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# MOBILE U-NET V3 AND BILSTM: PREDICTING STOCK MARKET PRICES BASED ON DEEP LEARNING APPROACHES

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## *ABSTRACT*

*Stock-market prediction is the task of forecasting future movements or trends in stock prices or overall market behavior. Investors can able to locate companies that offer the highest dividend yields and lower their investment risks by using a trading strategy. It's important to note that predicting stock markets accurately is extremely challenging and no approach can guarantee consistent success. Markets are influenced by a multitude of factors and there is inherent uncertainty involved. For instance, predicting stock-market prices is commonly used in financial disciplines, such as trade-execution strategies, portfolio optimization and stock-market forecasting. Therefore, it's crucial to approach stock-market prediction cautionsly and use it as a tool for informed decision-making rather than relying solely on predictions. To overcome the challenges, we proposed a new hybrid deep-learning technique to forecast future stock prices. Deep learning has recently enjoyed considerable success in some domains due to its exceptional capacity for handling data. In this research, we propose a hybrid technique of Mobile U-Net V3 and BiLSTM (Bi-Long Short-Term Memory) to predict stock prices. Initially, we utilize the min-max normalization method to normalize the input data in the preprocessing stage. After normalizing the data, we utilize hybrid deep learning techniques of Mobile U-Net V3 and BiLSTM to predict the closing price from stock data. To experiment, we collect data from Apple, Inc. and S&P 500 stock. The evaluation metrics Pearson's Correlation (R), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Normalization Root Mean Squared Error (NRMSE) were utilized to calculate the outcomes of the DL stock-prediction methods. The Mobile U-Net V3-BiLSTM model outperformed other techniques in forecasting stock-market prices.*



## *KEYWORDS*

*Stock market, Prediction, Future stock prices, Artificial intelligence, Deep learning, Mobile U-Net V3, BiLSTM.*


## 1. INTRODUCTION

The stock market is an important phase of every country’s economy. It is one of the most significant investment opportunities for investors and businesses. Through an Initial Public Offering, a firm can make a sizable profit by growing its enterprise. The company's shareholder bonus program provides dividends at an opportune moment for investors to buy additional equities and profit from them [1]-[3]. An investor who trades on the stock market can do so with stocks.

For accurate decision-making to hold, sell or purchase extra stocks, stock traders must predict patterns in the stock-market behavior. Stock traders must purchase stocks the prices of which are anticipated to rise soon and sell those the prices of which are anticipated to fall to make a profit. Stock traders can make substantial profits if they correctly forecast stock-price patterns [4]-[6]. Consequently, forecasting future stock-market patterns is crucial for stock traders' decision-making. So far, stock markets are most challenging to forecast and unpredictable and external influences, such as daily financial news and social media, have an immediate negative or positive impact on stock values. For a precise stock-market prediction, these aspects must be taken into account.

Although investing in the stock market carries some risk, it is one of the most effective ways to make sizable returns when carried out with discipline [7]-[8]. Investors, however, cannot fully evaluate such a vast volume of financial news and social-media information. Investors must therefore use an automated decision-support system, since it will automatically assess stock movements using such massive amounts of information. In earlier studies on stock prediction, machine-learning algorithms were employed to forecast the stock market utilizing historical data. Various predictive models that employ either type of data have been suggested. Investors can utilize the information from these systems

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to help them decide whether to sell or buy a stock [9]-[12]. Nevertheless, using only one type of data could not result in improved stock-market prediction accuracy.

