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Fitting Multi-Layer Feed Forward Neural Network and Autoregressive Integrated Moving Average for Dhaka Stock Exchange Price Predicting

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Abstract

The stock market plays a vital role in the economic development of any country. Stock market performance can be measured by the market capitalization ratio as well as many other factors. The primary purpose of this study is to predict the movement of the stock market based on the total market capitalization of the Dhaka Stock Exchange (DSE) using autoregressive integrated moving average (ARIMA) models as well as artificial neural networks (ANN). The data set covers monthly time series data of total market capitalization from November 2001 to December 2018. This study also shows the best model for forecasting the movement of DSE market capitalization. The ARIMA (2,1,2) model is chosen from among the several ARIMA model combinations. From several artificial neural networks (ANN) models as a modern tool, a three-layer feed-forward topology using a backpropagation algorithm with five nodes in the hidden layer, one lag, and a learning rate equal to 0.01 is selected as the best model. Finally, these selected two models are compared based on the Root-Mean-Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil's U statistic. The results showed that the estimated error of ANN is less than the estimated error of the traditional method.

Keywords:

Dhaka Stock Exchange; Predicting; ARIMA; ANN; Multi-Layer Feed Forward Neural Network; Bangladesh.

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1- Introduction

The stock exchange provides a reflection of companies and the economy's long-term growth prospects. Predicting the future is, by all accounts, a skill that everyone should acquire, especially when it may be beneficial. This might explain why stock price estimates are so well-known. Several features have been linked to stock price undulation, including but not deficient to macroeconomic aspects, market expectations, and faith in the organization's governance and activities. People may now access a larger amount of data in a more efficient manner because of technological advancements. As a result, stock analysis has grown increasingly strenuous, as an enormous mass of data must be refined in a correspondingly tiny period of time. Individuals believe that advances in big data, particularly in the discipline of artificial intelligence, will aid them in deciphering stock data [1]. Many exploratory studies have looked into the future evolution of stock costs. On the one hand, proponents of the Capital Asset Pricing (CAP) [2] model insist that stock prices cannot be predicted. However, there have been studies that indicate how, given proper display, stock costs may be predicted with a really healthy degree of consistency. The last option focused on factor selection, appropriate utilitarian structures, and deciding methods. Even though proponents of the effective market theory acknowledge that stock price variations are difficult to predict, a large number of analysts believe that a few models are enough as long as they can supply forecasts with considerable precision [3].

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Academicians, data analysts, and financial practitioners have repeatedly focused attention on Artificial Neural Networks (ANN), notably in the economic arena. ANN deep learning techniques have been used in many different fields, for example, automated car driving, robot-supported operation, intelligent drone navigation, software development, nuclear physics, and finance. Regarding the financial system, various types of models have been considered relevant to forecasting asset price changes and the conduct of more structured financial instruments. In most cases, the suggested methods focused primarily on statistical models for evaluating time series of interest [4].

Thus, stock price forecasting is critical for capitalists to ensure that most of their investment earns a profit. As a result of these factors, the stock market has seen increased volatility and a significant quantity of noise. This is why anticipating stock market data can be difficult. Forecasting future movement using historical and current data is critical in inventory planning. Numerous strategies for forecasting the future behavior of a series of events have been developed in light of this dilemma.

The univariate neural network is used [5] to study the profitability of daily stock market index returns. In contrast, Bayesian regularized artificial neural networks as a novel method to forecast financial market behavior [6]. For the Istanbul Exchange, it was shown that artificial neural networks' forecasting power was higher than linear regression [7]. For the Indian Stock market, ANN is used to model the Indian stock market in terms of Bombay stock exchange data [8]. An ANN model with three layers in the network uses the Backpropagation Algorithm to forecast Istanbul Stock Exchange National-100 Indices (ISE National -100) with an accuracy of 74.51% [9].

This study applied the method of multi feed-forward neural network (MF-FNN) from artificial neural networks (ANN) and autoregressive integrated moving average (ARIMA) as a modern method of forecasting technique to forecast the stock market prices in terms of the market capitalization of the DSE. This paper also checked how it could be used as an alternative method to traditional methods in the case of the Dhaka Stock Exchange (DSE) market. However, until recently, not too much work related to market capitalization forecasting based on ANN methods has been found in Bangladesh. The research aims to propose a suitable ANN model for the Total Market Capitalization of DSE and then discuss the forecasting power in terms of forecasting errors. This study also compares the best strategy for forecasting stock price with previous studies and provides a comparison between ANN and ARIMA. The comparative study results outshone the prior analysis of stock price prediction, with the best result from this study allowing shareholders to pick their new technique of investing their money based on the anticipated value.

2- Literature Review

Many articles, publications, and research initiatives are centered on forecasting stock prices using Exchange pricing databases. Some of the recent work reviews are presented below:

Time Series Analysis and Multiple Regression Techniques [10] are additional common ways to anticipate the future value of a series; however, as the series becomes nonlinear or non-stationary, the forecasting power of these tools is degraded [11]. Because of their ability to be taught from the nature of the series and accuracy, Neural Network has become a popular tool. There have been a lot of studies comparing Neural Networks to statistical approaches [12-14]. Yoon and Swales [12] discovered that the Neural Network strategy outperformed the Multivariate Discriminant Analysis approach in forecasting stock price. In terms of 500 Index volatility predictions, the neural network outperforms the Barone-Adesi and Whaley (BAW) American futures options pricing model [16]. ANN forecasting is more accurate than point estimates by regression [17] or linear models [18].

Artificial neural networks were compared to the adaptive exponential smoothing approach, and it was discovered that ANN performed better in anticipating market movement [19]. ANN has been used in a variety of stock exchanges, including the Canadian Stock Exchange [17], the Chinese Stock Exchange [18], the Brazilian Stock Exchange [19], the Portuguese Stock Exchange [20], the Indian Stock Exchange [21], and the Indian Stock Exchange [22]. A comparative study of GRACH and ARIMA Models to forecast the market capital of Dhaka Stock Exchange in Bangladesh was done where ARIMA (2,1,2) Model was selected as the best predicting model [23]. Data scientists have started using machine learning to improve efficiency, Statistical modeling, and statistical precision. The next step is developing deep learning predicting stock market movements using high-performance machine learning and deep learning algorithms [24]. As in many situations, the relationship between past and future results is not deterministic; this is conditional Probability distribution dependent on past observations [25]. Many conventional econometric models for forecasting time series, such as the Autoregressive (AR) Model [26], Autoregressive Moving Average (ARMA) Model [27], Vector Autoregressive model, and Box – Jenkins [28] with a good number of stocks of price prediction results.

