac{1}{2}\ln(\frac{1-e_t}{e_t})$

                  Update the distribution weight set: $w_{t+1}^i = normalize(w_t^i * \exp(-\alpha_t))$

Output:       The combined classifier: $H = \sum_{t=1}^{T} \alpha_t h_t$
```

5.3.2. Phase two: Classifier selection

In addition to diversity, the accuracy of the base classifiers is another critical factor in base classifier selection (Woloszynski and Kurzynski, 2011; Woloszynski et al., 2012) and can guarantee the effectiveness of the MCS.

The proposed selection phase seeks to discover sets of classifiers (fusion set) that improve the classification accuracy in integration. In order to specify the optimum number of classifiers in fusion sets, it is suggested to determine the optimum number of clusters of the dataset first and then find the sets of classifiers with the same number. To achieve this, the k-means clustering algorithm is first applied on the dataset for different values of k, after which the best value is chosen.

The k-means algorithm is one of the simplest unsupervised learning methodologies, using a simple method to classify a given dataset into a certain number of clusters (k clusters). The aim is to determine k centroids that should be cunningly placed as different locations resulting in different outputs. Thus, it is better to place these centroids as far as possible from each other. Next, each point of the dataset should be associated with the nearest centroid. When no point is left, early grouping is complete. At this point, k new centroids must be recalculated for the centres of clusters built in previous step. A new binding must be carried out on the dataset points toward the new k centroids. This loop continues until no more changes occur in centroids' locations and they do not move any further. For a given set of observations (x_1, x_2, …, x_n), where each observation is a d-dimensional real vector, the best condition in k-means clustering is to partition the n observations into k (≤n) sets S={S_1, S_2, …, S_k} in which the within-cluster sum of squares is minimized:

$$\arg\min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \left\| x - \mu_i \right\|^2 , \qquad (2)$$

where μ_i is the mean of points in S_i.

The k-means algorithm is then performed for different values of k. In order to specify the optimum number of clusters (k), the streamlined silhouette criterion average (SSCA) is calculated (Covões and Hruschka, 2011). SSCA evaluates the closeness of each object of a cluster to the objects of nearby clusters. For the *i*th observation of the *k*th cluster, the Silhouette index is defined as follows:

$$s_{i,k} = \frac{b_{i,k} - a_{i,k}}{Max\,(b_{i,k}, a_{i,k})} \qquad (3)$$

where $b_{i,\,k}$ is the minimum average distance between observation *i* and all other observations to the nearest neighbouring clusters except the *k*th cluster, and $a_{i,\,k}$ represents the average distance between observation *i* and the remaining (n_k-*1*) observations of the *k*th cluster. The most effective clustering is the one that results in maximum SSCA, computed as:

$$SSCA = \frac{1}{k}\sum_{j=2}^{k}\frac{1}{n_j}\sum_{i=1}^{n_j} s_{i,j}. \qquad (4)$$

The optimum number of clusters (*k*) resulting from SSCA calculations determines the number of base classifiers in ensemble that create the widest decision boundaries. The proposed classifier selection process is illustrated in Fig. 5.1. The cross-validation is first performed on training data for diversity creation among base classifiers. In order to increase the base classifiers' accuracy, the heuristic Meta cost method is applied. This method intensifies the error of prediction by multiplying it by an integer number. In other words, if the classifier predicts class *A* for an input data but the real class is two steps above or below the predicted class, Meta cost penalizes the error by doubling it. Similarly, if the real class is three steps away from the predicted one, the error will be multiplied by three. Table 5.1 illustrates the error penalty scores of the Meta cost method.

Based on the optimum value of *k* achieved by SSCA, all possible sets of *k* classifiers are formed and their outputs, including the real class of the samples, are passed down as inputs to the meta-classifier. For each set of classifiers, the accuracy index is calculated. If it is higher than 75%, the related set is selected; otherwise, it will be removed from the set of classifiers.

The accuracy of the meta-classifier is defined as the percentage of the correctly predicted sets of tuples on the given dataset. For a five-class prediction problem, the accuracy can be measured by means of a confusion matrix, as shown in Table 5.2 with the associated formula:

$$Accuracy = \frac{a_1 + b_2 + c_3 + d_4 + e_5}{\sum_{i=1}^{5} a_i + b_i + c_i + d_i + e_i} . \qquad (5)$$

Table 5.1. Meta cost penalty score matrix.

				Real class		
		1	**2**	**3**	**4**	**5**
Predicted class	**1**	0	1	2	2	3
	2	1	0	1	2	2
	3	2	1	0	1	2
	4	2	2	1	0	1
	5	3	2	2	1	0

Table 5.2. Confusion matrix for a five-class prediction problem.

				Predicted class		
		Very low	Low	Normal	High	Very high
Actual class	Very low	a_1	b_1	c_1	d_1	e_1
	Low	a_2	b_2	c_2	d_2	e_2
	Normal	a_3	b_3	c_3	d_3	e_3
	High	a_4	b_4	c_4	d_4	e_4
	Very high	a_5	b_5	c_5	d_5	e_5

The proposed method considers the accuracy and diversity of the candidate classifiers simultaneously and results in a set of competent classifiers for the subsequent integration stage. The entire selection phase is formalized in Algorithm 5.1 as follows:

Algorithm 5.1. Classifier selection phase

Input:

Pool of classifiers, denoted as $P= \{c_1,c_2,\ldots,c_M\}$;

Training dataset, denoted as *Train_data*;

Optimum number of clusters achieved by *k*-means and SSCA, denoted as *k* ($k \leq M$).

Output: Set of selected base classifiers denoted as *Bc*.

Algorithm.

```
$Bc = \emptyset$
Perform 10-fold cross-validation on Train_data.
for all $c_i \in P$ do
    Train $c_i$ by Train_data.
    Perform Meta cost algorithm.
end for
for j = 1:$C_k^M$
    Form $Set_j$ with $k$ members taken from $P$ without replacement.
    Achieve the outputs of classifiers in $Set_j$ and the real class of sample data, and pass them down to the Meta-classifier.
    if Average Accuracy > 75%
        $Bc = Bc \cup Set_j$
    end if
end for
Return $Bc$
```

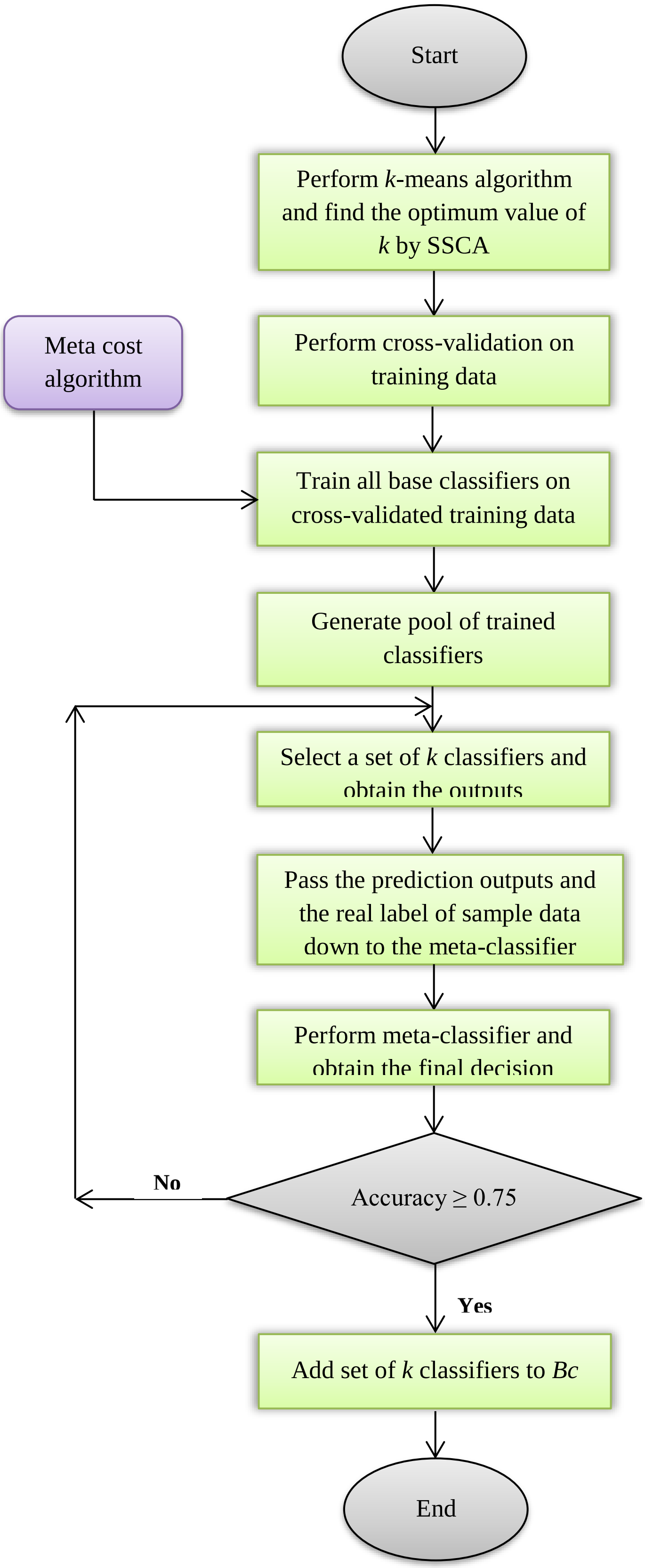

Start
Perform *k*-means algorithm and find the optimum value of *k* by SSCA
Perform cross-validation on training data
Meta cost algorithm
Train all base classifiers on cross-validated training data
Generate pool of trained classifiers
Select a set of *k* classifiers and obtain the outputs
Pass the prediction outputs and the real label of sample data down to the meta-classifier
Perform meta-classifier and obtain the final decision
Accuracy ≥ 0.75
No
Yes
Add set of *k* classifiers to *Bc*
End

Figure 5.1. Selection phase process

5.3.3. Phase three: Fusion

In the generation phase, different diversity algorithms were introduced for the initial generation and training of classifiers. The cross-validation is used in the selection phase and the remaining algorithms, including Bagging, Boosting and AdaBoost, will be used for this final fusion phase. Because different machine learning algorithms have dissimilar errors, the fusion of multiple different classifiers is expected to decrease the overall error rate.

- ***Fusion scheme: training and operation***

Apart from the initial diversifications, the fusion scheme is similar to the previous selection phase. In order to train the fusion scheme, the three above mentioned diversity algorithms are first used to train the classifiers of every selected set in *Bc*. Then, for a given sample dataset, the classification results, including the real class, are passed down as inputs to the meta classifier. Based on the achievements of base classifiers and the real response, the meta classifier will return the final classification of the given sample data.