In a technical analysis method, historical data has been utilized to examine information to forecast future stock-market patterns. Researchers analyzed historical stock-price data using a various of machine-learning methods, including DL and regression analysis. However, it is crucial to consider external factors, because unexpected events that are discussed on social media and in the news can also an impact on stock prices. Those who want to invest in the stock market sometimes have no idea how the market operates [13]-[14]. They are unable to optimize their gains, because they are unsure of which shares to buy and which to sell. These investors are aware of that connected news influence the stock-market growth. They must therefore have timely and reliable information regarding stock-market listings to make informed trading selections. As financial news on websites are a reliable source of this information, the majority of these websites have developed into important informational resources for traders. Expectations of investors based on financial information as a trading technique, however, could not be sufficient [15]. In this research, we utilized novel DL techniques to predict the stock-market analysis. Here, we utilize the min-max normalization approach to normalize the given input data in the preprocessing stage and then predict the stock-market analysis. To predict the stock-market analysis of S&P 500 stock data and Apple, Inc. stock data, we employed hybrid Mobile U-Net V3 and BiLSTM techniques. This model analyzes the forecast of the closing prices of these two companies. The key contribution is as follows:

- Predicting the stock-market analysis more closely is a trending domain and many individuals using stock-market trades in recent years.
- In the preprocessing stage, the input data is normalized using the min-max normalization method.
- To predict the stock-market analysis, we utilized hybrid Mobile U-Net V3 and BiLSTM techniques to determine whether a stock will go up or down.
- For the experiments, we used two datasets; namely, S&P 500 stock data and Apple, Inc. data.

The remaining sections of the research are divided into the following steps, Section 2 lists the literature that is related to the paper. The problem statement is given in Section 3. The proposed technique is explained in Section 4. Section 5 presents the outcomes. Finally, Section 6 presents the conclusions.

## 2. LITERATURE SURVEY

Many research studies are recently focused on forecasting the prices of stock markets and currency exchanges. The study "Framework for predicting and modeling stock-market prices based on deep-learning algorithms" was conducted by the authors in [16]. They suggested a design based on a hybrid of CNN-LSTM to forecast the closing prices of Apple and Tesla companies. These forecasts were produced utilizing information gathered during the previous two years. The outcomes of the DL stock-estimation techniques were computed using the RMSE, MSE, R and NRMSE measures.

The study "Stock-price prediction based on deep neural networks" was conducted by the authors in [17]. Financial product price information is viewed as a 1-D series produced by the projection of a chaotic model made up of numerous components into the time dimension and the price series is rebuilt utilizing the time-series phase-space reconstruction (PSR) approach. To predict stock prices, a deep neural network-based prediction algorithm is developed based on the PSR technique using LSTMs for DL. Several stock indices for various periods are predicted using the suggested prediction model, as well as some other methods.

The study "A CNN-BiLSTM-AM method for stock-price prediction" was conducted by the authors in [18]. To forecast the stock closing price of the following day, they presented a CNN-BiLSTM-AM method. CNN, BiLSTM and AM make up this technique. To retrieve the attributes from the input information, a convolutional neural network is utilized. The stock closing price of the following day is predicted by BiLSTM using the retrieved attribute data. To increase forecast accuracy, AM is utilized to capture how feature states affected the closing price of the stock at various points in the past. This technique and seven other techniques are utilized to forecast the Shanghai Composite Index's stock closing price for 1000 trading days to demonstrate the method's efficacy.

The study "An innovative neural network approach for stock-market prediction" was conducted by the authors in [19]. To predict the stock market, they presented an automated encoder with LSTM neural network and the embedded layer in a deep LSTM neural network. To vectorize the data in these two approaches so that an LSTM neural network can forecast the stock, they employed the embedding layer and the automatic encoder, respectively.

The study "An improved deep-learning model for predicting stock-market price time series" was conducted by the authors in [20]. In contrast to conventional models, they suggested an approach for projecting stock closing prices that provides a more accurate prediction. The components that form this deep hybrid framework are the deep-learning predictor portion, the data processing portion and the predictor optimization algorithm. Data-processing techniques include preparation based on the empirical wavelet transform (EWT) and post-processing based on the outlier robust extreme learning machine (ORELM) approach. The major component of the mixed frame, an LSTM network-based DL network predictor, is jointly improved by the dropout approach and PSO algorithm. Table 1 shows the literature survey's comparison.

