Integrating Fundamental and Technical Analysis of Stock Market through Multi-layer Perceptron

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***Abstract*—We use Multi-layer Perceptron and propose a hybrid model of fundamental and technical analysis by utilizing stock prices (from 2012-06 to 2017-12) and financial ratios of Technology companies listed on Nasdaq. Our model uses data discretization and feature selection preprocesses. The best results are obtained through topology optimizations using a three-hidden layer MLP. We examine the predictability of our hybrid model through a training/test split and cross-validation. It is found that the hybrid model successfully predicts the future stock movements. Our model results in the greatest average directional accuracy (65.87%) compared to the results obtained from the fundamental and technical analysis in isolation. The numerical results provide enough evidence to conclude that the market is not perfectly efficient.**

Keywords—fundamental analysis, technical analysis, neural network, multi-layer perceptron, topology optimization, data discretization, feature selection

I. INTRODUCTION

Stock market analysis is important due to its potential monetary benefits. However, this analysis is complex since stock market is dynamic and influenced by many factors. Fundamental and technical are two primary analyses for making investment decisions in stock markets. In fundamental analysis, it is believed that the securities are mispriced and intrinsic values can be determined based on financial ratios of the companies, macro-economic variables, management policies, and other quantitative or qualitative factors. The main purpose of fundamental analysis is to identify the fundamentally strong/weak firms [12]. On the other hand, technical analysis is the evaluation of stocks by means of statistics. Technicians assume that market is efficient and the current stock price reflects all available information including financial ratios. According to this stock market analysis, the pattern in historical data will repeat itself in future; therefore, past stock prices and trading volumes can be used in order to forecast the future stock movements [16]. Moreover, the two primary stock market analyses can be integrated into a hybrid model in order to evaluate the complementary nature of them [1].

Artificial intelligence-based methods including neural networks have become popular techniques for forecasting stock movements due to their ability to learn how to do tasks through a learning algorithm [15]. Neural networks are appropriate for predicting stock prices and outperform the statistical techniques such as Regressions for the following reasons. One, neural networks are numeric and fit the financial data sets. Two, a distribution of input data is not required in neural networks. Three, a model formulation is not required in neural networks. Four, neural networks can predict unseen data without reprocessing training data. However, determination of a neural network architecture including learning algorithms, number of layers, number of neurons in each layer, and transfer functions between the layers is complicated. Different network architectures result in different generalization errors; therefore, generalization error can be used as a measure to evaluate the performance of the network. An appropriate network architecture can be achieved through topology optimizations [9].

In this paper, we use a Multi-layer Perceptron (MLP) neural network and design a hybrid model integrating the firm's financial ratios and historical stock prices, and predict the future stock movements. It is shown that the hybrid model is beneficial for stock market participants, in the sense of producing return greater than a buy-and-hold strategy.

This paper proceeds in six sections. In Section II, we conduct a brief review of related research. Section III introduces the Multi-layer Neural Network, Section IV defines the input and output data sets as well as the data preprocessing methods, Section V proposes our fundamental, technical, and hybrid models, Section VI presents the results and discusses the findings, and Section VII concludes the paper and provides the future work directions.

II. RELATED WORK

There exists a vast literature on stock market predictability. Jegadeesh and Titman [8] showed that short-term returns tend to continue meaning that stocks with higher returns in the previous year are likely to have higher future returns. In other words, past winners are future winners and past losers are future losers. Malkiel [11] developed a Federal Reverse model and measured the relation between price/earnings ratios (P/E ratios) and interest rates. The stock market direction was predicted in his research. However, the results of the proposed model does not outperform a buy-and-hold strategy. Zhang, et al. [17] focused on input variables in a fundamental analysis. They attempted to identify the most significant features and

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presented a useful algorithm for predicting stock returns. They used a Casual Feature Selection (CFS) algorithm to find the significant input variables in Shanghai stock exchanges. Zhong and Enke [18] studied a Fuzzy Robust PCA and a Kernel-based PCA and forecasted the daily stock market returns. The results of related work confirm that stock market is not a perfect random walk and stock movements are predictable from historical prices and financial variables.