In recent studies, researchers and academics have employed artificial neural networks (ANN), hybrid neural networks (HNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Natural Language Processing (NLP), and other methodologies to estimate stock values for a variety of purposes. Senapati [29] debuted Adaline Neural Network, a novel hybrid neural network for stock price prediction (ADNN). The neural network model used Particle Swarm Optimization (PSO) techniques to develop the hybrid model. They have used the CNN model to explore the share market with certain specific product pricing projected [30]. Several of the researchers used time series analysis to predict stock prices, but they also revealed that stock prices are influenced by social and political aspects in addition to time [31]. The model may become confused and forecast a value erroneously. Many researchers have used deep learning with hybrid ANN models to forecast stock and forex prices, and they have observed how deep learning and hybrid ANN models respond to time series data [32]. It was also discovered that multivariate analysis provides more accurate model performance, rather than univariate analysis [33]. Some researchers use natural language processing (NLP) to analyze sentiment from shareholder tweets to see how the tweet affects share market price [34].

However, in Bangladesh, Roy & Ashrafuzzaman [35] were unable to effectively predict stock values. Another research tried to predict stock market efficiency in the weak form of the Dhaka Stock Exchange by using some non-parametric as well as some parametric methods [36]. A robust method was suggested where Principal Component Analysis (PCA) is done to the data set to reduce high dimensionality for using a backpropagation neural network [37]. This method is used for the prediction of next-day share prices using DSE share prices. Hossain et al. (2019) has tried to forecast the General Index of Dhaka Stock Exchange (DSE) using ARIMA, ARCH, and GARCH models as well as making a comparison among their forecasting power [38].

Last year, financial data forecasting drew a lot of attention. Prediction becomes difficult due to the nonlinear and complicated nature of this sort of data. Since market capitalization is financial data, the same problem arises in the case of its prediction. From several types of research, it has been observed that nonlinear models have more ability to predict financial data precisely. There have been several types of research in this context in Bangladesh but applied to other kinds of data. This study attempted to analyze the market behavior of DSE, using Market Capitalization (MCAP) data, and to compare the traditional methods and ANN methods under univariate analysis.

Academicians, data analysts, and financial practitioners have repeatedly focused attention on Artificial Neural Networks (ANN), notably in the economic arena. ANN deep learning techniques have been used in many different fields, for example, automated car driving, robot-supported operation, intelligent drone navigation, software development, nuclear physics, and finance [3]. Regarding the financial system, various types of models have been considered relevant to forecasting asset price changes and the conduct of more structured financial instruments. In most cases, the suggested methods focused primarily on statistical models for evaluating time series of interest [3].

The capital challenge for shareholders is to choose stock price by dissecting monetary information which is a humble undertaking as of mutilate related and huge example. Consequently, choosing stock postures is probably the best trouble for financial patrons. The forecast and investigation of the stock price is likewise a quiescent area of research because of its indispensable importance in decision-making by monetary financial backers. This study brings an advantage for the shareholders by overcoming the conventional way and using artificial intelligence and time series-enabled analysis for Dhaka stock market price forecast, allowing them to invest their money according to the findings of the study.

3- Materials and Methods

Several underlying processes must be completed to accomplish the research goal, including data collection, data processing, and model training-testing (ANN and ARIMA model implementation: activation function, backpropagation, Augmented Dickey-Fuller (ADF) Test, and others), data analyzing, and result generation. Figure 1 depicts a flowchart of the working procedure for this proposed study.

3-1- Dataset and Data Pre-processing

The data set which has been used for this study is secondary. The data set covers monthly time series data of total market capitalization from November 2001 to December 2018 as the study attempted to analyze the market behavior of DSE, using Market Capitalization (MCAP) data. The information was derived from Bangladesh Bank's Monthly Economic Trends which are available on the Bangladesh Bank website. Data preprocessing has been used to handle missing values by using the average value and min-max scaling to transform between 0 and 1. The research was carried out using R software version 3.2.3.

3-2- Artificial Neural Network (ANN)

The human brain consists of neurons that transmit stimulation signals to each other and can learn from experiences using a complicated system of electrical pulses between neurons to send and receive them. This reality inspired many researchers and contributed to the development of the cognitive sciences known as artificial intelligence and the creation of the net, known as the artificial neuron. The increase in the number of hidden layers may increase the risk of overfitting and calculation time and poor prediction performance. ANN applications are utilized in a variety of sectors to forecast a variety of domains [39, 40]. Bailey & Thompson (1990) [41] proposed that in a three-layer neural network, hidden layer neurons must be 75% of input neurons. Klimasauskas (1993) [42] recommends that there must be a minimum of five times as many training details as weights, putting an upper limit on inputs and neurons. Because of these attributes, various configurations are applied to all details.