Table 1. The comparison table of literature survey.

| **Ref.** | **Technique** | **Dataset** | **Advantages** | **Disadvantages** |
|---|---|---|---|---|
| [16] | CNN-LSTM | Tesla and Apple Stock-market Data | The majority of economies and people have long sought reliable future predictions, which may be provided by this method. | The authors didn't make use of the sentiment data that came from the analysis of the financial markets. |
| [17] | LSTM | S&P 500 | Predicting and analyzing financial data nonlinear and accurately achieving better accuracy. | The running time complexity was higher than in other techniques. |
| [18] | CNN-BiLSTM-AM | Shanghai Composite Index Stock | It can serve as a useful resource for investors looking to maximize the return on their investments and can also be used by those conducting research on financial time-series information to gain first-hand experience. | To enhance the accuracy of the outcomes, the parameters of the model were not primarily changed. |
| [19] | ELSTM | Shanghai A-Share Composite Index | The Shanghai A-Share Composite Index can be predicted more accurately using the applied methods. | Although the algorithms can somewhat enhance the effect of the Shanghai A-share composite index, there are still certain issues with historical-information input. The stock market underutilizes textual data such as news. |
| [20] | LSTM | S&P 500 | The model that incorporates decomposition and error correction makes predictions more accurately. The dropout technique and PSO algorithm can raise the LSTM network's forecasting precision. | The time complexity is higher. |

## 3. PROBLEM STATEMENT

Most of the time, financial analysts who invest in the stock market lack awareness of market behavior. They have a problem with trading, since they are unable to decide which stocks to sell or buy to increase their profits. The stock market's entire knowledge base is readily available in the modern world. It would be quite challenging to analyze all of this data manually or individually. It is therefore necessary to automate the process. Data-mining methods are handy in this situation. Stock-price changes are usually complex. It has always been important for traders to predict changes in stock prices. Shareholders' investment challenge can be greatly decreased by making a realistic and precise estimate of the changes in stock prices.

### 3.1 Aim of This Research

To overcome the above problems, we utilized novel DL techniques to predict the stock-market analysis. Here, we utilize the min-max normalization approach to normalize the given input data in preprocessing stage. After that, we predict the stock-market analysis. To forecast the stock-market analysis of S&P 500 stock data and Apple, Inc. stock data, we employed hybrid Mobile U-Net V3 and BiLSTM techniques. This model analyzes the forecast of the closing prices of these two companies.

## 4. PROPOSED METHODOLOGY

On the stock market, stocks can be sold, swapped and moved about. Enterprises have used this to raise finance for 400 years. By problem stocks, a sizeable number of capitals is introduced to the stock market. In this research, we utilized new DL techniques to predict the stock-market analysis. Here, we utilized the min-max normalization approach to normalize the given input data in the preprocessing stage. After that, we predict the stock-market analysis. To predict the stock market analysis from S&P 500 stock data and Apple, Inc. stock data, we employed hybrid Mobile U-Net V3 and BiLSTM techniques. This model analyzes the forecast of the closing prices of these two companies. Figure 1 shows the architecture of the proposed methodology.

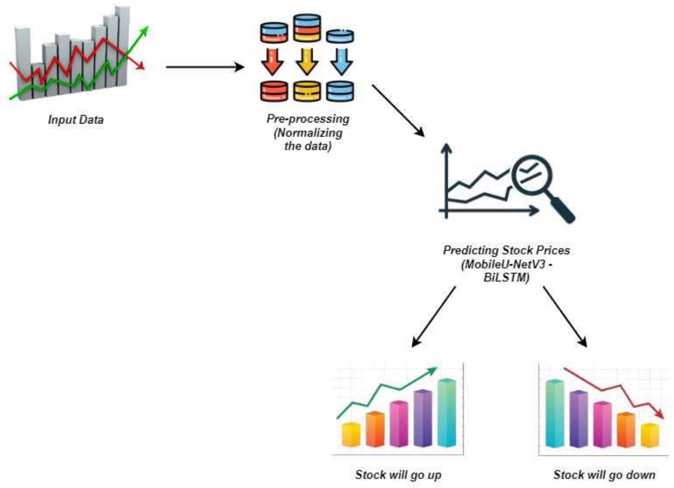


Figure1. The proposed methodology architecture of stock-market prediction.