Suppose we have a set of *k* stock classifiers, C_k, with $1 \le k \le K$. The feature vector, X_i, for the *i*th instance ($1 \le i \le I$) that is used for training all C_k of set *j* ($1 \le j \le J$) is defined as:

$$X_i = [\alpha_1, \alpha_2, ..., \alpha_p, ..., \alpha_P], \qquad i = 1, 2, \ldots, I \qquad (6)$$

where α_p is the *p*th feature ($1 \le p \le P$) of the feature vector X_i.

When all the C_k are trained, they are fed with the test data and the outcomes are the set of individual classifiers' predictions for *i*th instance, y_i^k , which are defined as:

$$y_i^k = f_{C_k}(X_i) \qquad i = 1, 2, \ldots, I \qquad (7)$$

The vector Y_i, is formed by individual predictions, y_i^k , with the real label of the *i*th instance, R_i, being used to train the upper level meta classifier.

$$Y_i = \{y_i^k\}^T \qquad i = 1, 2, \ldots, I \qquad (8)$$

Once the meta classifier is trained, the fusion scheme is prepared for further operations.

For each set *j* of *Bc*, the feature vector of the *i*th instance of test data, X_i, is given to the *k* individual classifiers, C_k, as input data. The outputs, y_i^k , form the prediction vector, Y_i, and together with real label, R_i, are used as input data for the meta classifier. The final decision for *i*th instance is made as given by:

$$D_i = g(Y_i, R_i) \qquad i = 1, 2, \ldots, I \qquad (9)$$

for some real values of D_i. Fig. 5.2 shows the generalized flowchart of the fusion phase.

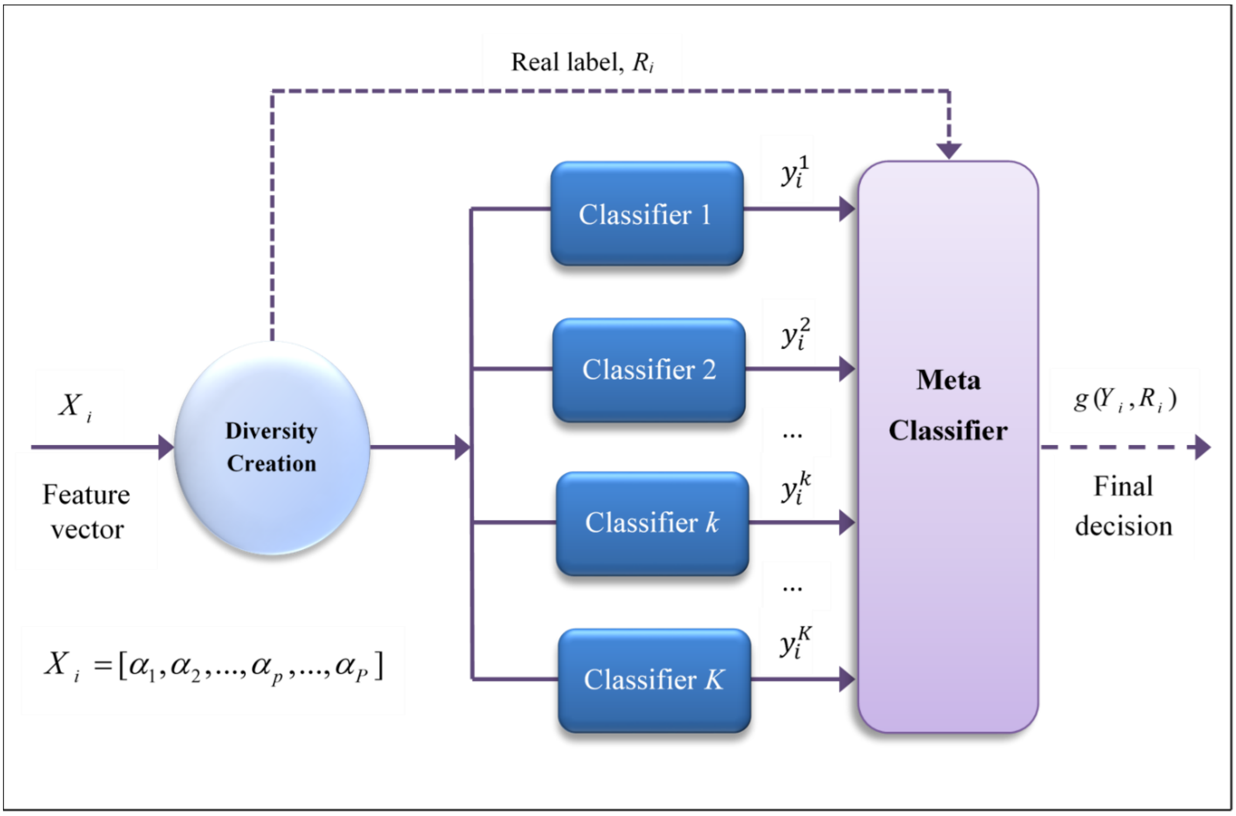


Figure 5.2. Generalized flowchart of proposed Fusion phase

5.4. Experimental Results

5.4.1. Datasets

In this paper, the dataset comprises data from the Tehran Stock Exchange (TSE) from 2002 to 2012 for a total of 1963 records for 400 companies.

According to the literature, negative and positive returns and return trends are widely used for predicting returns (Patel et al., 2015a; Tsai et al., 2011; Yu et al., 2014). In order to enhance accuracy, however, and based on a group of experts' opinions, a set of intervals are introduced in this paper for real return and risk prediction. Therefore, more information will be given to the investors for selecting the best optimal portfolio. For real returns, 5 intervals are specified: very high with a range higher than 9.3, high with a range of 4 to 9.3, average with a range of 1.14 to 4, low with a range of -1.3 to 1.14 and very low with a range lower than -1.3. Similarly, 3 intervals are specified for risk: high with a range higher than 15.5, average with a range of 6.3 to 15.5 and low with a range lower than 6.3. Fig. 5.3 illustrates the entire proposed process of stock return and risk prediction.

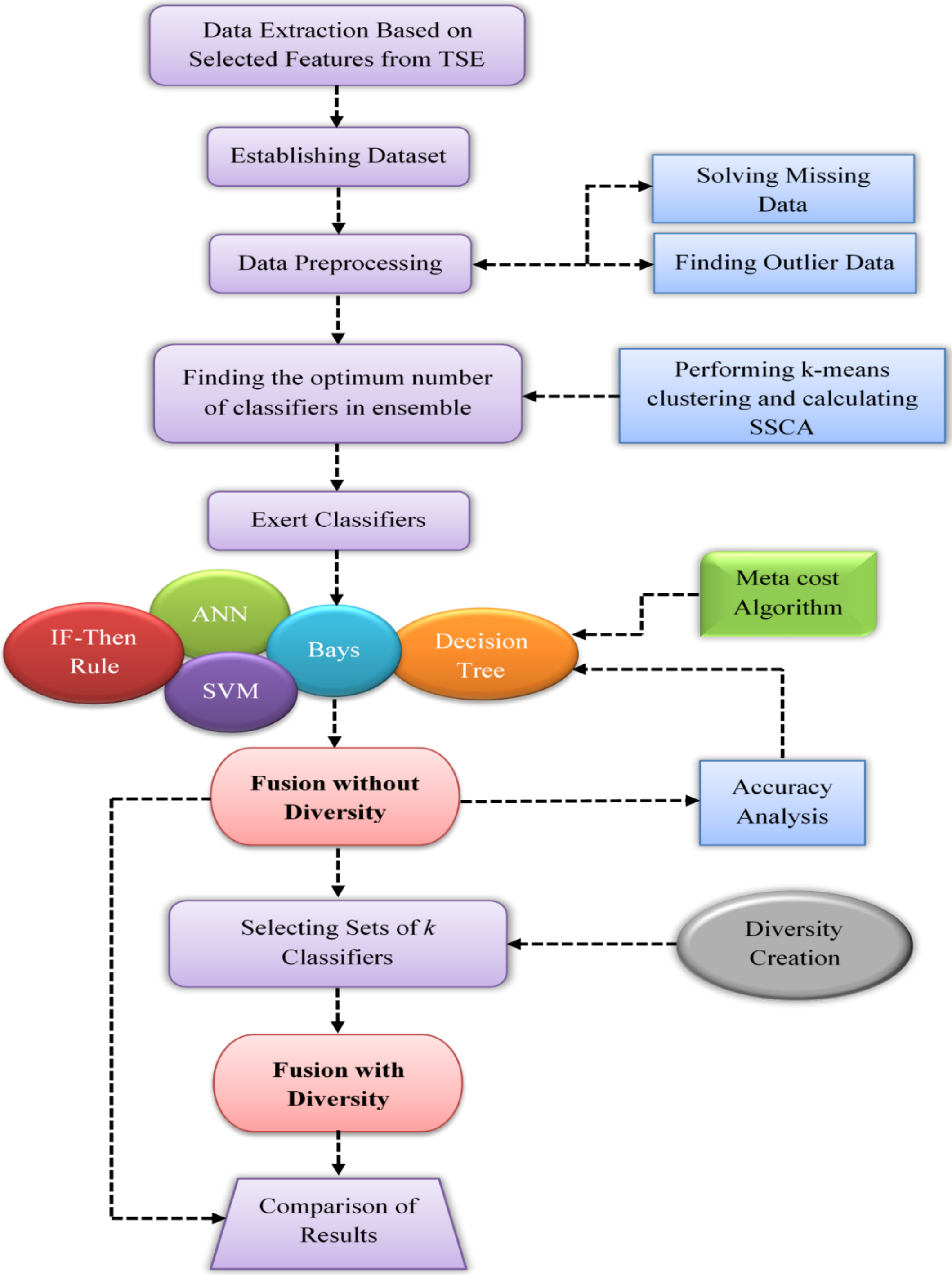


Figure 5.3. The proposed process of stock return and risk

- ***Data pre-processing***

In order to find the outlier data in the dataset, the distance-based approach was first used to analyse the remote records. The results show certain very large governmental companies as outlier data. The density approach was also used and 12 records were identified as outlier points, 7 of which were large companies that remained in dataset. The remaining 5 records were deleted, mostly because they were not sufficiently accurate for the process. By using the clustering approach, 6 points were identified as outliers because they did not belong to any of the clusters. The input feature of the companies was analysed and no suspected case was detected; therefore all the companies remained in the dataset. Finally, a number of techniques based on deviation were used that found 5 outlier records, all of which were removed. Moreover, because of a lack of information, 12 records out of 1963 were identified as missing data and therefore omitted from the dataset.