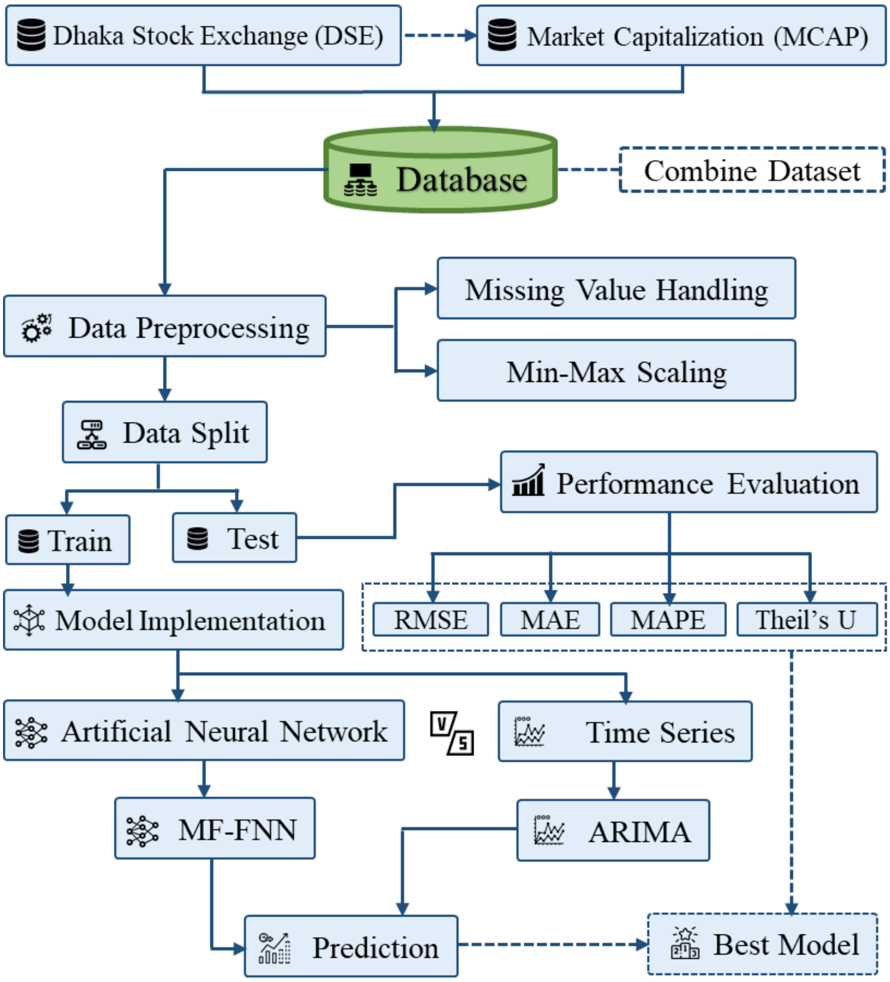


Figure 1. Working procedure diagram to the prediction of Dhaka stock price using ANN and ARIMA

3-3- Multilayer Feed-Forward Neural Network (MF-FNN)

The primary function of ANN is to model the human reasoning process as a computer-efficient algorithm. The multilayer feed network consists of more than one layer of artificial neurons, making unidirectional input and output forward connections. There are also two choices to make on the hidden layers: how many hidden layers are in the network and how many neurons are in each layer. Nearly all existing neural networking challenges are well solved with only one hidden layer. Although the hidden layers are not connected directly with the outside world, they affect the final production amazingly. In comparison, while the ANN model attempts to be consistent with the use of a minimal number of hidden layers and neurons, it may also be appropriate to increase the exact structure of the model by raising hidden layers. A multilayer feed-forward neural network is shown in Figure 2 as an example.

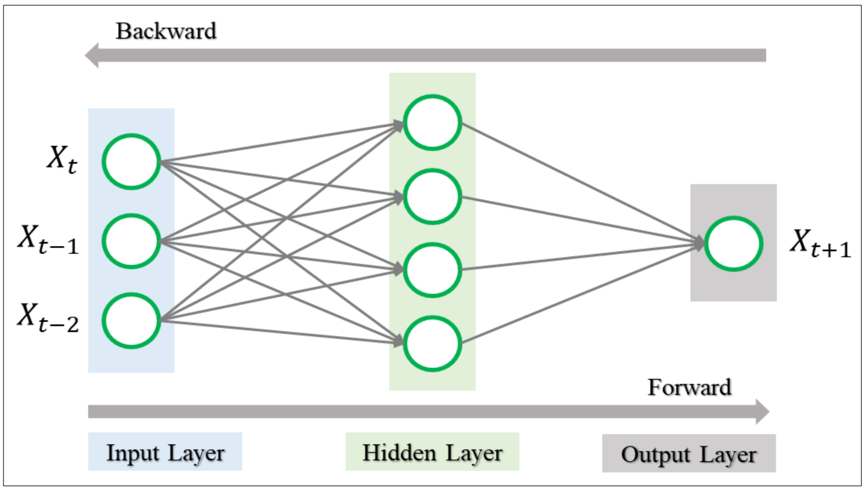


Figure 2. Multilayer Feed-Forward Neural Network with one hidden layer

3-4- Activation Function in ANN

The activation function of the ANN model transforms the input signal into the output motion of the node that is being regarded as an input in the following phase. As an input to the following layer, this layer's activation function (X) receives its output and feeds it through to its output function (Y).

3-5- Operational Definition

The operational definition is the method by which a variable is measured in particular research; steps are provided below:

- ***Input Layer:*** In this study up to lag 5 of monthly values of market capitalization are used as the input variables.
- ***Output Layer:*** The predicted monthly value of the market capitalization using the input layer through the hidden layer is considered as output.
- ***Hidden Layer:*** Single hidden layer with 8 neurons is used for this study. The hidden layer is the combination of weighted lag of monthly value of market capitalization to produce forecasted value through the Activation function.

3-6- Jarque-Bera Test

The Jarque-bera test is based on the following statistic.

$$\mathrm{JB} = \frac{\mathrm{N}}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{1}$$

where, S, K, and N indicate the sample skewness, the sample kurtosis, and the sample size, respectively

3-7- Time Series Analysis

Time series analysis is a technique for examining the relationship between a response variable and an independent variable [43]. Instead of capturing data points intermittently or arbitrarily, time series analyzers record data points at constant intervals over a predetermined length of time. Be using the time variable as a benchmark to estimate the target variable in the name of predicting or forecasting. The application of time series analysis is the most frequently used approach for stock market analysis as well as stock exchange price prediction.

3-8- Autoregressive Integrated Moving Average Model (ARIMA)

The Autoregressive Integrated Moving Average model [44] is abbreviated as ARIMA. In time-series data, a type of model may catch a variety of common transitory occurrences. ARIMA models are factual models that are used to analyze and figure out time-series data. In the model, each of these elements is clearly stated as a border. ARIMA (p, d, q) is a type of standard documentation in which the borders are replaced by numerical attributes in order to recognize the ARIMA method.

$$\Delta Y_t = \varphi_0 + \varphi_1 \times \Delta y_{t-1} \ldots + \varphi_m \times \Delta y_{t-m} + \sigma_0 + \sigma_1 \times \Delta\alpha_{t-1} + \cdots + \sigma_k \times \Delta\alpha_{t-k} \tag{2}$$

3-9- Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) allows us to assess how well your model fits the illuminating data without overfitting it. Furthermore, the AIC score promotes models with a high fairness of-fit score while rejecting them if they become too complicated. The AIC score isn't particularly relevant unless we compare it to the AIC score of one of my competing time series models. It depended on the model with the lowest AIC score to establish a balance between its ability to fit the informational index and its ability to avoid overfitting the index. The AIC value formula is as follows:

$$AIC = 2m - 2\ln(\delta) \tag{3}$$

Here the parameters define that, m = Number of model parameters. $\delta = \delta(\theta)$ = highest value of the possible function of the method. For my model here, θ = maximum likelihood.

3-10- Autocorrelation Function (ACF)

The Autocorrelation Function (ACF) demonstrates how data values in a time series are associated to data values subsequent to them on the mean value.

3-11- Partial Autocorrelation Function (PACF)

The theoretical partial autocorrelation function (PACF) for an AR model "closes off" after the model is solicited. On a fundamental level, the articulation "turned off" implies that the partial auto-relationships are equivalent to 0 beyond that point. In other words, the ARIMA model receives the request from the number of non-zero midway autocorrelations. "Demand for the model" is the most ludicrous leeway of the 'Dhaka Stock Exchange (DSE) Price' that is utilized as a guide.