### 4.1 Preprocessing

The historical data, such as opening price, high and low price, closing price and volume of these variables, can be used as input features to train a Mobile U-Net V3-BiLSTM model for predicting closing prices. The input data is normalized or scaled to a small range, such as between 0 and 1, to ensure stable training. In the preprocessing stage, we normalize the input data using the min-max normalization method. When using a large amount of stock-price data, normalization is a helpful method for scaling the stock information so that it fits within a specific range. Gradient descent is accelerated and becomes more precise after normalization [21]. By applying a linear change to the starting date, scaling the data between specific ranges is typically done using min-max normalization. The notations $x_{\min}$ $x_{\max}$, respectively, stand for an attribute's lowest and highest values. To calculate the distinction between the two values, the value in the range [ $x_{\min}$ - $x_{\max}$ ] is used for the computation of the value x. The normalized data for S&P 500 and Apple is shown in Figure 2:

$$z_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \left( New_{\max x} - New_{\min x} \right) + New_{\min x} \tag{1}$$

where the variables $x_{\min}$ and $x_{\max}$ stand for the lowest and highest values, respectively. The notation $New_{\min_x}$ represents the smallest integer, whereas the notation $New_{\max_x}$ represents the largest integer.

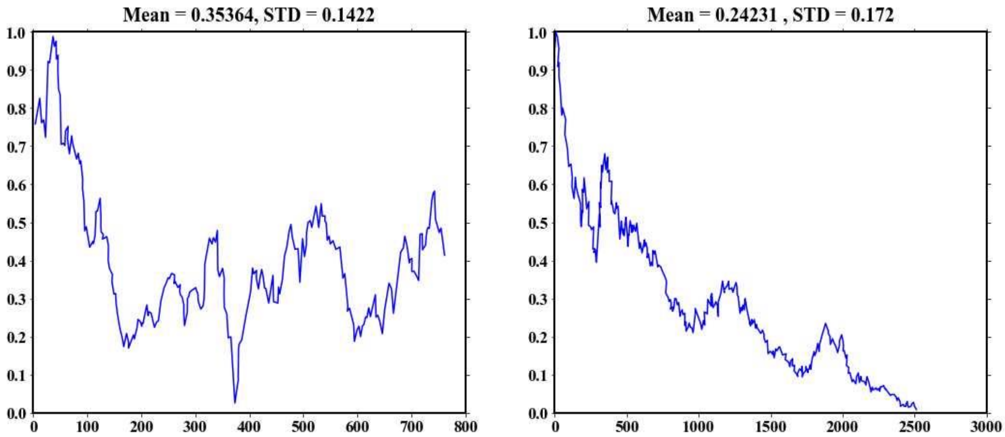


Figure 2. The normalization data of (a) S&P 500, (b) Apple.

## 4.2 Prediction Models

In the prediction stage, we utilize hybrid deep-learning techniques of Mobile U-Net V3 and BiLSTM. These methods are predicting the closing price of given two datasets' stock data. Combining these two algorithms may produce a better output compared to other algorithms.

### 4.2.1 BiLSTM

#### 4.2.1.1 Long Short-term Memory Network (LSTM)

J. J. Hopfield suggested a Recurrent Neural Network (RNN) in 1982 for handling sequence data. The outcome of an RNN is linked back to the input by feedback, acting as a dynamic memory, unlike a standard ANN. For short-term predicting, this network showed the best performance, but when it comes to long-term predicting, it becomes unreliable. This instability is caused by the gradient explosure or by sudden, significant changes in training weights. By enabling memory cells in the hidden layer (s), the LSTM network solve the gradient-explosure problem. Figure 3 depicts the LSTM's basic architecture.