A voluminous literature has examined the ability of AI-based techniques to predict the future stock movements. Kimoto, et al. [9] used Modular Neural Networks to identify the relationships among different market factors and developed a prediction system for the Tokyo stock price index (TOPIX). Moreover, they compared their proposed model to Multiple Regressions. It was concluded that NNs result in higher coefficients compared to Regressions. Their research on stock market prediction is one of the work in which the problem of overfitting has been tested by using cross-validations. Chang and Liu [4] attempted to integrate the effect of qualitative factors with technical indices trough a Genetic Algorithm-based Fuzzy Neural Network (GFNN). They evaluated their prediction system on data obtained from Taiwan stock exchange (TSE) and concluded that the proposed system outperforms the ANNs that only consider the quantitative factors. Boyacioglu and Avci [3] examined the predictability of the Istanbul Stock Exchange index by using six macroeconomic variables and three indices as input of their Adaptive Network-based Fuzzy Inference System (ANFIS). The authors showed that their proposed model is capable of predicting the monthly returns of ISE national 100 indices with an accuracy of 98.3%.

More recently, Sheta, et al. [15] used Support Vector Machines and MLP and presented an algorithm for predicting the S&P 500 market index. They selected 27 financial variables on weekly bases and found the relationship between stock indices and those variables. They compared three different techniques; Regression, ANN, and SVM and reported that SVM contributes to better predictions compared to the other two models. Hafezi, et al. [7] presented a Bat-neural Network Multi-agent System (BNNMAS) for forecasting stock returns based on data obtained from DAX stock market index. They considered both fundamental and technical analyses in their model and evaluated the accuracy of the model on long-term prediction. Additionally, they performed a Data Normalization, Time Lag Selection, and Feature Selection. They concluded that BNNMAS outperforms other models such as Genetic Algorithm Neural Network (GANN) and General Regression Neural Network (GRNN). Patel, et al. [14] proposed a technical approach based on historical prices and predicted future stock returns. They compared four prediction models (ANN, SVM, Random Forest, and Naive-Bayes) and predicted the market directions. It was found that Random Forest outperforms the other models. Li, et al. [10] used Extreme Learning Machine (ELM) for forecasting stock return changes in H-share market in year 2001. They stated that their proposed ELM has high accuracy and fast prediction speed. Namdari, et al. [13] examined the predictability of stock returns using a Self-optimizing Neural Network. In their proposed network, the learning process and topology optimization are preformed simultaneously. They used training/test splits to evaluate their model based on stock prices of healthcare firms obtained from Nasdaq. They concluded that their model is capable of forecasting stock returns with certain accuracies.

An integrated model of fundamental and technical analysis using multi-layer perceptron neural networks has not previously been tested in the literature, which is the subject of this study.

III. MULTI-LAYER PERCEPTRON NEURAL NETWORKS

Multi-layer perceptron (MLP) is a class of feedforward artificial neural network (ANN) and uses backpropagation as a technique for training. In multi-layer perceptron neural networks, the output of each layer forms the input of the next layer. In this study, we use a three-hidden-layer MLP in order to obtain the optimum results. $P.H_1.H_2.H_3.Q$ describes the architecture of an MLP with three hidden layers, where H_1, H_2, and H_3 are the hidden layers, and P and Q are the input and output layers, respectively. This network can be translated into a matrix form as a function $f: R^D \rightarrow R^L$, where D is the size of input vector x and L is the size of the output vector f(x) [5].

Assuming a training data set $D = \{x_n, t_n\}_{n=1}^{N}$, we can form a data matrix X containing the training data as follows:

$$\underset{N \times (P+1)}{X} = \begin{pmatrix} x_1^\tau \\ \vdots \\ x_N^\tau \end{pmatrix} \quad (1)$$

In order for the MLP to learn the relationships between the variables based on the training data, the first stage is to build the product that connects the input layer to the first hidden layer,

$$\underset{H_1 \times (P+1)}{y_1} = \underset{H_1 \times (P+1)}{\Omega_1} \underset{(P+1) \times 1}{x} \quad (2)$$

where Ω_1 is the first weight matrix. Similarly, the first and second hidden layers, the second and third hidden layers, as well as the last hidden layer and the output layer are connected as follows:

$$\underset{H_2 \times (H_1+1)}{y_2} = \underset{H_2 \times (H_1+1)}{\Omega_2} \underset{H_1 \times (P+1)}{y_1} \quad (3)$$

$$\underset{H_3 \times (H_2+1)}{y_3} = \underset{H_3 \times (H_2+1)}{\Omega_3} \underset{H_2 \times (H_1+1)}{y_2} \quad (4)$$

$$\underset{Q \times 1}{z} = \underset{Q \times (H_3+1)}{\gamma} \underset{H_3 \times (H_2+1)}{y_3} \quad (5)$$

where Ω_2, Ω_3, and γ are the second, third, and the last weight matrices, respectively.