3-12- Augmented Dickey-Fuller (ADF) Test for Stationarity Test

The Augmented Dickey – Fuller (ADF) test is a unit root test applies to time series data for checking non-stationary property.

3-13- Performance Evaluation

The acceptability of a model is determined by how well it performs on the dataset and forecasts the value with the least amount of error. We computed root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and uncertainty coefficient (Theil's U) to select the most appropriate model for forecasting the stock price.

- **Root Mean Square Error (RMSE)**: Root mean square error is a commonly utilized fraction of the differ between allying rate (test and real) by a technique or assessor and the characteristics perceived. The RMSE is calculated as in "(4)":

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{4}$$

where, n = number of non-missing data points, i = variable, y_i = actual value, $\bar{y}_i$ = forecast value.

- **Mean Absolute Error (MAE):** The amplitude of the difference between the forecast of an observation and the real value of that observation is referred to as absolute error in artificial intelligence. The scale of errors for a collection of predictions and observations is measured using the mean of absolute errors for the entire group.

$$MAE = \frac{\sum_{i=1}^{n} y_i - x_i}{n} \tag{5}$$

where, n = total number of data points, y_i = prediction value, x_i = true value.

- **Mean Absolute Percentage Error (MAPE):** The mean absolute percentage error (MAPE) is a measure of how accurate a forecast system is. It measures this accuracy as a percentage and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{6}$$

where, n = number of times the summation iteration happens, A_t = actual value and F_t = forecasted value.

- **Uncertainly Coefficient (Theil's U):** Theil's U statistic is a measure of relative accuracy that compares projected results to forecasted results using minimum previous data. It also squares the deviations, giving huge mistakes more weight and exaggerating errors, which can aid in the elimination of approaches with enormous errors.

$$Theil's\ U = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{\bar{y}_{t+1} - y_{t+1}}{y_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{y_{t+1} - y_t}{y_t}\right)^2}} \tag{7}$$

where y_t = actual value of a point for a given time (t), n = number of data points, and $\bar{y}_t$ = forecasted value.

4- Results and Discussion

As there are 165 observations for market index from November 2001 to December 2018, it is required for forecasting the time series to test normality and stationarity. Table 1 showed the results of Jarque-Bera test for normality of the data and for stationarity of the data, the Augmented Dickey-Fuller (ADF) Unit Root Test, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test and the Phillips-Perron (PP) Unit Root Test are used.

Table 1. The normality test and stationarity test of the three series

Statistics	Original Index (MCAP)	Logarithmic Index (LogMCAP)	Logarithmic Returns (Diff LogMCAP)	Decisions
Jarque-Bera Normality Test	19.87 ($p<0.05$)	17.25 ($p<0.05$)	91.76 ($p<0.05$)	All the three series are not normal.
ADF Test for Unit Root	-2.21 ($p>0.10$)	-1.08 ($p>0.10$)	-3.87 ($p<0.05$)	Original and logarithmic data are non-stationary.
P-P Unit Root Test	-2.09 ($p>0.10$)	-0.50 ($p>0.10$)	-12.38 ($p<0.05$)	Logarithmic returns data is stationary.

The Jarque-Bera test rejected the null hypothesis of normality for MCAP as well as for its transformed series (LogMCAP and DiffLogMCAP) at a 5% level. Furthermore, outcomes from the Augmented Dickey-Fuller (ADF) Test and Phillips-Perron (PP) Test in Table 1 indicate that at 5% level the series MCAP and LogMCAP are non-stationary. On the other hand, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test rejects the null hypothesis of stationarity for the data MCAP as well as for its transformed series LogMCAP and DiffLogMCAP).

The summary statistics (the number of observations, maximum, minimum, mean, quartiles, median, standard deviation, skewness, and kurtosis as well) of dependent variable i.e., market capitalization (MCAP) is provided in Table A1 in the appendix I.

Figure 3 represents the time series Market capitalization (MCAP) monthly data which will be analyzed and indicate that it is a nonstationary time series. This series varies randomly over time and there is no global trend or seasonal note.