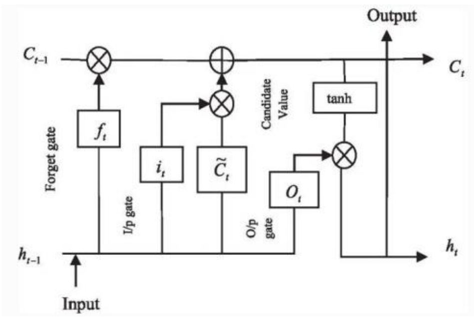


Figure 3. The basic architecture of LSTM.

Every LSTM cell has an input gate ( $i_t$ ), a forget gate ( $f_t$ ) and an output gate ( $O_t$ ) that can accept or reject data. The network has ignored the preceding cell state " $C_{t-1}$ " for a forward-movement function. Inputs ' $GHI_i(t)$ ', ' $h_{t-1}$ ' and ' $b_f$ ' of the forget-gate bias are the three inputs that the LSTM network currently has at the time't'. Hence, the activation values can be written as follows:

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, GHI_i(t)\right] + b_f\right) \tag{2}$$

The network uses the following equations to determine whether the data needs to be destroyed or maintained.

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, GHI_i(t)\right] + b_i\right) \tag{3}$$

$$\tilde{C}_t = \tanh\left(W_c \cdot \left[h_{t-1}, GHI_i(t)\right] + b_c\right) \tag{4}$$

$$C_t = f_t * C_{t-1} + i_i * \tilde{C}_t \tag{5}$$

The memory cell's outcome now changes to:

$$O_t = \sigma\left(W_O \cdot \left[h_{t-1}, GHI_i(t)\right] + b_O\right) \tag{6}$$

$$h_t = O_t * \tanh\left(C_t\right) \tag{7}$$

where "$b_i$", "$b_f$", "$b_c$" & "$b_o$" are bias vectors of the LSTM network; σ is a sigmoid function ranging from '0' to '1' and "$W_i$", "$W_f$", "$W_c$" & "$W_o$" are weight vectors of the LSTM network.

#### 4.2.1.2 Bidirectional Long Short-term Memories (BiLSTM)

The BiLSTM technique is employed to predict the stock prices of S&P 500 and Apple data combined with the Mobile U-Net V3 technique. The forward and backward LSTM networks that constitute the BiLSTM network allow for both forward and backward data processing [22]. The data's underlying patterns and attributes are captured *via* processing in the reverse direction, which LSTM often ignores. Fig. 4 depicts the basic design of the BiLSTM network.

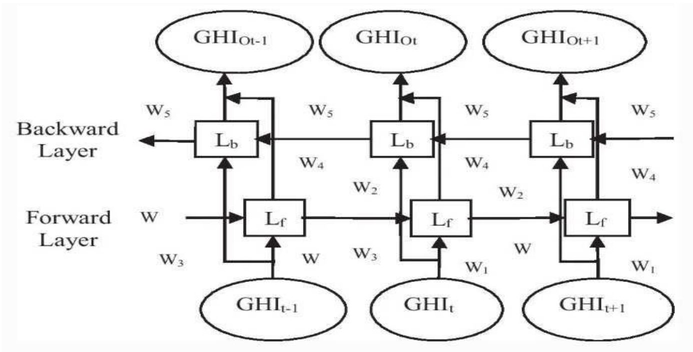


Figure 4. The basic architecture of the BiLSTM technique.