Therefore, the MLP fitted model can be defined as follows:

$$\mathrm{mlp}(x) = f_Q(z)$$
$$= f_Q(\gamma[1, f_{H_3}(\Omega_3[1, f_{H_2}(\Omega_2[1, \{f_{H_1}(\Omega_1 x)\}^\tau]^\tau)^\tau]^\tau)^\tau]^\tau) \quad (6)$$

The activation function f_Q is

$$f_Q(z_q) = z_q^* = \frac{\exp(z_q)}{\sum_{q_1=1}^{Q} \exp(z_{q_1})} \tag{7}$$

where z_q^* is the output. Assuming that t_n is the target vector, the weight matrices are chosen to minimize the MLP cross-entropy penalty function ρ_c

$$\rho_c = \sum_{n=1}^{N} \sum_{q=1}^{Q} t_{nq} \log \frac{t_{nq}}{z_{nq}^*} \tag{8}$$

The performance of the multi-layer perceptron can be evaluated based on two measures: accuracy and generalization error. Accuracy represents the learning ability of the model. Generalization error shows how accurately the model is capable of predicting unseen data. Generalization error is an appropriate indicator of performance of neural networks. Topology optimization is the process of selecting weights from the architecture in order to improve the performance of learning algorithms and obtain the optimal solutions. Topology optimizations can be used in order to achieve the best network architecture that results in the least generalization errors. In this study, we use MLP topology optimizations to obtain the best network architecture with respect to generalization error and accuracy.

IV. DATA DESCRIPTION

Finance, energy, healthcare, technology, etc. are sectors of stock markets. In this paper, in order to lower the noise level, we decide to study stocks of the firms that belong to the same sector. Hence, we choose 578 Technology companies whose data is available on Nasdaq website.

Financial ratios of the companies are the main input variables in fundamental analysis of stock market. This study focuses on twenty-four financial ratios compiled from the financial statements of the Technology companies in the fiscal year of 2016 selected on the basis of the previous literature and for reasons of importance and tractability. Twelve financial ratios are selected as the most significant variables through a Feature Selection preprocess by conducting the topology optimizations. The selected financial ratios are as follows: Current Ratio, Inv/Curr Assets, Inventory Day Sales, Net Inc/Comm Equity, Net Inc/Net Sales, Net Inc/Total Assets, Net Sales/PP&E, Net Sales/Work Cap, Pretax Inc/Net Sales, Quick Ratio, Total Liab/Comm Equity, and Total Liab/Total Assets.

Next, the financial ratios, which are continuous variables, are discretized into discrete counterparts through a Data Discretization preprocess by conducting the topology optimizations. The twelve financial ratios are discretized as shown in TABLE I. For instance, Inv/Curr Assets is discretized into the following five classes: 0.1, 0.3, 0.5, 0.7, and 0.9. The combination of twelve financial ratios discretized into their classes contributes to the least MSE by comparing the simulated results from MLP neural networks and actual data.

TABLE I. LIST OF FINANCIAL RATIOS AND DISCRETIZATION NUMBERS DETERMINED THROUGH FEATURE SELECTION AND DATA DISCRETIZATION PREPROCESSES

Financial Ratios	Discretization #
Current Ratio	2
Inv/Curr Assets	5
Inventory Day Sales	4
Net Inc/Comm Equity	2
Net Inc/Net Sales	6
Net Inc/Total Assets	3
Net Sales/PP&E	6
Net Sales/Work Cap	1
Pretax Inc/Net Sales	4
Quick Ratio	4
Total Liab/Comm Equity	6
Total Liab/Total Assets	4

In our technical analysis, we study stock prices of the same companies to forecast the future stock movements. We normalize the input data to reduce the data redundancies and improve the data integrity. The number of input data may vary depending on how much of an impact the historical stock prices have on the future prices [2]. We use IXIC daily stock prices form 2012-06 to 2017-12. In order to enhance the comparison between the stock prices, we should manipulate the time series of stock prices to become stationary. First, we convert the stock prices into a logarithmic format since stock prices are based on returns and returns are based on percentages. Next, we calculate the differences between each time series point and multiply them by 100. This will compute the compound returns, r. The historical raw stock prices and the prices transformed into a stationary form are depicted in Fig. 1.