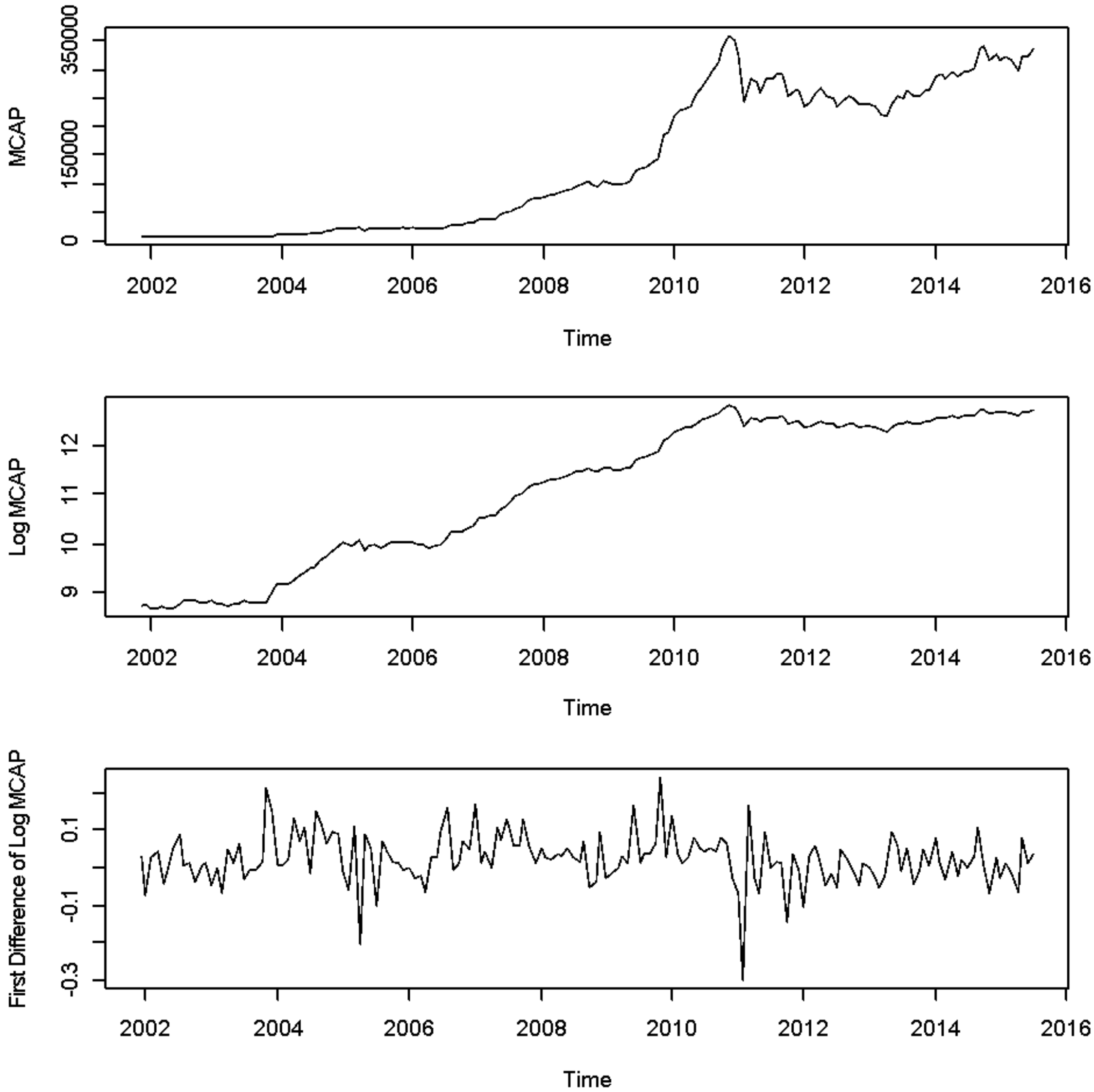


Figure 3. **Time series plots of monthly Market capitalization, log Market capitalization, and return series (first difference) of Market capitalization data**

To reduce heteroscedasticity the original data were transformed using the natural logarithm. So, data will be expressed as Market capitalization (MCAP) (i.e., LogMCAP), and the first difference of logarithm of the Market capitalization (MCAP) (i.e., DiffLogMCAP) to make the original time series data stationary are also presented in Figure 3.

4-1- ARIMA (p, d, q) Model Selection

Figure 4 showed the ACF and PACF plots of natural logarithmic and natural logarithmic return (first differenced) of Market capitalization time series data respectively. The autocorrelation function (ACF) of LogMCAP in Figure 4-a shows that this study dealing with a typical situation of a nonstationary time series. It is observed that the first difference of natural logarithm series (i.e., DiffLogMCAP) in Figure 4-b has become stationary.

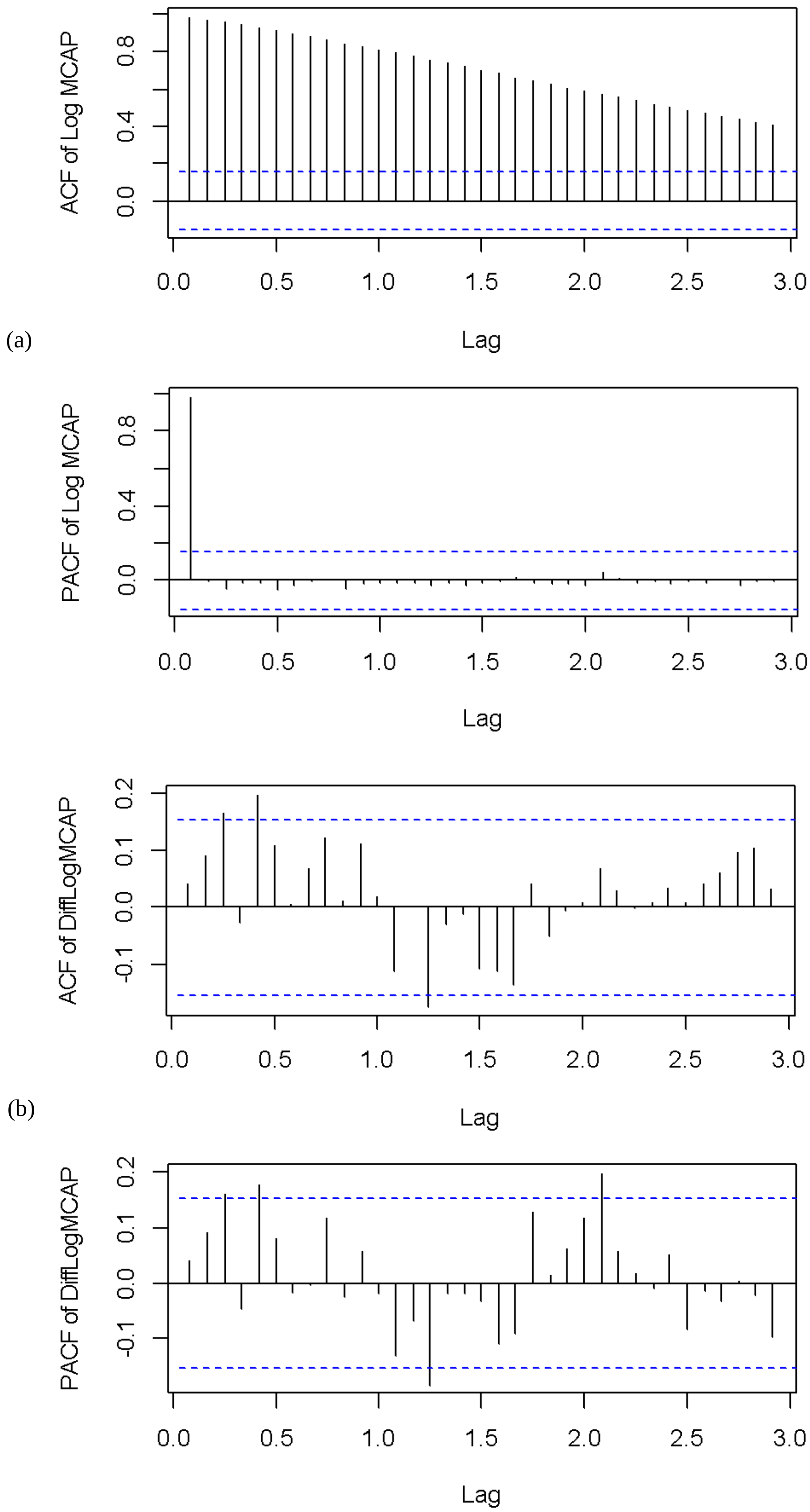


Figure 4. The ACF and PACF plot for the time series (a) natural logarithmic of Market capitalization data (LogMCAP) and (b) natural logarithmic return (first differenced) of Market capitalization data (DiffLogMCAP)

Akaike Information Criterion (AIC) is used for different values of p and q to choose the best ARIMA model calculated (Table 2).