The network was updated using the output sequence "$GHI_o(t)$" and the forward hidden layer "$L_f$", as well as the backward hidden layer "$L_b$". The network iteratively updates from "T" to "1" and from "1" to "T" in backward and forward directions, respectively. The network's updated parameters can be stated mathematically as follows:

$$L_f = \sigma\left(W_1 GHI_i(t) + W_2 L_{f-1} + b_{L_f}\right) \tag{8}$$

$$L_b = \sigma\left(W_3 GHI_i(t) + W_5 L_{b-1} + b_{L_b}\right) \tag{9}$$

$$GHI_O = W_4 L_f + W_6 L + b_{GHI_O} \tag{10}$$

where $L_b$ is backward pass, $GHI_o(t)$ stands for the final output layers and $L_f$ is the forward pass. 'W' is the weight coefficient and '$b_{L_f}$', '$b_{L_f}$'& '$b_{GHI_o}$' are the biases. Bidirectional LSTM (BiLSTM) is a variant of the RNN structure that incorporates data from both previous and future contexts to make predictions or analyze sequential data. BiLSTM addresses the limitation of traditional LSTMs by capturing dependencies in both backward and forward directions.

***Advantages:*** BiLSTM networks have the advantage of being able to capture long-term dependencies in the input sequence, which is important for many NLP tasks. However, they can be computationally expensive and may require a much to train effectively.

***Disadvantages:*** BiLSTM networks are powerful, but computationally expensive. BiLSTM is a much slower model and requires more time for training.

### 4.2.2 The Proposed MobileU-NetV3 Method

The Mobile U-Net V3 technique is employed with BiLSTM for predicting the S&P 500 and Apple stock prices. To make use of MobileNetV3's powerful predicting capabilities for stock-price data, the proposed model contains the U-Net structure with it, giving it the designation MobileU-NetV3. It is a lightweight deep neural network constructed with depth-wise convolution. Mobile U-Net V3 is a variant of the U-Net architecture that is designed for efficient and accurate prediction tasks, particularly in scenarios with limited computational resources, such as mobile devices. The proposed MobileUNetV3 model's structure comprises all of its building pieces and the input feature maps [23]. In the encoder section, down-sampling is used in conjunction with the chosen MobileNetV3 layers to minimize the data size.

The system uses MobileNet V3 as the backbone encoder of the U-Net structure and passes the input data *via* it (16, 20, 38, 93 and 214). For example, layer 16 modifies the data size with 64 bands to 112 × 112. Layer 20 modifies the data size with 64 bands to 56 × 56. Layer 38 modifies the data size with 78 bands to 28 × 28. Layer 93 modifies the data size with 240 bands to 14 × 14. Finally, layer 214 modifies the data size with 960 bands to 7 × 7. After that, each layer of MobileNetV3 is concatenated with the preceding output layer and up-sampled using the U-Net decoder. The output Layer 93 is concatenated with layer 214, the first up-sampling, which has a data size of 14 by 14 and 512 bands. To obtain the output, a transposed convolution layer, which is another name for a de-convolution layer, is utilized along with a Softmax activation method.

To efficiently train the Mobile U-Net V3 framework, indicated by $L_{ce}$, the $L_{ce}$ training set's loss is calculated as follows:

$$L_{ce} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{C} 1\left(y_i = k\right)\ln\left[p\left(y = k \mid x\right)\right] \tag{11}$$

where C is the amount of classes and N is the amount of training samples.

Mobile U-Net V3 has a U-Net-like structure and they have some similarities. There are some variations, though. The connecting way in the U-Net framework is easier. Deconvolution is used in the U-Net model's expanding or up-sampling phase to decrease the amount of feature maps while enhancing their dimensions. To preserve the pattern structure in the data, feature mappings from the network's contracting portion are replicated in the expanding portion. The MobileNetV3 structure, on the other hand, is optimized utilizing an algorithmic search technique to determine the optimal structure and MobileUNetV3 makes use of a more advanced contracting component based on that architecture. The Mobile U-Net V3-BiLSTM technique is utilized to pretrain parameters, such as dropout rate, dropout period and batch size, in order to improve the overall accuracy.

***Advantages:*** Mobile U-Net V3 maintains the right ratio of precision and model size. It adopts various techniques, such as skip connections and multi-scale feature fusion, to capture both local and global information in the input data. This helps improve the accuracy of tasks.