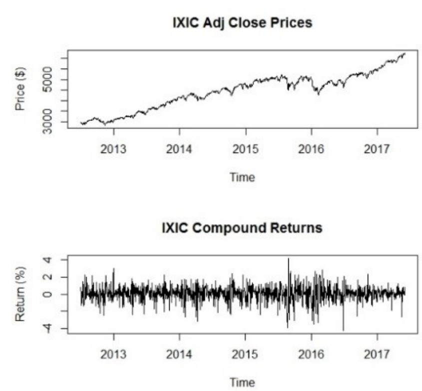

Fig. 1. Time series of IXIC prices and compound returns

As it can be seen in Fig. 1, time series of adjusted closing prices has a moving average while time series of compound returns has a constant mean, variance and autocorrelation. This indicates that our data is now stationary. In addition, we determine the autocorrelations in order to further examine the time series of compound returns. The autocorrelation between any two data points r_t and r_{t-h} only depends on the time lag h between them.

Lag-*h* covariance is defined as:

$$\gamma_h = \mathrm{Cov}(r_t, r_{t-h}) \tag{9}$$

Therefore, the theoretical lag-h autocorrelation is

$$\rho_h = \mathrm{Corr}(r_t, r_{t-h}) = \frac{\gamma_h}{\gamma_0} \tag{10}$$

where γ_0 is the lag-0 covariance.

The theoretical partial autocorrelation $\phi_{h,h}$ is the autocorrelation between r_t and r_{t-h} after removing the effect of confounders. The theoretical autocorrelation and partial autocorrelation can be estimated using sample autocorrelation and sample partial autocorrelation. For the data points $r_1, r_2, \ldots, r_T$, the sample lag-h autocorrelation is

$$\hat{\rho}_h = \frac{\sum_{t=h+1}^{T}(r_t - \bar{r})(r_{t-h} - \bar{r})}{\sum_{t=1}^{T}(r_t - \bar{r})^2} \tag{11}$$

where $\bar{r}$ is the sample mean. Similarly, $\hat{\phi}_{h,h}$ denotes the sample partial autocorrelation. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are illustrated in Fig. 2.

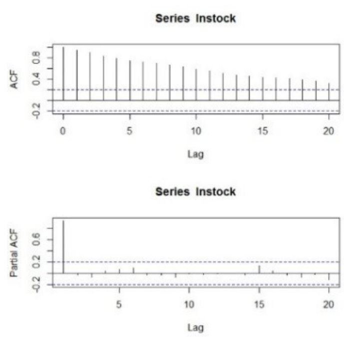

Fig. 2. Correlogram of sample autocorrelation function (ACF) and partial autocorrelation function (PACF)

Each vertical line, in both graphs in Fig. 2, represents the correlation between the lags. It can be seen in the upper graph that there is a very gradual decent in the lags. However, there is an immediate drop in the correlation of the first lags in the partial autocorrelation function depicted in the lower graph. From the autocorrelations demonstrated in this correlogram, we can infer that our data is stationary which was also observed in the lower plot in Fig. 1.

Once the prices are transformed into the stationary form, the resultant compound returns are discretized into discrete counterparts. Similar to the process of data discretization in the fundamental analysis we conduct the MLP topology optimizations to obtain the optimum discretization number. The computational results reveal that the stock returns should be discretized into five classes.

V. Model Development

In this section, two separate models are presented in order to study the predictability of stock movements using fundamental and technical analysis in isolation. Then, a hybrid model is examined and compared to the first two models.

The number of layers, number of neurons in each layer, and the transfer functions between the layers are determined through MLP topology optimization. The results of the optimized network reveals that the transfer functions between the input layer and the 1st hidden layer as well as the transfer function between the 3rd hidden layer and the output layer are Log-sigmoid. Interestingly, the same type of transfer function connects the hidden layers. There are 60, 51, and 1 neurons in the 1st, 2nd, and 3rd hidden layers of the optimized network, respectively. The neural network depicted in Fig. 3 represents the fundamental analysis of stock market. According to the results of the fundamental analysis, this model contributes to the least MSE among all the trials of the topology optimization process.