Table 2. Akaike Information Criterion (AIC) arrangement

		MA(q)					
		0	**1**	**2**	**3**	**4**	**5**
AR(p)	0	-392.2437	-392.9848	-394.9451	-398.1726	-396.2115	-403.0381
	1	-393.8604	-409.0113	-408.2684	-397.5182	-395.5489	-414.5000
	2	-397.1040	-408.1327	-415.5324	-406.9237	-405.1907	-415.5551
	3	-403.3528	-401.9096	-407.3568	-407.2816	-405.8388	-415.4332
	4	-401.3540	-400.5606	-405.8418	-405.6898	-405.1984	-405.9696
	5	-407.6262	-408.3145	-406.3849	-405.5726	-406.7241	-406.6724

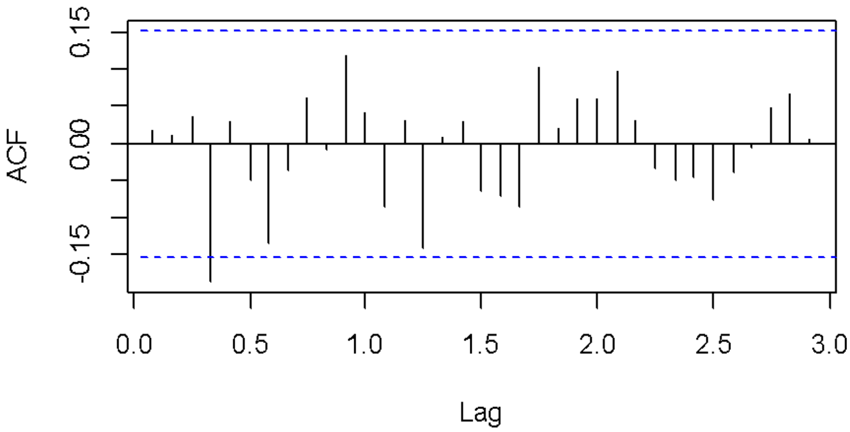
The Akaike Information Criterion (AIC and AICC), the Bayesian Information Criterion (BIC) and Log-Likelihood values are presented in Table 3 to confirm the superiority of the ARIMA (2, 1, 2) model.

Table 3. Akaike Information Criterion (AIC) arrangement

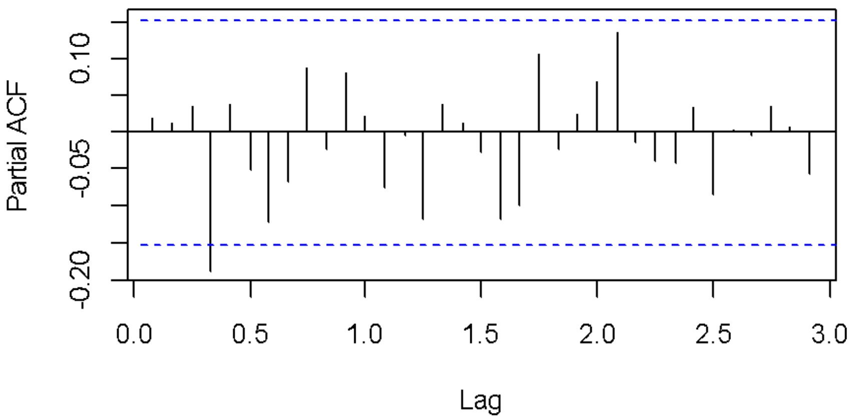
ARIMA Model	AIC	AIC$_C$	BIC	Log-Likelihood
ARIMA (1, 1, 1)	-409.01	-408.86	-399.71	207.51
ARIMA (1, 1, 2)	-408.27	-408.02	-395.87	208.13
ARIMA (2, 1, 1)	-408.13	-407.88	-395.73	208.07
ARIMA (2, 1, 2)	**-415.53**	**-415.15**	**-400.03**	**212.77**

4-2- Diagnostic Testing for the Model

Figure 5 recommends that the suggested model ARIMA (2, 1, 2) fit the time series data very well.



(a)



(b)

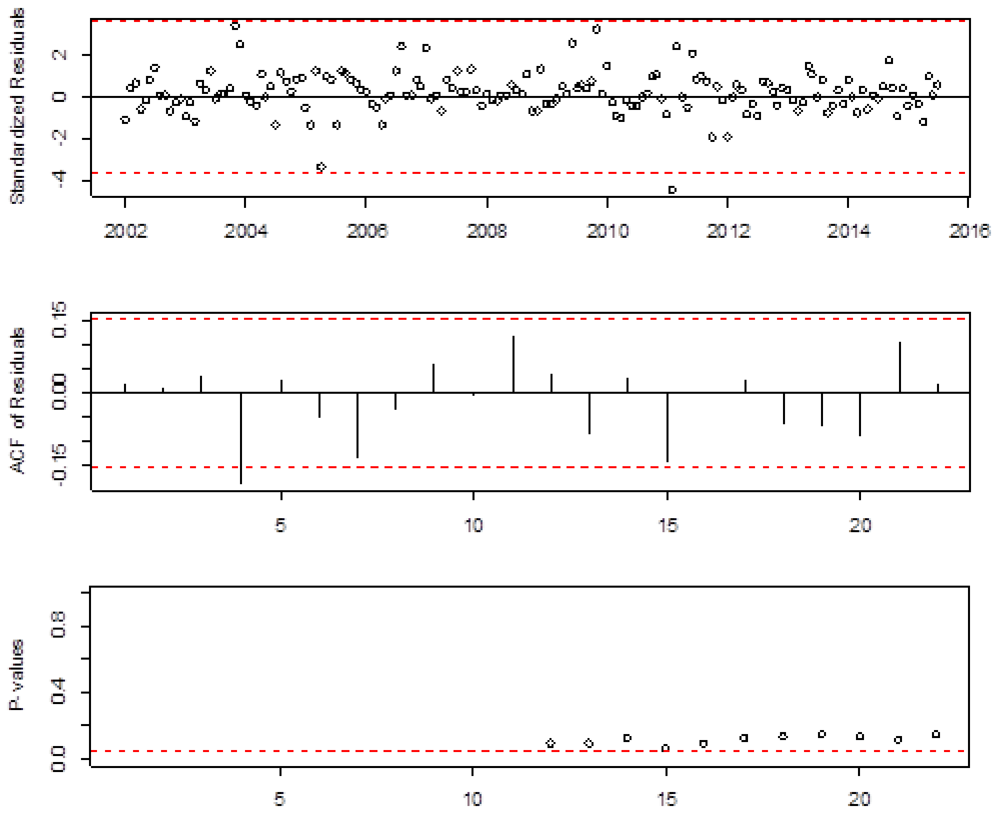


Figure 5. The (i) ACF and PACF plot for the residuals of the model ARIMA (2, 1, 2) of LogMCAP, (ii) Diagnostic Display of the model ARIMA (2, 1, 2) of LogMCAP

Table 4 showed the Chi-square values and P-values of Lijung-Box test statistics using several lags for the Model ARIMA (2, 1, 2) of the natural logarithmic of the Market capitalization data (LogMCAP).