5.4.2. Feature selection

In order to accurately predict the risk and return variables, the most effective features of these variables must be identified first. In fact, the selection of representative features plays a key role in an efficient stock prediction design. Referring to (Barak and Modarres, 2015) and based on the fundamental approach, features that have the potential to be effective in risk and return predictions are first gathered from the company's financial ratios, stock pricing models and profit and loss reports. Then, a comprehensive procedure is used to sort out the most effective ones as the best representative features for risk and return classification. The procedure is based on a hybrid algorithm of filter and function-based clustering and selects 15 features for return prediction as well as 8 features for risk prediction from a group of 45 different financial features. In our proposed model, the same features shown in Table 3 are used in all classifications. The full list of all determined features is provided in Table 3.2.

Table 5.3. Selected features for risk and return factors.

Response variable	**Selected features**
Risk	Return, Beta coefficient, Efficiency, Market return, EPS prediction, Percent of growth EPS, DPS, *P/E*, EPS, Equity ratio, Stock book value, Debt to total asset ratio, Predicted profit margin, *P/S*, Total incomes growth.
Return	Return, Market return, Beta coefficient, Return on asset (ROA), Percent of growth EPS, EPS, Predicted profit margin, EPS coverage percent.

- *Response variables*

In our proposed model, the most important response variables are considered as real return and risk, as follows:

$$R = \sqrt[n]{(1+\frac{r_1}{100})(1+\frac{r_2}{100})...(1+\frac{r_n}{100})} \tag{10}$$

where r_1, r_2,…,r_n represent the real return of 1,…,*n*th periods.

The standard deviation of the stock return is assumed to be the risk response variable, as follows:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - E(r)^2)} \qquad (11)$$

5.4.3. Individual classifiers

In stock prediction, the complexity of the data necessitates applying models that are capable of defining such intricacy. Different methods, including statistical methods and neural networks, are studied and it is found that the results gained by machine learning and data mining algorithms are much more prominent (Patel et al., 2015a). In this research, Decision Trees (DT), Artificial Neural Networks (ANN), rule based algorithms and Support Vector Machines (SVM) are used as the individual classifiers.

Decision trees and rule based algorithms are known to be powerful prediction algorithms with outstanding performance in stock return prediction (Ou and Wang, 2009a). Rule-based classifiers use a set of IF-THEN rules for classification, which is especially useful when there are specific relationships among input variables. A decision tree is composed of decision rules that separate the independent variables into homogeneous areas and build rules that can be used for the output prediction of a set of input variables. In fact, the rules obtained from this group of classifiers are of importance to investors seeking to make their best portfolio. In this study, the LAD tree, Cart decision tree, Rep tree, BF tree and certain other popular, rule-based algorithms such as decision tree naive Bayes (DTNB) rule, J RIP rule, RIDOR rule and Part Rule are used.

Artificial Neural Networks (ANNs) are a group of analytical techniques capable of approximating extremely sophisticated non-linear functions. The multi-layer perceptron (MLP) is a popular neural network architecture that is a strong function estimator for prediction or classification problems. The MLP is able to learn complex non-linear functions to an arbitrary level of accuracy.

Support Vector Machines (SVMs) are the third group of classifiers used in this research. SVMs are categorized as generalized linear models that achieve the classification/regression decision by means of features linear combination. The approximated function in SVMs can be either a classification function, which is also used for the data categorization of this research, or a regression function for estimating the numerical value of input data.

5.4.4. Selection of classifier sets

In second phase, sets of classifiers with size *k* should be generated. In order to specify the optimum number of classifiers (*k*), the *k*-means algorithm is first performed with different values of *k*. Then, the SSCA is calculated for each cluster based on Euclidean distance. The results in Table 5.4 shows that if we increase the number of clusters, the maximum amount of SSCA will be achieved in *k*=3, after which its value starts to decrease. Thus, using *k*=3 and based on Algorithm 1, sets of classifiers with three members are generated that are then used in the final fusion phase.

Table 5.4. SSCA calculations on different number of clusters.

Number of cluster	2	3	4	5
SSCA	12.27	14.43	11.38	9.74

Tables 5.5 and 5.6 show the performance of each individual classifier for forecasting the return and risk of stocks on the given dataset (Barak and Modarres, 2015). In order to specify the meta-classifiers, the algorithms that provide greater prediction accuracy on the given dataset are chosen as meta-classifiers. Investigations state that trees and rule based algorithms with a denser structure generally display better accuracy than larger ones. Thus, the meta-classifiers are chosen from such dense and accurate algorithms.

Table 5.5. Individual classifier comparisons for real return prediction.

Algorithm	Accuracy	Number of rules	Tree size	Number of leaves
LAD Tree	78.00	-	31	15
Cart Decision Tree	76.50	-	13	7
DTNB rule	76.00	998	-	-
Decision table	75.50	56	-	-
Rep Tree	75.00	-	33	17
BF Tree	74.50	-	9	5
Part Rule	72.60	104	-	-
J48 Graph	71.50	-	1619	810
Neural Net (MLP)	69.00	-	-	-
Bays	60.00	-	-	-
SVM	60.00	-	-	-

Table 5.6. Individual classifier comparisons for risk prediction.

Algorithm	Accuracy	Number of rules	Tree size	Number of leaves
LAD Tree	78.24	-	31	20
DTNB rule	77.41	426	-	-
Decision table	76.57	297	-	-
BF Tree	76.15	-	109	55

Part Rule	73.64	55	-	-
Rep Tree	72.8	-	77	39
Neural Net (MLP)	59.00	-	-	-
Bays	55.65	-	-	-

The 10-fold cross-validation is performed and the average accuracy of classifier sets with 3 members for stock return and risk predictions are given in Tables 5.7 and 5.8, respectively. These selected sets are specified as the best ensembles whose performance with three diversity methods is analysed in the fusion step. The results reveal that although some of algorithms did not individually display an accurate performance (e.g., SVM, Bayes, MLP), they could achieve an acceptable level of accuracy in an ensemble model.

Table 5.7. Average accuracy percentage of selected sets for stock return prediction (without diversity).

Set Number	**Base classifiers**			**Fusion algorithm**	**Accuracy**
1	Decision Tree	LAD Tree	BF Tree	DTNB	78.69%
2	BF Tree	Bays	SVM	LAD Tree	78.04%
3	Decision Tree	LAD Tree	Rep Tree	BF Tree	77.34%
4	Decision Table	DTNB	Rep Tree	Decision Tree	76.23%
5	MLP	Part Rule	J48 Graf	BF Tree	75.84%

Table 5.8. Average accuracy percentage of selected sets for stock risk prediction (without diversity).

Set Number	**Base classifiers**			**Fusion algorithm**	**Accuracy**
1	Decision Tree	LAD Tree	DTNB	Decision Table	78.94%
2	DTNB	LAD Tree	BF Tree	Decision Table	78.34%
3	Part Rule	Decision Tree	MLP	BF Tree	77.10%
4	Decision Tree	LAD Tree	BF Tree	DTNB	77.01%
5	Rep Tree	LAD Tree	BF Tree	Decision Table	76.90%
6	Rep Tree	Decision Table	DTNB	LAD Tree	75.43%
7	Bays	SVM	Part Rule	LAD Tree	75.16%

5.4.5. Stock return and risk predictions with the proposed fusion scheme

In the final phase, as illustrated in Fig. 5.2, three diversity algorithms (Bagging, Boosting and AdaBoost) are performed separately for each selected set, as shown in Tables 5.7 and 5.8, and the final results for risk and return predictions are reported in Tables 5.9 and 5.11, respectively. To make more reliable results with more baseline algorithms, Random Forest as well as K-Nearest Neighbours (K-NN), SVM, and Bayes algorithms' set are also implemented.

For return prediction, the highest prediction accuracy is estimated as 83.65%, which is achieved by the Decision Tree, LAD Tree and Rep Tree ensemble with BF Tree as its fusion algorithm and Bagging as its diversity method. The detailed prediction results of the superior ensemble are presented in Table 5.10.

Table 9. Average accuracy percentage of stock return prediction with diversity creation.

Base classifiers			**Diversity**	**Fusion algorithm**	**Accuracy**
Decision Tree	LAD Tree	BF Tree	Bagging	DTNB	**80.05%**
Decision Tree	LAD Tree	BF Tree	Boosting	DTNB	66.55%
Decision Tree	LAD Tree	BF Tree	AdaBoost	DTNB	64.50%
Decision Tree	LAD Tree	Rep Tree	Bagging	BF Tree	**83.65%**
Decision Tree	LAD Tree	Rep Tree	Boosting	BF Tree	70.02%
Decision Tree	LAD Tree	Rep Tree	AdaBoost	BF Tree	68.12%
Decision Table	DTNB	Rep Tree	Bagging	Decision Tree	**82.23%**
Decision Table	DTNB	Rep Tree	Boosting	Decision Tree	79.32%
Decision Table	DTNB	Rep Tree	AdaBoost	Decision Tree	77.72%
MLP	Part Rule	J48 Graph	Bagging	BF Tree	78.74
BF Tree	Bays	SVM	Bagging	LAD Tree	70.66
K-NN	SVM	Bayes	Bagging	Decision Tree	64.27%
Random Forest			-	-	73.05%

Table 5.10. Prediction results of the best ensemble for real return prediction.

Accuracy: 83.65%	true Very low	true High	true Very high	true Normal	true Low	Class precision
pred. Very low	14	1	0	1	3	73.16%
pred. High	0	48	2	3	0	90.57%
pred. Very high	1	2	19	2	1	76.00%

pred. Normal	0	9	1	56	1	83.67%
pred. Low	2	1	1	1	31	86.11%
Class recall	82.00%	78.69%	82.60%	88.88%	86.11%	

As shown in Table 5.11, the highest accuracy of 88.23% in risk prediction is achieved by the BF Tree, DTNB and LAD Tree ensemble with Decision Table as the fusion algorithm and Bagging as the diversity method. The detailed prediction results of this ensemble are presented in Table 5.12.

Table 11. Average accuracy percentage of stock risk prediction with diversity creation.

Base classifiers			**Diversity**	**Fusion algorithm**	**Accuracy**
BF Tree	DTNB	LAD Tree	Bagging	Decision Table	**88.23%**
BF Tree	DTNB	LAD Tree	Boosting	Decision Table	78.90%
BF Tree	DTNB	LAD Tree	AdaBoost	Decision Table	80.27%
BF Tree	Decision Tree	LAD Tree	Bagging	DTNB	**81.34%**
BF Tree	Decision Tree	LAD Tree	Boosting	DTNB	78.56%
BF Tree	Decision Tree	LAD Tree	AdaBoost	DTNB	80.12%
BF Tree	Rep Tree	LAD Tree	Bagging	Decision Table	**82.46%**
BF Tree	Rep Tree	LAD Tree	Boosting	Decision Table	66.51%
BF Tree	Rep Tree	LAD Tree	AdaBoost	Decision Table	70.55%
DTNB	Decision Tree	LAD Tree	Bagging	Decision Table	79.14%
DTNB	Decision Table	Rep Tree	Bagging	LAD Tree	76.43%
Part Rule	Bays	SVM	Bagging	LAD Tree	68.66%
MLP	Decision Table	Part Rule	Bagging	BF Tree	80.56%
K-NN	SVM	Bayes	Bagging	Decision Tree	69.71%
Random Forest			-	-	74.36%

Table 5.12. Prediction results of the best ensemble for risk prediction.