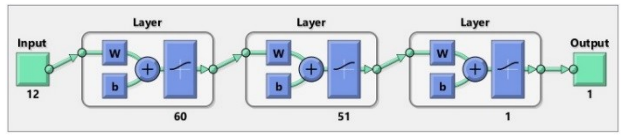

Fig. 3. Multi-layer Perceptron (MLP) network implemented for the prediction of stock prices through fundamental analysis

Similar to the fundamental analysis, we conduct MLP topology optimizations for the technical analysis to obtain the optimum results. There are 30, 32, and 1 neurons in the 1st, 2nd, and 3rd hidden layers, respectively. The transfer functions between the input layer and the 1st hidden layer, the 1st and the 2nd hidden layers, and the 2nd and the 3rd hidden layers are all Log-sigmoid. However, the last hidden layer, which contains only one neuron, is connected to the output layer via a Tan-sigmoid transfer function. Fig. 4 displays the architecture of the neural network in the technical analysis, which results in the least MSE among all the trials.

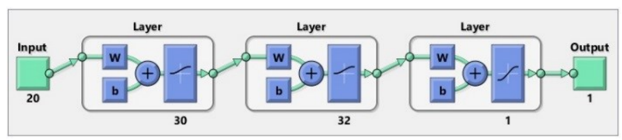

Fig. 4. Multi-layer Perceptron (MLP) network implemented for the prediction of stock prices through technical analysis

Next, we present a hybrid model by combining the fundamental and technical analyses. We combine the models in order to integrate financial ratios and historical prices, and see how this affects the simulated results. Fig. 5 illustrates the prediction system used in order to predict the future stock movements. The input of the hybrid model are the same financial ratios and stock prices examined by the first two models and the output of this model is the same as the output of those models.

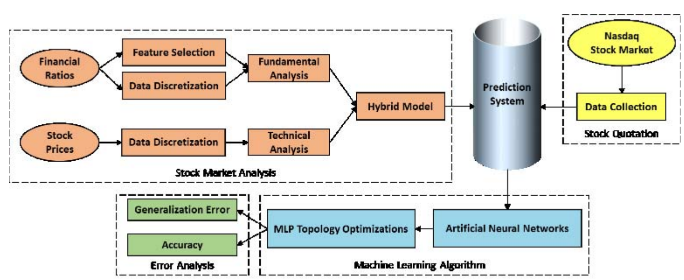

Fig. 5. Prediction system of stock movements based on the hybrid model of fundamental and technical analysis

The three-hidden layer neural network learns the relationship between the stock prices, financial ratios, and the future stock movements. Similar to the first two models, MLP topology optimizations are conducted for the hybrid model and the optimum results are as follows: 6, 10, 6, 17, 6, 1, and 6. According to these results, the transfer functions between all layers are Log-sigmoid, which are displayed by number 6. There are 10, 17, and 1 neurons in the 1st, 2nd, and 3rd hidden layers, respectively. This network architecture contributes to the least MSE.

VI. Results and Findings

In this section, first, we evaluate the performance of our models through a training/test split and cross-validation test. Next, we examine the directional accuracies of our simulated results using the three different models.

A. Training/Test Split and Cross-Validation Tests

In order to validate the fundamental, technical, and hybrid models we test the accuracy and generalization error of each model. We use MSE as the measure of risk function and compare the simulated results with actual data obtained from Nasdaq. First, we split our data into two subsets: training and test data. MSE of the model on the training data set captures the accuracy of the model. On the other hand, MSE of the model on test data set represents the generalization errors. Fig. 6 displays MSEs produced by fundamental, technical, and hybrid models on training and test data sets.

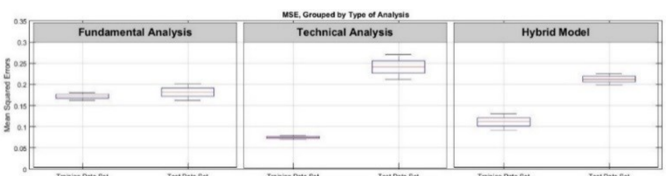

Fig. 6. MSE on training and test data sets for the fundamental, technical and hybrid models

From Fig. 6, the following items become readily noticeable: (1) fundamental analysis results in the best generalization error and the worst accuracy, (2) technical analysis results in the best accuracy and the worst generalization error, (3) MSE of the hybrid model on training data set is 0.1167 which is a favorable indicator of generalization ability of the model, and (4) the hybrid model contributes to the best results due to its overall performance on training and test data sets.

Furthermore, we split our data into three subsets: training, validation and test data, and use cross-validation in order to prevent overfitting and underfitting in the hybrid model. Overfitting and underfitting affect the predictability of the hybrid model. If overfitting happens, the hybrid model learns the noises instead of the trends in the data. On the other hand, underfitting happens when the model misses the relationships between the input and output variables. The relation between objectives to be achieved and the estimated stock prices are shown in Fig. 7. The results are shown for all data used as well as the training, validation and test data sets, separately.