Table 4. The Chi-square values and P-values of Lijung-Box test

	Chi-square value	P-value
Lag-10	10.796	0.0949
Lag-12	13.588	0.09316
Lag-18	19.769	0.1376

The P-values of the Lijung-Box test statistics for several lags such as 6, 8, and 12 confirm that the ARIMA (2, 1, 2) Model fits quite well to the time series data. Determined ARIMA (2, 1, 2) can be express as,

$$y_t = 1.7590y_{t-1} - 0.81412y_{t-2} - 1.85(t-1) + 0.9646(t-2) \quad (8)$$

4-3- ARCH/GARCH Approach

Before attempting any ARCH/GARCH modeling, this study has attempted to establish the presence of ARCH effects in the data. After observing Table A2 in the appendix I the results recommended that no ARCH/GARCH model should be suggested.

4-4- Artificial Neural Network (ANN) Model Fitting

The neural network models are constructed using the back propagation technique. Table 5 demonstrates that perhaps the network which takes 1 lag as input and has 5 neurons in the hidden layer with a learning rate of 0.01 has the minimum RMSE value (0.0303) and is thus chosen to apply to the data under consideration.

Table 5. The root mean square error (RMSE) values for different neural network models

Lag Input	Units in Hidden Layer	RMSE values for different Learning Rates			Lag Input	Units in Hidden Layer	RMSE values for different Learning Rates		
		(0.01)	(0.05)	(0.10)			(0.01)	(0.05)	(0.10)
1	1	1.6802	1.6802	1.6802	3	5	0.0594	0.0594	0.0594
	2	0.0345	0.0345	0.0345		6	0.0620	0.0620	0.0620
	3	0.0332	0.0332	0.0332		7	0.0622	0.0622	0.0622
	4	0.0325	0.0325	0.0325		8	0.0622	0.0622	0.0622
	5	**0.0303**	0.0303	0.0303	4	1	1.6409	1.6409	1.6409
	6	0.0330	0.0330	0.0330		2	0.0706	0.0706	0.0706
	7	0.0326	0.0326	0.0326		3	0.0700	0.0700	0.0700
	8	0.0307	0.0307	0.0307		4	0.0711	0.0711	0.0711
2	1	1.6673	1.6673	1.6673		5	0.0665	0.0665	0.0665
	2	0.0475	0.0475	0.0475		6	0.0724	0.0724	0.0724
	3	0.0465	0.0465	0.0465		7	0.0745	0.0745	0.0745
	4	0.0453	0.0453	0.0453		8	0.0700	0.0700	0.0700
	5	0.0455	0.0455	0.0455	5	1	1.6293	1.6293	1.6293
	6	0.0478	0.0478	0.0478		2	0.0814	0.0814	0.0814
	7	0.0494	0.0494	0.0494		3	0.0780	0.0780	0.0780
	8	0.0465	0.0465	0.0465		4	0.0930	0.0930	0.0930
3	1	1.6541	1.6541	1.6541		5	0.0786	0.0786	0.0786
	2	0.0601	0.0601	0.0601		6	0.0812	0.0812	0.0812
	3	0.0598	0.0598	0.0598		7	0.0832	0.0832	0.0832
	4	0.0574	0.0574	0.0574		8	0.0777	0.0777	0.0777

Before applying the ANN technique to the logarithmic market capitalization (MCAP) time-series data, Brock, Dechert, and Scheinkman (BDS) Test of non-linearity in data is performed and the findings conclude that the time series is non-linearly dependent. This finding from BDS test justifies the fitting of ANN to the series under study.

Figure 6 showed the pattern of the suggested Back Propagation neural network Model with one lag in input layer, five hidden neurons in the hidden layer, and one output neuron in the output layer.

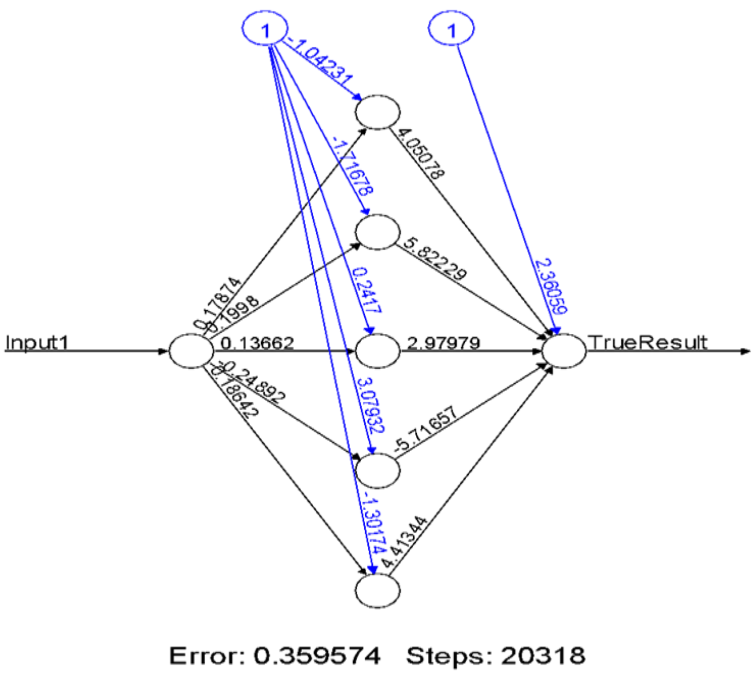


Figure 6. The Proposed Neural Network model with 1 hidden layer

4-5- Comparison of the Approaches

The accuracy indices show that the ANN model exhibits fewer errors with better forecast accuracy compared to the ARIMA model (Table 6).

Table 6. The forecast accuracy measures for selected ARIMA and ANN model

Accuracy Measure	ARIMA	ANN
RMSE	0.1184182	0.0303001
MAE	0.1037667	0.0239697
MAPE	0.8081693	0.1870350
Theil's U	0.0091702	0.0023628

Figure 7 showed the prediction pattern of the ARIMA (2, 1, 2) model and ANN model which suggest that the Artificial Neural Network (ANN) model provides a better prediction for the time series data than the ARIMA model which is also supported by Adebiyi et al. (2014) [45].