Accuracy: 88.23%	true High	true Low	true Normal	Class precision
pred. High	246	3	8	95.72%
pred. Low	14	388	32	89.40%
pred. Normal	65	54	685	85.20%
Class recall	75.69%	87.19%	94.48%	

Based on the results in Tables 5.9 and 5.11, Bagging generally displayed better performance in improving the prediction accuracy of ensembles in comparison with Boosting and AdaBoost; however, it could not effectively improve the prediction accuracy of ensembles with weak base classifiers. In order to predict the real return and risk of stocks, voting methods such as simple averaging and weighted averaging are also used as the meta-classifier algorithms, which resulted in maximum accuracy of 80% for real return prediction, although performance was poor for risk prediction.

5.5. Discussion

A comparison of the findings presented in Tables 5.7 and 5.9 shows the significant role of applying Bagging as a diversity method on accuracy improvement in real return prediction. Bagging enhanced the accuracy of almost all ensembles except the ensemble of BF Tree, Bayes and SVM with LAD Tree fusion algorithm. The reason may be the weakness of Bayes and SVM algorithms (in our dataset) used as base classifiers, whose performance could not be improved even with Bagging.

Moreover, based on findings shown in Tables 5.5 and 5.9, the performance of almost all stock classifiers has greatly improved in fusion system with the exception of the LAD Tree and Decision Tree, which provided higher accuracy only in concert with the Bagging diversity algorithm.

The results achievements show that the fusion of the strongest individual classifiers has led to more accurate prediction, but this is not necessarily always true. For instance, the accuracy of MLP is 69%, but in fusion with Part Rule and J48 Graph algorithms, the accuracy improved to 78.74%. One reason for this may be that the weakness of some algorithms can be covered by other classifiers used in fusion system. In other words, the algorithms can demonstrate complementary behaviour when they are combined in this way.

Among several classification algorithms used in this paper, the SVM and Bayes algorithms demonstrated different behaviour. Although their individual accuracies in both real return and risk prediction were improved by the fusion system, the findings revealed that the fusion system without diversity resulted in better accuracy. The high sensitivity of SVM to the missed data individually resulted in a low accuracy of 60% for real return prediction, but the ensemble with the Bayes and BF Tree algorithms diversified by Bagging led to an accuracy of 70.66%; without diversity creation, an accuracy of 78.04% was achieved.

Similar to real returns, the achievements on risk prediction also revealed that the fusion system with diversity successfully improved the performance of individual classifiers in all combinations except for the SVM and Bayes algorithms, whose performance was not improved by diversity creation. The superiority of Bagging in improving accuracy in comparison with the other two diversity algorithms shows its high consistency with the proposed prediction procedure.

Because of the low accuracy, the fusion results of some sets of classifiers with Boosting and AdaBoost methods are not reported in Tables 5.9 and 5.11.

As stated above, Bagging significantly outperformed the Boosting and AdaBoost methods. An important question to ask is why Bagging outperforms other methods and what exactly differentiates it from Boosting and AdaBoost. One reason for its superior performance may be the level of “sensitivity” displayed by each of these algorithms towards the degree of clearance in the dataset. The existence of missing values and outlier data is inevitable in problems with large datasets. Although the pre-processing functions decrease the effects of such deficiencies, they are not capable of completely resolving it. The findings reveal that Boosting and AdaBoost are more sensitive to the robustness of the dataset whereas Bagging is scarcely affected by such imperfections.

Another reason for the significant outperformance of Bagging may be related to the instability of the prediction procedure. As (Breiman, 1996) notes, Bagging is highly capable of improving the accuracy of unstable prediction procedures where a small change in training data can result in large changes in the predictor/classifier structure. Neural networks, classification and regression trees are specified as unstable methods in which Bagging works well. The achievements also show the superiority of Bagging to the other two algorithms in similar circumstances.

We will now shift our focus to a new selection scheme that will be compared with the hybrid method proposed by (Barak and Modarres, 2015). In this paper, a Wrapper-GA algorithm was also developed for feature selection part. In this algorithm, a population is generated from candidate solutions, and in each iteration a new set of individuals is generated by means of mutation and crossover functions. The fitness of individuals in the current population is evaluated by a Decision Tree algorithm and the best individuals are selected as the next generation. The overview of the proposed Wrapper framework is presented in Fig 4.1 (Barak et al., 2015).

In this methodology, after the pre-processing stage, the GA selects a set of features and then tests the prediction error of the selected features using the CART decision tree algorithm. Ten-fold cross-validation is applied in order to generate the training and test data. GA uses a uniform mutation with a probability of 0.1, tournament algorithm for selecting children (crossover) with rate of 0.8, and a population size of 60. The Decision Table is set as the fitness function. Additionally, the GA was run with varying parameter values (population size, mutation and crossover rates, etc.) in order to enhance the accuracy. Because the Decision Table algorithm is sensitive to missing data, these missed values are substituted with the average value of that column.

Table 5.13 gives the selected features with the best accuracy by Wrapper-GA for real return prediction.

Table 5.13. Selected features for real return prediction with Wrapper-GA algorithm.

Average payment period	current assets turnover	predicted profit margin	Equity ratio
quick ratio	EPS prediction	profit margin growth rate	β coefficient
return on equity (ROE)	Debt ratio	EPS growth percentage	percentage of net profit to sale
prediction difference percentage of EPS with the real amount	Return on asset (after tax) ROA	long-term debt to equity ratio	P/E, EPS cover

The accuracy of real return prediction with the selected features provided in Table 5.13 was estimated as $78.86 \pm 0.94\%$. The findings reveal that if we use all of the specified features (given in Table 3.2) for return prediction with the Decision Tree, the accuracy on test data is estimated as 76.5%. The reason for this improvement may be the diversity created by several iterations of the Decision Table with various types of features. Diversity creation as a critical factor in enhancing the accuracy of prediction models is widely discussed in section 5.2.3. Fig. 5.4 illustrates the GA trend diagram with the Decision Table fitness function.

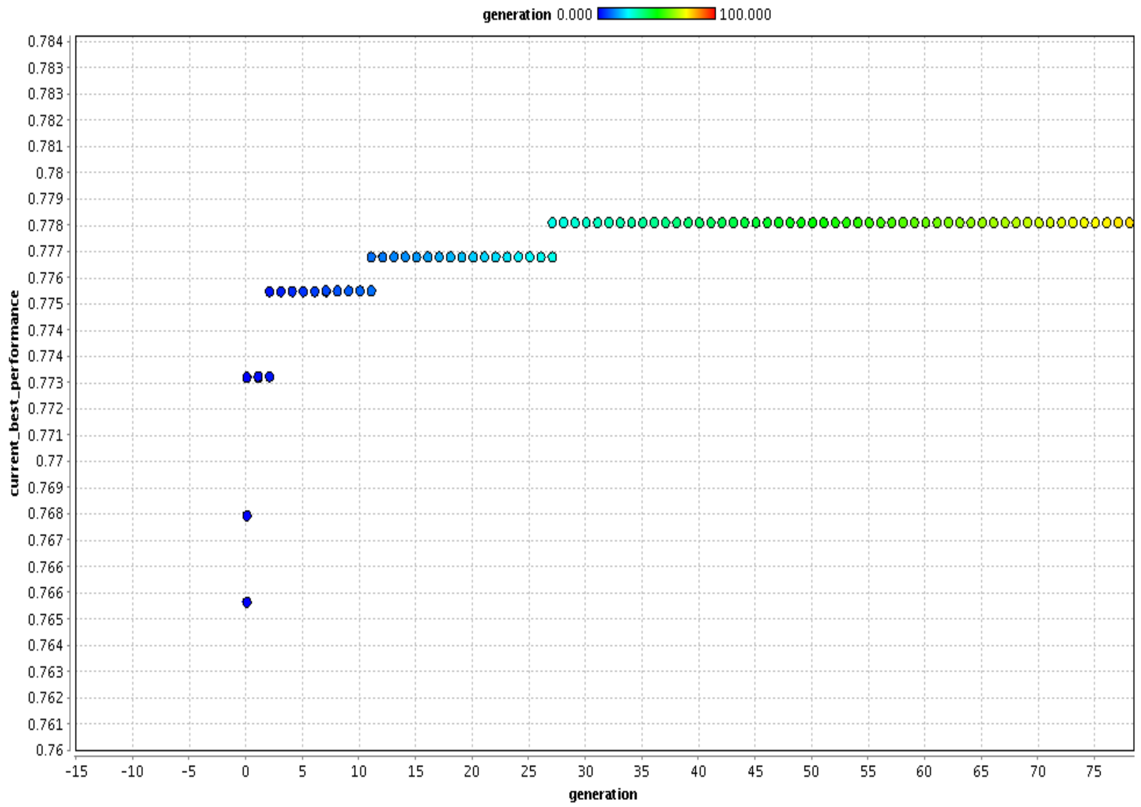


Figure 5.4. Improvement points of GA with Decision Table fitness function for real return prediction

The proposed Wrapper-GA algorithm is also applied for feature selection in risk prediction. Although various fitness and error functions were used in GA, surprisingly, the achievements did not show improvements in prediction accuracy above 70%. Fig. 5.5 displays the improvement points of GA for risk prediction when the Decision Table and LAD Tree are used as GA evaluation function and error assessment of selected features, respectively.