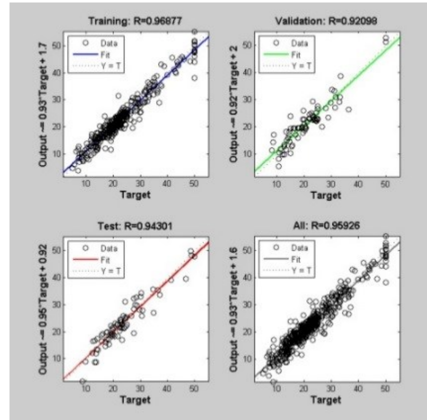

Fig. 7. Multi-layer perceptron (MLP) performance for the training, validation, test and all data sets

As it can be seen in Fig. 7, the regression correlation coefficients for the training, validation, test and all data sets are 0.96877, 0.92098, 0.94301 and 0.95926, respectively. It can be concluded that the cross-validation test verifies the quality of the obtained hybrid model being able to accurately reproduce the stock prices. The error histogram with 20 bins is also examined and shown in Fig. 8 in order to identify the outliers and obtain additional verification of the MLP network performance. The blue, green and red bars represent the training, validation and test data sets, respectively. As it can be seen in Fig. 8, the MSEs are distributed within a reasonably good range around zero. It can be understood that the data fitting of the hybrid model is quite precise.

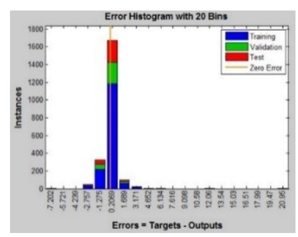

Fig. 8. Error histogram with 20 bins for the hybrid model

B. Directional Accuracy

In order to examine our hybrid in terms of directional accuracy of the simulated results, we predict the future stock returns and compare them with actual data obtained from Nasdaq. The outputs of both fundamental and technical analysis are discretized into five classes similar to the classes of input data in the technical analysis. The discretization numbers 1, 2, 3, 4, and 5 represent a sharp fall, downward trend, non-trending, upward trend, and sharp rise in stock returns, respectively. The numerical results for the directional accuracies are shown in TABLE II.

TABLE II. Directional Accuracies

	Fundamental	**Technical**	**Hybrid**
Sharp Fall	63.43%	63.15%	65.67%
Downward Trend	62.87%	60.36%	61.45%
Non-trending	63.32%	62.31%	66.11%
Upward Trend	66.31%	65.23%	68.56%
Sharp Rise	65.98%	63.19%	67.55%

In all cases, directional accuracies obtained from fundamental analysis are better than those of reported by the technical analysis. The reason is the ability of MLP for fundamental analysis to generalize the results. In all cases, the hybrid model performs better than the other two models in terms of directional accuracy with an exception of stocks with downward trend. The average directional accuracy obtained from the hybrid model is 65.87% that is sizable relative to results of a buy-and-hold strategy. Our results are consistent with the previous study by Bettman, et al. [1], who showed that fundamental and technical analyses are complements rather than substitutes.

VII. CONCLUSION

In this research, multi-layer perceptron neural networks are adopted to build a hybrid model by integrating fundamental and technical analysis and forecast the future stock movements. MLP topology optimizations are conducted in order to select the most significant financial ratios and discretize the ratios as well as prices through feature selection and discretization preprocess. The number of stock prices as our input data are determined through an autocorrelation preprocess. This study reveals that fundamental and technical models are capable of predicting the future stock movements with certain accuracies, and this prediction accuracy will be improved by integrating the two primary stock market analyses into a hybrid model. MSE of the hybrid model on training and test data sets are compared to those of fundamental and technical models in isolation and the results yield support for the overall efficiency of the hybrid model. It is also shown that a cross-validation verifies the quality of our hybrid model and the data fitting of this model is precise. The directional accuracy of the simulated results obtained from the hybrid model is compared with the directional accuracy of the fundamental and technical analyses and it is found that the hybrid model results in the best performance except with the stocks that have downward trend.

Future work should examine the effect of clustering input data on stock market predictability using K Mean Clustering Algorithm. How different clusters of financial ratios may result in different generalization errors can be tested by determining the risk quantities. It would also be worthwhile to examine statistical methods such as Principal Component Analysis (PCA) in order to prepare input data for the purpose of predicting future stock movements.

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