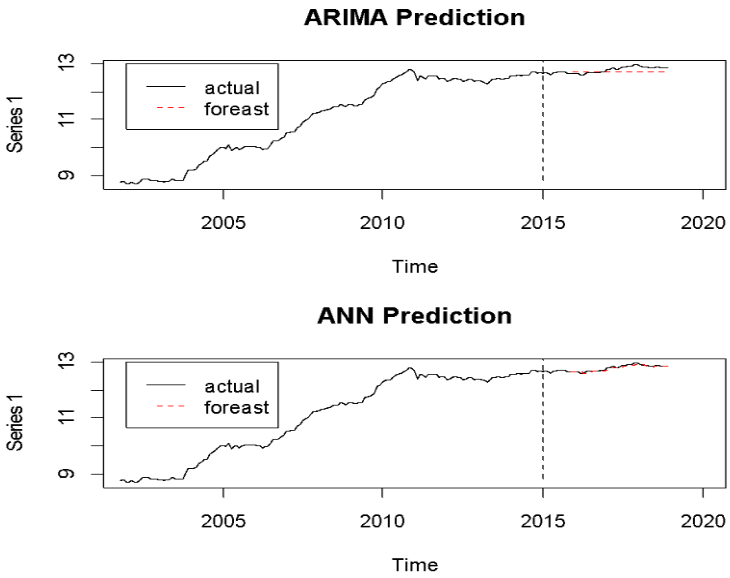


Figure 7. The forecasted pattern of ARIMA and ANN model

4-6- Comparison with Previous Study

In the terms of comparative study, our findings are juxtaposed to those of other studies, it becomes noticeable that the values for forecasting stock prices are rather comparable throughout all investigations. With their adopted strategy, some academics are attempting to anticipate the stock price. Table 7 compares previous work with the accuracy or minimal error of the applied model with our proposed work. Various research concentrates on specific objectives, with some attempting to apply the ANN model, hybrid model, and classic time series ARIMA model to their data. With their countryfies data, some academics are attempting to anticipate stock price indexing, price movement, and market capital. This work uses an ANN model on very recent data with a minimum error to overcome the handicap of Bangladeshi stock price prediction. Market capitalization rose, dropped, or fluctuated throughout the pandemic, and accurate stock price forecasting using current data is one of the key consequences of this work. Another aspect to consider is that the most accurate forecast is the most difficult element of any model, and our ANN model outperformed all prior work with a lower RMSE score (0.0303).

Table 7. The forecast accuracy measures for selected ARIMA and ANN model

Reference	Context	Dataset	Best Methods	RMSE
Persio et al. [4]	Stock price prediction	S&P500	Average ensemble	0.4795
Dutto et al. [8]	Stock price index	BSC- SENSEX	ANN	0.0482
Yildiz et al [9]	Forecasting stock exchange	ISE National-100	ANN	0.1226
Cao et al. [18]	Predict stock price movement	Shanghai stock exchange	UANN	0.5432
Rajeb et al. [23]	Forecast market capital	DSE	ARIMA	2.3200
Present Study	Stock exchange price prediction	DSE + MCAP	ANN	**0.0303**

5- Conclusion

To forecast stock market movement based on the Dhaka Stock Exchange (DSE), total market capitalization, ARIMA and ANN models have been used. Artificial Neural Networks (ANN) are constructed in such a way that they are capable of forming relationships among input layer values and output layer values to generate a network that would be capable of predicting future values with optimum accuracy. However, back propagation has some problems regarding Local Minima. In this study, the ARIMA (2,1,2) model was chosen as the best traditional method, and the ANN model (involving a three-layer feed-forward topology) using a Back Propagation algorithm with 5 nodes or neurons in the hidden layer, one lag, and a learning rate equal to 0.01 was nominated as the best model. In this section, we also tried to fit an ARCH/GARCH model, but our data did not support it. Therefore, in selecting the best model, special care should be given. The fitted ANN model exhibited a superior prediction pattern with smaller error values. This model can be used for forecasting the movement of the market capitalization and can be applied for investment policy to optimize gain.

This paper focuses mainly on short-time perspective analysis. It can be extended in the future to predict long-term perspective analysis. Further testing could be included, such as ANFIS or a genetic algorithm, which can be used to do more research. To get a better prediction, other techniques like Holte's algorithm and the genetic algorithm can also be used. These are left for future work.

6- Declarations

6-1- Author Contributions

Conceptualization, M.A.R., S.C., N.M.Z., and K.M.A.I.; methodology, M.A.R., S.C., N.M.Z., and K.M.A.I.; software, M.A.R., N.M.Z., and K.M.A.I.; validation, M.A.R., S.C., N.M.Z., and K.M.A.I.; formal analysis, M.A.R., S.C., N.M.Z., and K.M.A.I.; investigation, M.A.R., N.M.Z., and K.M.A.I.; resources, M.A.R., S.C., N.M.Z., and K.M.A.I.; data curation, M.A.R., S.C., N.M.Z., and K.M.A.I.; writing—original draft preparation, M.A.R., S.C., N.M.Z., and K.M.A.I.; writing—review and editing, M.A.R., S.C., N.M.Z., and K.M.A.I.; visualization, M.A.R., S.C., N.M.Z., and K.M.A.I.; supervision, N.M.Z., and K.M.A.I.; project administration, N.M.Z., and K.M.A.I.; funding acquisition, A.A.A.R., A.M., and K.M.A.I. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6-5- Institutional Review Board Statement

Not applicable.

6-6- Informed Consent Statement

Not applicable.

6-7- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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Appendix I

Table A-1. The descriptive statistics of the original, logarithmic, and logarithmic return series

Statistics	Original Index (MCAP)	Logarithmic Index (LogMCAP)	Logarithmic Returns (Diff LogMCAP)
Observations	165	165	165
Minimum	5881.90	8.68	-0.30
Maximum	359833.00	12.80	0.24
Mean	137625.70	11.10	0.02
First Quartile	20950.17	09.95	-0.01
Median	96987.03	11.48	0.02
Third Quartile	255747.40	12.45	0.06
Std. Deviation	122035.80	1.44	0.07
Skewness	0.30	-0.40	-0.43
Kurtosis	-1.59	-1.37	3.56

Table A-2. Results of the Lijung-Box test for autocorrelation and the Engle ARCH test for heteroscedasticity at different

Test	Lag	Chi-square	p-value
Lijung-Box autocorrelation test for returns data	6	10.64	0.09
	8	10.73	0.22
	12	13.76	0.32
	15	26.63	0.03
	20	38.06	0.01
Lijung-Box autocorrelation test for squared returns data	6	3.86	0.69
	8	4.16	0.84
	12	5.56	0.93
	15	10.58	0.78
	20	15.95	0.72
Engle's test for heteroscedasticity	6	3.77	0.71
	8	3.87	0.87
	12	5.49	0.94
	15	10.69	0.77
	20	13.53	0.85