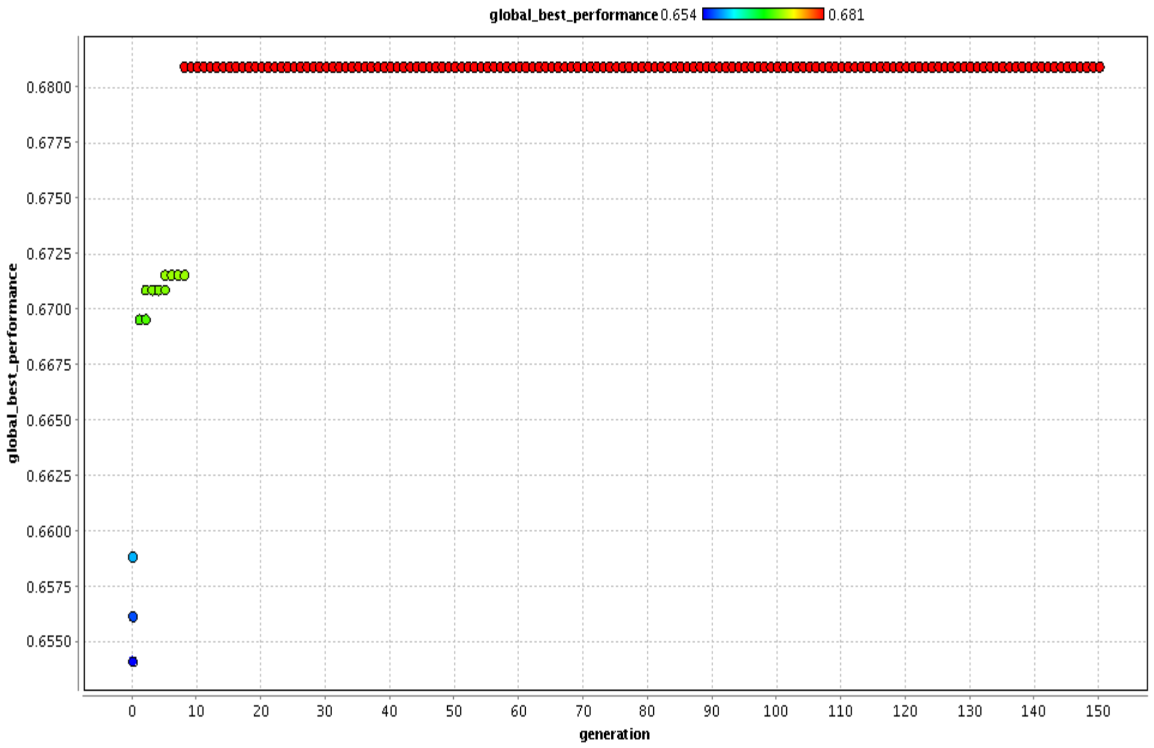


Figure 5.5. Improvement points of GA with LAD Tree fitness function for risk prediction

Table 5.14 provides the selected features with the best accuracy of 68.26 ± 2.55 via Wrapper-GA for risk prediction.

Table 5.14. Selected features for risk prediction with Wrapper-GA algorithm.

Average payment period	Equity ratio	Quick ratio	percentage of net profit to gross profit
Asses the loan usefulness	market return	EPS prediction	β coefficient
P/E	EPS cover percentage	Total income growth percentage	Book value
Efficiency	Debt coverage ratio	Total asset turnover	Fixed asset turnover
current asset turnover	EPS growth percentage	long-term debt to equity ratio	return on equity (ROE)
fixed asset return percentage	current ratio	percentage of net profit to sale	

Although the Wrapper-GA feature selection algorithm could improve the prediction accuracy compared to the case in which all the features are involved, the feature selection ensemble model developed by (Barak and Modarres, 2015) outperformed Wrapper-GA in accuracy enhancement. Thus, its related features reported in section 5.4.2 were used for the proposed hybrid prediction method of this paper.

A comparison between our method and similar studies is shown in Table 5.15. Different hybrid methods that have excellent accuracy in return forecasting in different national stock exchanges were compared based on input data, base classifier, feature selection, hybrid prediction model and degree of accuracy, as follows:

Table 5.15. Comparison of the proposed fusion scheme versus other studies

Author /Year	**Stock Exchange**	**Input Data**	**Base Classifier**	**Feature selection**	**Hybrid Model**	**The Best Accuracy%**
Tsai et al. (2011)	Electronic Industry in Taiwan	19 Financial ratios and 11 Macroeconomic indicators	MLP- Cart - Logistic Regression	---	Bagging - Voting	66.67
Huang (2012a)	30 special companies in Taiwan	14 Financial ratios	SVR- GA	---	---	85- 76.71
Cheng et al. (2010b)	Taiwan	10 Technical Indexes and 8 Macroeconomic indicators	PNN- C4.5- Rough Set	---	Hybrid	76
Huang et al. (2008a)	South-Korea and Taiwan	23 Technical Indexes	SVM- K-NN- Cart- Logistic Regression- Back Propagation	Wrapper	Voting	76.06 80.28
Tsai and Hsiao (2010)	Taiwan	8 Fundamental Index and 11 Macroeconomic indicators	---	GA-PCA-Cart	Back Propagation	79
Tsai et al. (2012)	Taiwan	61 intangible assets value variable	MLP	PCA- Stepwise Regression- decision trees- association rules- GA	MLP	75
Barak and Modarres (2015)	Return Forecasting in TSE-Iran	44 Financial ratios and Fundamental Index	Cart, Rep Tree, LAD Tree, …	Function based Clustering	Hybrid	80.24
Barak and Modarres (2015)	Risk Forecasting in TSE-Iran	44 Financial ratios and Fundamental Index	DTNB, BF Tree, LAD Tree, …	Function based clustering	Hybrid	79.01
Current paper	Return Forecasting in TSE-Iran	44 Financial ratios and Fundamental Index	Cart, Rep Tree, LAD Tree, …	Wrapper-GA	Hybrid	78.86
Current paper	Risk Forecasting in TSE-Iran	44 Financial ratios and Fundamental Index	DTNB, BF Tree, LAD Tree, …	Wrapper-GA	Hybrid	70
Current paper	Return Forecasting in TSE-Iran	44 Financial ratios and Fundamental Index	Cart, Rep Tree, LAD Tree, …	Function based clustering with diversity	Fusion	**83.65**
Current paper	Risk Forecasting in TSE-Iran	44 Financial ratios and Fundamental Index	DTNB, BF Tree, LAD Tree, …	Function based clustering with diversity	Fusion	**88.23**

5.6. Conclusions and Future Research

In this paper, a study of fusion models based on the use of multiple diversity classifiers is presented for stock return and risk prediction. Bagging, Boosting and AdaBoost were applied as three diversity algorithms for generating a pool of classifiers. An empirical study was later undertaken on the Tehran Stock Exchange that compared the performance of diversity algorithms with different sets of classifiers in a fusion system. Bagging consistently outperformed the other two algorithms, regardless of the type of individual classifiers employed.

Almost all of the fusion strategies provided statistically significant improvements in performance over the best individual classifiers. Bagging performed well with Decision Trees in fusion systems that are stated as being unstable prediction methods. The limitation of this method is that collecting all of the fundamental data and information may be difficult for certain cases.

Future research directions of the paper include but are not limited to

1. Optimizing the parameters of classification algorithms using metaheuristics algorithms to improve the prediction results;

2. Predicting other important response variables (in addition to risk and return) such as liquidity (Barak et al., 2013);

3. Using technical features and textual information, in addition to fundamentals features, in order to use more comprehensive features and be able to predict the short term situations of stocks; and

4. Customizing the proposed approach for the prediction of risk and return in a particular industry or investigating the accuracy of the procedure using data from other popular stock markets, such as the US stock market, which may result in new dimensions for this procedure.

6. Conclusion

Recently data mining and machine learning algorithms are applied extensively to predict risk and return rates in financial field and for investment decision making (Zhang and Zhou, 2004). Here, considering an overview of the life cycle of a data mining project based on The CRISP-DM reference model, three researches of this field provided by the author are reviewed. In chapter three, the author has developed a novel approach to predict stocks' return and risks by means of a three stage method through which, risk and return are predicted by applying data mining techniques for the given features. In this chapter, a hybrid algorithm based on filter and function-based clustering is developed. The results show that the proposed hybrid model is a proper tool for effective feature selection and these features are good indicators for the prediction of risk and return. To illustrate the approach as well as to train data and test, Tehran Stock Exchange (TSE) data from 2002 to 2011 was applied.

Chapter four presents a novel forecasting model for stock markets on the basis of the wrapper ANFIS (Adaptive Neural Fuzzy Inference System) – ICA (Imperialist Competitive Algorithm) and technical analysis of Japanese Candlestick. The Author has implemented two approaches of Raw-based and Signal-based to extract the model's input variables with 15 and 24 features, respectively. The correct predictions percentages for periods of 1- 6 days with the total number of buy and sell signals are considered as output variables. In the proposed model, the ANFIS prediction results are used as a cost function of wrapper model and ICA is used to select the most appropriate features. This novel combination of feature selection not only takes advantage of ICA optimization swiftness, but also the ANFIS prediction accuracy. The emitted buy and sell signals of the model revealed that Signal databases approach gets better results with 87% prediction accuracy and the wrapper features selection obtains 12 % improvement in predictive performance regarding to the base study. Additionally, since the wrapper-based feature selection models are considerably more time-consuming, the presented wrapper ANFIS-ICA algorithm's results have superiority in time decreasing as well as prediction accuracy increasing regarding to other algorithms such as wrapper Genetic algorithm (GA).

Finally in chapter five, the author proposed a fusion model based on the use of multiple diverse base classifiers that operate on a common input and a meta-classifier that learns from base classifiers' outputs to obtain more precise stock return and risk predictions. A set of diversity methods, including Bagging, Boosting, and AdaBoost is applied to create diversity in classifier combinations. Moreover, the number and procedure for selecting base classifiers for fusion schemes is determined using a methodology based on dataset clustering and candidate classifiers' accuracy. The results demonstrate that Bagging exhibited superior performance within the fusion scheme and could achieve a maximum of 83.6% accuracy with stacking of Decision Tree, LAD Tree and Rep Tree for return prediction and 88.2% accuracy with stacking of BF Tree, DTNB and LAD Tree in risk prediction. For feature selection part, a wrapper-GA algorithm is developed and compared with the fusion model. This Chapter seeks to help researcher selecting the best individual classifiers and fusing the proper scheme in stock market prediction. Again, the model is applied to Tehran Stock Exchange (TSE) data for the period from 2002 to 2012.

Future research directions of the reviewed chapters include but are not limited to:

Optimizing the parameters of classification algorithms using metaheuristics algorithms to improve the prediction results; Predicting other important response variables (in addition to risk and return) such as liquidity (Barak et al., 2013); Using technical features and textual information, in addition to fundamentals features, in order to use more comprehensive features and be able to predict the short term situations of stocks; and Customizing the proposed approach for the prediction of risk and return in a particular industry or investigating the accuracy of the procedure using data from other popular stock markets, such as the US stock market, which may result in new dimensions for this procedure.

References:

Alceu S. Britto, J., Sabourin, R., Oliveira, L.E.S., 2014. Dynamic selection of classifiers-A comprehensive review. Pattern Recogn. 47, 3665-3680.

Araújo, R.d.A., Ferreira, T.A., 2013. A morphological-rank-linear evolutionary method for stock market prediction. Information Sciences 237, 3-17.

Asadi, S., Hadavandi, E., Mehmanpazir, F., Nakhostin, M.M., 2012. Hybridization of evolutionary Levenberg–Marquardt neural networks and data pre-processing for stock market prediction. Knowledge-Based Systems 35, 245-258.

Atashpaz-Gargari, E., Lucas, C., 2007. Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition, Evolutionary Computation, 2007. CEC 2007. IEEE Congress on. IEEE, pp. 4661-4667.

Atsalakis, G.S., Dimitrakakis, E.M., Zopounidis, C.D., 2011. Elliott Wave Theory and neuro-fuzzy systems, in stock market prediction: The WASP system. Expert Systems with Applications 38, 9196-9206.

Atsalakis, G.S., Valavanis, K.P., 2009. Surveying stock market forecasting techniques–Part II: Soft computing methods. Expert Systems with Applications 36, 5932-5941.

Bagheri, A., Mohammadi Peyhani, H., Akbari, M., 2014. Financial forecasting using ANFIS networks with Quantum-behaved Particle Swarm Optimization. Expert Systems with Applications 41, 6235-6250.

Barak, S., Abessi, M., Modarres, M., 2013. Fuzzy turnover rate chance constraints portfolio model. European Journal of Operational Research 228, 141-147.

Barak, S., Dahooie, J.H., Tichý, T., 2015. Wrapper ANFIS-ICA method to do stock market timing and feature selection on the basis of Japanese Candlestick. Expert Systems with Applications 42, 9221-9235.

Barak, S., Modarres, M., 2015. Developing an approach to evaluate stocks by forecasting effective features with data mining methods. Expert Systems with Applications 42, 1325-1339.

Barak, S., Sadegh, S.S., 2016. Forecasting energy consumption using ensemble ARIMA–ANFIS hybrid algorithm. International Journal of Electrical Power & Energy Systems 82, 92-104.

Bartholdy, J., Peare, P., 2005. Estimation of expected return: CAPM vs. Fama and French. International Review of Financial Analysis 14, 407-427.

Bauer, R., Guenster, N., Otten, R., 2004. Empirical evidence on corporate governance in Europe: The effect on stock returns, firm value and performance. Journal of Asset Management 5, 91–104.

Bernstein, L., Wild, J., 1999. Analysis of Financial Statements, 5 edition ed. McGraw-Hill; .

Bezdek, J.C., 1981. Pattern recognition with fuzzy objective function algorithms. Kluwer Academic Publishers.

Biabangard-Oskouyi, A., Atashpaz-Gargari, E., Soltani, N., Lucas, C., 2008. Application of imperialist competitive algorithm for materials property characterization from sharp indentation test. To be appeared in the International Journal of Engineering Simulation.

Bisoi, R., Dash, P.K., 2014. A hybrid evolutionary dynamic neural network for stock market trend analysis and prediction using unscented Kalman filter. Applied Soft Computing 19, 41-56.

Brealey, R.A., Myers, S.C., Allen, F., 2007. Principles of Corporate Finance, 9 ed. McGraw-Hill.

Breiman, L., 1996. Bagging Predictors. Machine Learning 24, 123-140.

Cao, J., Kwong, S., Wang, R., 2012. A noise-detection based AdaBoost algorithm for mislabeled data. Pattern Recognition 45, 4451-4465.

Cao, Q., Leggio, K.B., Schniederjans, M.J., 2005. A comparison between Fama and French's model and artificial neural networks in predicting the Chinese stock market. Computers & Operations Research 32, 2499-2512.

Carnes, T.A., College, B., 2006. Unexpected changes in quarterly financial-statement line items and their relationship to stock prices. Academy of Accounting and Financial Studies Journal 10, 99-116.

Cervelló-Royo, R., Guijarro, F., Michniuk, K., 2015. Stock market trading rule based on pattern recognition and technical analysis: Forecasting the DJIA index with intraday data. Expert Systems with Applications 42, 5963-5975.

Chang, P.-C., Liu, C.-H., 2008. A TSK type fuzzy rule based system for stock price prediction. Expert Systems with Applications 34, 135-144.

Chang, T.-S., 2011. A comparative study of artificial neural networks, and decision trees for digital game content stocks price prediction. Expert Systems with Applications 38, 14846-14851.

Chavarnakul, T., Enke, D., 2008. Intelligent technical analysis based equivolume charting for stock trading using neural networks. Expert Systems with Applications 34, 1004-1017.

Chen, Y.-S., Cheng, C.-H., 2012. A soft-computing based rough sets classifier for classifying IPO returns in the financial markets. Applied Soft Computing 12, 462-475.

Chen, Y., Mabu, S., Shimada, K., Hirasawa, K., 2009. A genetic network programming with learning approach for enhanced stock trading model. Expert Systems with Applications 36, 12537-12546.

Cheng, J.-H., Chen, H.-P., Lin, Y.-M., 2010a. A hybrid forecast marketing timing model based on probabilistic neural network, rough set and C4.5. Expert Systems with Applications 37, 1814-1820.

Cheng, J.-H., Chen, H.-P., Lin, Y.-M., 2010b. A hybrid forecast marketing timing model based on probabilistic neural network, rough set and C4. 5. Expert systems with Applications 37, 1814-1820.

Cheng, S.-H., 2014. A Hybrid Predicting Stock Return Model Based on Bayesian Network and Decision Tree, in: Ali, M., Pan, J.-S., Chen, S.-M., Horng, M.-F. (Eds.), Modern Advances in Applied Intelligence. Springer International Publishing, pp. 218-227.

Cheng, S.-H., 2015. A Hybrid Predicting Stock Return Model Based on Logistic Stepwise Regression and CART Algorithm, in: Nguyen, N.T., Trawiński, B., Kosala, R. (Eds.), Intelligent Information and Database Systems. Springer International Publishing, pp. 624-633.

Chiang, W.-C., Urban, T.L., Baldridge, G.W., 1996. A neural network approach to mutual fund net asset value forecasting. Omega 24, 205-215.

Covões, T.F., Hruschka, E.R., 2011. Towards improving cluster-based feature selection with a simplified silhouette filter. Information Sciences 181, 3766-3782.

Crone, S.F., Kourentzes, N., 2010. Feature selection for time series prediction–A combined filter and wrapper approach for neural networks. Neurocomputing 73, 1923-1936.

Dasarathy, B.V., Sheela, B.V., 1979. A composite classifier system design: Concepts and methodology. Proceedings of the IEEE 67, 708-713.

Dastgir, M., Afshari, M.H., 2004. Evaluating Stock Pricing models on Tehran Stock Exchange Assets. Accounting Studies 3, 60-94.

de Oliveira, D.F., Canuto, A.M.P., de Souto, M.C.P., 2009. Use of multi-objective genetic algorithms to investigate the diversity/accuracy dilemma in heterogeneous ensembles, Neural Networks, 2009. IJCNN 2009. International Joint Conference on, pp. 2339-2346.

de Oliveira, F.A., Nobre, C.N., Zárate, L.E., 2013. Applying Artificial Neural Networks to prediction of stock price and improvement of the directional prediction index – Case study of PETR4, Petrobras, Brazil. Expert Systems with Applications 40, 7596-7606.

do Prado, H.A., Ferneda, E., Morais, L.C., Luiz, A.J., Matsura, E., 2013. On the Effectiveness of Candlestick Chart Analysis for the Brazilian Stock Market. Procedia Computer Science 22, 1136-1145.

duda, R.o., Hart, P.E., Strok, D.G., 2001. Pattern Classification. Wiley.

Dumais, S., Platt, J., Heckerman, D., Sahami, M., 1998. Inductive learning algorithms and representations for text categorization, In Proceedings of the International Conference on Information Knowledge Management, pp. 148–155.

Enke, D., Thawornwong, S., 2005. The use of data mining and neural networks for forecasting stock market returns. Expert Systems with Applications 29, 927-940.

Esfahanipour, A., Aghamiri, W., 2010. Adapted neuro-fuzzy inference system on indirect approach TSK fuzzy rule base for stock market analysis. Expert Systems with Applications 37, 4742-4748.

Esposito, F., Malerba, D., Semeraro, G., Kay, J., 1997. A comparative analysis of methods for pruning decision trees. IEEE transactions on pattern analysis and machine intelligence 19, 476-491.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E.F., French, K.R., 2012. Size, value, and momentum in international stock returns. Journal of Financial Economics 105, 457-472.

Ferreiro, S., Sierra, B., Irigoien, I., Gorritxategi, E., 2011. Data mining for quality control: Burr detection in the drilling process. Computers & Industrial Engineering 60, 801-810.

Finlay, S., 2011. Multiple classifier architectures and their application to credit risk assessment. European Journal of Operational Research 210, 368-378.

Frank, E., Witten, I.H., 1998. Generating Accurate Rule Sets Without Global Optimization, Fifteenth International Conference on Machine Learning, , pp. 144-151.

Freund, Y., 1995. Boosting a Weak Learning Algorithm by Majority. Information and Computation 121, 256-285.

Freund, Y., Schapire, R.E., 1996. Experiments with a New Boosting Algorithm. Machine Learning: Proceedings of the Thirteenth International Conference, 48-56.

Freund, Y., Schapire, R.E., 1997. A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting. Journal of Computer and System Sciences 55, 119-139.

Friedman, J., Hastie, T., Tibshirani, R., 2001. The elements of statistical learning. Springer series in statistics New York.

Fumera, G., Roli, F., 2005. A theoretical and experimental analysis of linear combiners for multiple classifier systems. IEEE Transactions on Pattern Analysis and Machine Intelligence 27, 942-956.

Gargari, E.A., Hashemzadeh, F., Rajabioun, R., Lucas, C., 2008. Colonial competitive algorithm: a novel approach for PID controller design in MIMO distillation column process. International Journal of Intelligent Computing and Cybernetics 1, 337-355.

Gershenfeld, N.A., 1999. The nature of mathematical modeling. Cambridge university press.

Giraud-Carrier, C., 2008. Metalearning-a tutorial, Proceedings of the 7th international conference on machine learning and applications.

Gordon, M.J., 1982. The investment, financing, and valuation of the corporation. Greenwood Press Reprint.

Guyon, I., Elisseeff, A., 2003. An introduction to variable and feature selection. Journal of machine learning research 3, 1157-1182.

Hafezi, R., Shahrabi, J., Hadavandi, E., 2015. A bat-neural network multi-agent system (BNNMAS) for stock price prediction: Case study of DAX stock price. Applied Soft Computing 29, 196-210.

Haghighi, M.S., Vahedian, A., Yazdi, H.S., 2011. Creating and measuring diversity in multiple classifier systems using support vector data description. Applied Soft Computing 11, 4931-4942.

Hall, M., 1998. Correlation-based feature subset selection for machine learning. University of Waikato.

Hall, M., Frank, E., 2008. Combining Naive Bayes and Decision Tables, In Proceedings of the 21st Florida Artificial Intelligence Society Conference(FLAIRS), Florida.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I.H., 2009. The weka data mining software: an update. ACM SIGKDD Explorations Newsletter 11, 10-18.

Han, J., Kamber, M., 2006. Data Mining:Concepts and Techniques. The Morgan Kaufmann.

Hjalmarsson, E., 2010. Predicting global stock returns. Journal of Financial and Quantitative Analysis 45, 49-80.

Ho, T., Hull, J.J., Srihari, S., 1994. Decision combination in multiple classifier systems. IEEE Transactions on Pattern Analysis and Machine Intelligence 16, 66-75.

Hofmann, M., Klinkenberg, R., 2013. RapidMiner: Data Mining Use Cases and Business Analytics Applications. Chapman and Hall/CRC.

Holte, R.C., 1993. Very Simple Classification Rules Perform Well on Most Commonly Used Datasets. Machine Learning 11, 63-90.

Hong, T.-P., Wu, C.-W., 2011. Mining rules from an incomplete dataset with a high missing rate. Expert Systems with Applications 38, 3931-3936.

Huang, C.-F., 2012a. A hybrid stock selection model using genetic algorithms and support vector regression. Applied Soft Computing 12, 807-818.

Huang, C.-J., Yang, D.-X., Chuang, Y.-T., 2008a. Application of wrapper approach and composite classifier to the stock trend prediction. Expert Systems with Applications 34, 2870-2878.

Huang, C.-L., Tsai, C.-Y., 2009. A hybrid SOFM-SVR with a filter-based feature selection for stock market forecasting. Expert Systems with Applications 36, 1529-1539.

Huang, C.F., 2012b. A hybrid stock selection model using genetic algorithms and support vector regression. Applied Soft Computing 12, 807–818.

Huang, D.W., Sherman, B.T., Lempicki, R.A., 2008b. Systematic and integrative analysis of large gene lists using DAVID bioinformatics resources. Nature protocols 4, 44.

Huang, J., Cai, Y., Xu, X., 2007. A hybrid genetic algorithm for feature selection wrapper based on mutual information. Pattern Recognition Letters 28, 1825-1844.

Hyup Roh, T., 2007. Forecasting the volatility of stock price index. Expert Systems with Applications 33, 916-922.

Jang, J.-S., 1993. ANFIS: adaptive-network-based fuzzy inference system. Systems, Man and Cybernetics, IEEE Transactions on 23, 665-685.

Jasemi, M., Kimiagari, A.M., Memariani, A., 2011. A modern neural network model to do stock market timing on the basis of the ancient investment technique of Japanese Candlestick. Expert Systems with Applications 38, 3884-3890.

Kabir, M., Islam, M., 2010. A new wrapper feature selection approach using neural network. Neurocomputing 73, 3273-3283.

Kabir, M.M., Islam, M.M., Murase, K., A new wrapper feature selection approach using neural network. Neurocomputing 73, 3273-3283.

Kantardzic, M., 2003. Data Mining: Concepts, Models, Methods, and Algorithms. Technometrics 45, 277.

Kao, L.-J., Chiu, C.-C., Lu, C.-J., Chang, C.-H., 2013. A hybrid approach by integrating wavelet-based feature extraction with MARS and SVR for stock index forecasting. Decision Support Systems 54, 1228-1244.

Kaplan, S.N., Ruback, R.S., 1995. The Valuation of Cash Flow Forecasts: An Empirical Analysis. The Journal of Finance 50, 1059-1093.

Kar, S., Das, S., Ghosh, P.K., 2014. Applications of neuro fuzzy systems: A brief review and future outline. Applied Soft Computing 15, 243-259.

Khan, S.S., Ahmad, A., 2004. Cluster center initialization algorithm for K-means clustering. Pattern recognition letters 25, 1293-1302.

Khoshnevisan, B., Bolandnazar, E., Barak, S., Shamshirband, S., Maghsoudlou, H., Altameem, T.A., Gani, A., 2015. A clustering model based on an evolutionary algorithm for better energy use in crop production. Stochastic Environmental Research and Risk Assessment.

Klosgen, W., Zytkow, J., 1996. Knowledge discovery in databases terminology. Advances in Knowledge Discovery and Data Mining, 573-592.

Knorr, E.M., Ng, R.T., 1999. Finding intentional knowledge of distance-based outliers, in Proceedings of the 25th international conference on very large data bases, Edinburgh, Scotland, pp. 211–222.

Kohavi, R., John, G.H., 1997a. Wrappers for feature subset selection. Artificial intelligence 97, 273-324.

Kohavi, R., John, G.H., 1997b. Wrappers for feature subset selection. Artificial intelligence 97, 273-324.

Kononenko, I., 1994. Estimating attributes: analysis and extensions of relief, In Proceedings of the Seventh European Conference on Machine Learning, pp. 171–182.

Kourentzes, N., Barrow, D.K., Crone, S.F., 2014. Neural network ensemble operators for time series forecasting. Expert Systems with Applications 41, 4235-4244.

Krogh, A., Vedelsby, J., 1995. Neural network ensembles, cross validation, and active learning. Advances in Neural Information Processing Systems 7, 231-238.

Kumar, R., 2013. Decision tree for the weather forecasting. International Journal of Computer Applications 76.

Kuncheva, L., 2004a. Combining Pattern Classifiers: Methods and Algorithms. Wiley-Interscience.

Kuncheva, L., Whitaker, C., 2003. Measures of Diversity in Classifier Ensembles and Their Relationship with the Ensemble Accuracy. Machine Learning 51, 181-207.

Kuncheva, L., Whitaker, C., Shipp, C., Duin, R., 2003. Limits on the majority vote accuracy in classifier fusion. Pattern Analysis and Applications 6, 22-31.

Kuncheva, L.I., 2004b. Combining Pattern Classifiers: Methods and Algorithms. Wiley-Interscience.

Lahmiri, S., 2014. Ensemble with radial basis function neural networks for Casablanca stock market returns prediction, Complex Systems (WCCS), 2014 Second World Conference on, pp. 469-474.

Lai, R.K., Fan, C.-Y., Huang, W.-H., Chang, P.-C., 2009. Evolving and clustering fuzzy decision tree for financial time series data forecasting. Expert Systems with Applications 36, 3761-3773.

Lawrence, S., Giles, C.L., Tsoi, A.C., 1997. Lessons in neural network training: Overfitting may be harder than expected, AAAI/IAAI. Citeseer, pp. 540-545.

Lee, K., Jo, G., 1999. Expert system for predicting stock market timing using a candlestick chart. Expert Systems with Applications 16, 357-364.

Lee, W.-S., Tzeng, G.-H., Guan, J.-L., Chien, K.-T., Huang, J.-M., 2009. Combined MCDM techniques for exploring stock selection based on Gordon model. Expert Systems with Applications 36, 6421-6430.

Levin, N., Zahavi, J., 2001. Predictive modeling using segmentation. Journal of Interactive Marketing 15, 2-22.

Lewellen, J., 2004. Predicting returns with financial ratios. Journal of Financial Economics 74, 209-235.

Li, B., 2006a. A new approach to cluster analysis: the clustering-function-based method. Journal of the Royal Statistical Society, Series B (Statistical Methodology) 68, 457–476.

Li, B., 2006b. Sign eigenanalysis and its applications to optimization problems and robust statistics. Computational Statistics & Data Analysis 50, 154-162.

Lin, H.-Y., 2013. Feature selection based on cluster and variability analyses for ordinal multi-class classification problems. Knowledge-Based Systems 37, 94-104.

Lin, X., Yang, Z., Song, Y., 2011. Intelligent stock trading system based on improved technical analysis and Echo State Network. Expert Systems with Applications 38, 11347-11354.

Linoff, G.S., Berry, M.J.A., Data mining techniques: for marketing, sales, and customer relationship management. John Wiley & Sons.

Liu, H., Motoda, H., Setiono, R., Zhao, Z., Feature selection: An ever evolving frontier in data mining, Feature Selection in Data Mining, pp. 4-13.

Liu, H., Setiono, R., 1996. A probabilistic approach to feature selection – a filter solution, In Proceedings of the 13th International Conference on Machine Learning, pp. 319-327.

Lu, T.-H., 2014. The profitability of candlestick charting in the Taiwan stock market. Pacific-Basin Finance Journal 26, 65-78.

Lu, T.-H., Shiu, Y.-M., Liu, T.-C., 2012. Profitable candlestick trading strategies—The evidence from a new perspective. Review of Financial Economics 21, 63-68.

Majhi, R., Panda, G., Sahoo, G., 2009. Development and performance evaluation of FLANN based model for forecasting of stock markets. Expert Systems with Applications 36, 6800-6808.

Maldonado, S., Weber, R., 2009a. A wrapper method for feature selection using Support Vector Machines. Information Sciences 179, 2208-2217.

Maldonado, S.n., Weber, R., 2009b. A wrapper method for feature selection using support vector machines. Information Sciences 179, 2208-2217.

Mehrotra, K., Mohan, C.K., Ranka, S., 1997. Elements of artificial neural networks. MIT press.

Menkhoff, L., 2010. The use of technical analysis by fund managers: International evidence. Journal of Banking & Finance 34, 2573-2586.

Min, J.H., Lee, Y.-C., 2005. Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters. Expert Systems with Applications 28, 603-614.

Mitchell, T.M., 1997a. Machine Learning. McGraw-Hill

Mitchell, T.M., 1997b. Machine learning. McGraw-Hill.

Mousavi, R., Eftekhari, M., 2015. A new ensemble learning methodology based on hybridization of classifier ensemble selection approaches. Applied Soft Computing 37, 652-666.

Mozaffari, L., Mozaffari, A., Azad, N.L., Vehicle speed prediction via a sliding-window time series analysis and an evolutionary least learning machine: A case study on San Francisco urban roads. Engineering Science and Technology, an International Journal.

Mukherji, S., Dhatt, M.S., Kim, Y.H., 1997. A Fundamental Analysis of Korean Stock Returns Financial Analysts Journal 53, 75-80.

Murthy, S.K., 1998. Automatic construction of decision trees from data: A multi-disciplinary survey. Data mining and knowledge discovery 2, 345-389.

Ng, W.W., Liang, X.-L., Li, J., Yeung, D.S., Chan, P.P., 2014. LG-trader: Stock trading decision support based on feature selection by weighted Localized generalization error model. Neurocomputing.

Omran, M., Ragab, A., 2004. Linear Versus Non-linear Relationships Between Financial Ratios and Stock Returns: Empirical Evidence from Egyptian Firms, Review of Accounting and Finance, pp. 84 - 102.

Ou, P., Wang, H., 2009a. Prediction of stock market index movement by ten data mining techniques. Modern Applied Science 3, 28-42.

Ou, P., Wang, H., 2009b. Prediction of Stock Market Index Movement by Ten Data Mining Techniques. Modern Applied Science 3, 28–42.

Oza, N.C., Tumer, K., 2008. Classifier ensembles: Select real-world applications. Information Fusion 9, 4-20.

Patel, J., Shah, S., Thakkar, P., Kotecha, K., 2014. Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. Expert Systems with Applications.

Patel, J., Shah, S., Thakkar, P., Kotecha, K., 2015a. Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques. Expert Systems with Applications 42, 259-268.

Patel, J., Shah, S., Thakkar, P., Kotecha, K., 2015b. Predicting stock market index using fusion of machine learning techniques. Expert Systems with Applications 42, 2162-2172.

Pereira, F., Mitchell, T., Botvinick, M., 2009. Machine learning classifiers and fMRI: A tutorial overview. NeuroImage 45, S199-S209.

Piramuthu, S., 2004. Evaluating feature selection methods for learning in data mining applications. European journal of operational research 156, 483-494.

Priddy, K.L., Keller, P.E., 2005. Artificial neural networks: an introduction. SPIE press.

Qian, B., Rasheed, K., 2007. Stock market prediction with multiple classifiers. Appl Intell 26, 25-33.

Ragg, T., Braun, H., Landsberg, H., 1998. A comparative study of neural network optimization techniques, Artificial Neural Nets and Genetic Algorithms. Springer, pp. 341-345.

Rajabioun, R., Atashpaz-Gargari, E., Lucas, C., 2008. Colonial competitive algorithm as a tool for Nash equilibrium point achievement, Computational science and its applications–iccsa 2008. Springer, pp. 680-695.

Rapach, D.E., Zhou, G., 2012. Forecasting Stock Returns. Forthcoming in the Handbook of Economic Forecasting 2.

Rastrigin, L., Erenstein, R.H., 1981. Method of Collective Recognition. Energoizdat, Moscow.

Rizzo, G., d'Amato, C., Fanizzi, N., Esposito, F., 2017. Tree-based models for inductive classification on the Web Of Data. Web Semantics: Science, Services and Agents on the World Wide Web 45, 1-22.

Rokach, L., 2009. Taxonomy for characterizing ensemble methods in classification tasks: A review and annotated bibliography. Computational Statistics & Data Analysis 53, 4046-4072.

Sadka, G., Sadka, R., 2009. Predictability and the earnings–returns relation. Journal of Financial Economics 94, 87-106.

Salzberg, S., 1994. C4.5: Programs for Machine Learning by J. Ross Quinlan. Morgan Kaufmann Publishers, Inc., 1993. Machine Learning 16, 235-240.

Sarkheyli, A., Zain, A.M., Sharif, S., 2015. Robust optimization of ANFIS based on a new modified GA. Neurocomputing.

Schapire, R.E., 2001. The boosting approach to machine learning: an overview. in: MSRI Workshop on Nonlinear Estimation and Classification, Berkeley, CA, USA.

Sepehri Rad, H., Lucas, C., 2008. Application of imperialistic competition algorithm in recommender systems, 13th Int'l CSI Computer Conference (CSICC'08), Kish Island, Iran.

Sharky, A.J.C., Sharky, N.E., 1997. Combining diverse neural nets. The Knowledge Engineering Review 12, 231-247.

Shearer, C., 2000. The CRISP-DM model: the new blueprint for data mining. Journal of data warehousing 5, 13-22.

Shi, H., 2007. Best-first decision tree learning. Annals of statistics 2, 337-407.

Soliman, M.-T., 2008. The use of DuPont analysis by market participants. The Accounting Review 83, 823-853.

Svalina, I., Galzina, V., Lujić, R., Šimunović, G., 2013. An adaptive network-based fuzzy inference system (ANFIS) for the forecasting: The case of close price indices. Expert systems with applications 40, 6055-6063.

Tang, E.K., Suganthan, P.N., Yao, X., 2006. An analysis of diversity measures. Machine Learning 65, 247-271.

Tsai, C.-F., Hsiao, Y.-C., 2010. Combining multiple feature selection methods for stock prediction: Union, intersection, and multi-intersection approaches. Decision Support Systems 50, 258-269.

Tsai, C.-F., Hsu, Y.-F., Yen, D.C., 2014. A comparative study of classifier ensembles for bankruptcy prediction. Applied Soft Computing 24, 977-984.

Tsai, C.-F., Lin, Y.-C., Yen, D.C., Chen, Y.-M., 2011. Predicting stock returns by classifier ensembles. Applied Soft Computing 11, 2452-2459.

Tsai, C.-F., Lu, Y.-H., Yen, D.C., 2012. Determinants of intangible assets value: The data mining approach. Knowledge-Based Systems 31, 67-77.

Tsymbal, A., Pechenizkiy, M., Cunningham, P., 2005. Diversity in search strategies for ensemble feature selection. Information Fusion 6, 83-98.

Tumer, K., Ghosh, J., 1996. Analysis of decision boundaries in linearly combined neural classifiers. Pattern Recognition 29, 341-348.

Vairappan, C., Tamura, H., Gao, S., Tang, Z., 2009. Batch type local search-based adaptive neuro-fuzzy inference system (ANFIS) with self-feedbacks for time-series prediction. Neurocomputing 72, 1870-1877.

Wang, A., An, N., Chen, G., Li, L., Alterovitz, G., 2015. Accelerating wrapper-based feature selection with K-nearest-neighbor. Knowledge-Based Systems.

Wang, J.-L., Chan, S.-H., 2006. Stock market trading rule discovery using two-layer bias decision tree. Expert Systems with Applications 30, 605-611.

Wang, L., Wu, J., 2012. Neural Network Ensemble Model Using PPR and LS-SVR for Stock Market Forecasting, in: Huang, D.-S., Gan, Y., Bevilacqua, V., Figueroa, J. (Eds.), Advanced Intelligent Computing. Springer Berlin Heidelberg, pp. 1-8.

Wen, Q., Yang, Z., Song, Y., Jia, P., 2010. Automatic stock decision support system based on box theory and SVM algorithm. Expert Systems with Applications 37, 1015-1022.

Windeatt, T., 2005. Diversity measures for multiple classifier system analysis and design. Information Fusion 6, 21-36.

Witten, I.H., Frank, E., 2011. Data Mining: Practical Machine Learning Tools and Techniques, 3 ed. Morgan Kaufmann, San Francisco.

Woloszynski, T., Kurzynski, M., 2011. A probabilistic model of classifier competence for dynamic ensemble selection. Pattern Recognition 44, 2656-2668.

Woloszynski, T., Kurzynski, M., Podsiadlo, P., Stachowiak, G.W., 2012. A measure of competence based on random classification for dynamic ensemble selection. Information Fusion 13, 207-213.

Wolpert, D., 2001. The supervised learning no-free-lunch theorems. In: Proceedings of the 6th Online World Conference on Soft Computing in Industrial Applications, 25-42.

Wozniak, M., 2008. Experiments on Linear Combiners, in: Pietka, E., Kawa, J. (Eds.), Information Technologies in Biomedicine. Springer Berlin Heidelberg, pp. 445-452.

Woźniak, M., Graña, M., Corchado, E., 2014. A survey of multiple classifier systems as hybrid systems. Information Fusion 16, 3-17.

Wu, J.-L., Yu, L.-C., Chang, P.-C., 2014. An intelligent stock trading system using comprehensive features. Applied Soft Computing 23, 39-50.

Ye, N., 2003. The handbook of data mining. CRC Press.

Yu, H., Chen, R., Zhang, G., 2014. A SVM Stock Selection Model within PCA. Procedia Computer Science 31, 406-412.

Yu, L., Liu, H., 2003. Feature selection for high-dimensional data: A fast correlation-based filter solution, Proceedings of the 20th international conference on machine learning (ICML-03), pp. 856-863.

Yunos, Z.M., Shamsuddin, S.M., Sallehuddin, R., 2008. Data Modeling for Kuala Lumpur Composite Index with ANFIS, Modeling & Simulation, 2008. AICMS 08. Second Asia International Conference on. IEEE, pp. 609-614.

Zhang, D., Zhou, L., 2004. Discovering Golden Nuggets: Data Mining in Financial Application. IEEE Transaction on Systems, Man, and Cybernetics -Part C: Applications and Reviews 34, 513-522.

Zhang, G., Patuwo, B.E., Hu, M.Y., 1998. Forecasting with artificial neural networks:: The state of the art. International journal of forecasting 14, 35-62.

Zhang, X., Hu, Y., Xie, K., Wang, S., Ngai, E., Liu, M., 2014a. A causal feature selection algorithm for stock prediction modeling. Neurocomputing.

Zhang, X., Hu, Y., Xie, K., Zhang, W., Su, L., Liu, M., 2014b. An Evolutionary Trend Reversion Model for Stock Trading Rule Discovery. Knowledge-Based Systems.

Zhu, Y., Shasha, D., 2003. Efficient elastic burst detection in data streams, Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, pp. 336-345.

Zhu, Y., Zhou, G., 2009. Technical analysis: An asset allocation perspective on the use of moving averages. Journal of Financial Economics 92, 519-544.

A summary list of my publications during the PhD

Fusion of multiple diverse predictors in stock market
S Barak, S Ortobelli
Information Fusion 36, 90-102

Wrapper ANFIS-ICA method to do stock market timing and feature selection on the basis of Japanese Candlestick
S Barak, J Heidary dahooie, T Tichý
Expert Systems with Applications 42 (23), 9221-9235

Developing an approach to evaluate stocks by forecasting effective features with data mining methods
S Barak, M Modarres
Expert Systems with Applications 42 (3), 1325-1339

Dependency evaluation of financial market returns for classifying and grouping stocks
S Barak
Intelligent Systems and Signal Processing (ICSPIS), 2017 3rd Iranian …

Hybrid Fuzzy MCDM Model for Candidate Well Selection
S Barak
Expert Systems with Application Accepted, Under Editorial Proof

A novel hybrid fuzzy DEA-Fuzzy MADM method for airlines safety evaluation
S Barak, J Heidary
Journal of Air Transport Management 73, 134-149

Energy and GHG emissions management of agricultural systems using multi objective particle swarm optimization algorithm: a case study
S Barak, M Yousefi, H Maghsoudlou, S Jahangiri
Stochastic Environmental Research and Risk Assessment 30 (4), 1167-1187

A clustering model based on an evolutionary algorithm for better energy use in crop production
B Khoshnevisan, E Bolandnazar, S Barak, S Shamshirband
Stochastic environmental research and risk assessment 29 (8), 1921-1935