***Disadvantages:*** The performance of Mobile U-Net V3 can vary depending on the specific dataset and domain characteristics. Since the model is trained on a particular set of data, its effectiveness may be limited when applied to domains or datasets that significantly differ from the training data.

## 5. RESULTS AND DISCUSSION

The first half of this section uses the dataset analysis to anticipate stock-market prices and comparing our method with "state-of-the-art" approaches.

### 5.1 Experimental Setup

An Intel i5 2.60 GHz processor and 4 GB of RAM power Windows 10 on this device. Python, KERAS and TensorFlow are used to perform the investigations against the backdrop of the Anaconda3 environment. The Apple, Inc. dataset [24] and the S&P 500 stock dataset [25] are used in this study as validation datasets to determine the effectiveness of our proposed approach. In Table 2, the test environment is displayed.

Table 2. Test environment.

| Project | Environment |
|---|---|
| System | Python |
| Processor | Intel i5 2.60 GHz |
| RAM | 4GB |

## 5.2 Dataset Description

### 5.2.1 Apple, Inc. Dataset [24]

Apple, Inc. is a multinational innovation company that designs, produces and advertises a various of electronic goods, such as laptops, tablets, smartphones, wearable technologies and accessories. The New York Stock Exchange's ticker symbol for the company's stock is AAPL. Among the Company's valuable products, product lines include the iPhone, the Mac line of desktop and laptop computers, the Watch, the TV and the iPad. The rapidly expanding service division of the business, as well as its extra revenue sources, are exemplified by the Apple's digital streaming entertainment services and iCloud cloud service, including Apple TV+ and Apple Music. This dataset provides historical statistics on Apple, Inc.'s share prices. Every day, one can get information on the Company’s share prices.

### 5.2.2 S&P 500 Stock Dataset [25]

Data for six stock indices, including the S&P 500, Nikkei 225 (N 225), Dow Jones industrial average (DJIA), Hang Seng Index (HSI), China Securities Index 300 (CSI 300) and ChiNext index, was gathered from relevant organizations, as well as TuShare financial data interface (tushare.org) and Yahoo Finance (finance.yahoo.com). The prices at which trading day's markets closed used as the analytical data. Table 3 shows the training, testing and validation values for each dataset.

Table 3. Training, testing and validation values for each dataset.

| Dataset | Training | Testing | Validation |
|---|---|---|---|
| Apple, Inc. dataset | 65% | 20% | 15% |
| S&P 500 stock dataset | 65% | 20% | 15% |

## 5.3 Evaluation Metrics

The approaches used to test the forecasting effectiveness of the Mobile U-Net V3-BiLSTM and BiLSTM approaches used the RMSE, MSE, R and NRMSE metrics:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_{i,\exp} - y_{i,pred}\right)^2 \tag{12}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{\left(y_{i,\exp} - y_{i,pred}\right)^2}{n}} \tag{13}$$

$$R\% = \frac{n\left(\sum_{i=1}^{n} y_{i,\exp} \times y_{i,pred}\right) - \left(\sum_{i=1}^{n} y_{i,\exp}\right)\left(\sum_{i=1}^{n} y_{i,pred}\right)}{\sqrt{\left[n\left(\sum_{i=1}^{n} y_{i,\exp}\right)^2 - \left(\sum_{i=1}^{n} y_{i,\exp}\right)^2\right]\left[n\left(\sum_{i=1}^{n} y_{i,pred}\right)^2 - \left(\sum_{i=1}^{n} y_{i,pred}\right)^2\right]}} \times 100 \tag{14}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_{i,\exp} - y_{i,pred}\right)^2}{\sum_{i=1}^{n}\left(y_{i,\exp} - y_{avg,\exp}\right)^2} \tag{15}$$

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(y_{i,\exp} - y_{i,pred}\right)^2}}{y_{i,pred}} \tag{16}$$

where the prediction and experimental values are represented by $y_{i,pred}$ and $y_{i,\exp}$, whereas the sample’s number is represented by n.

## 5.4 Performance Metrics

Throughout the experiments, the difference between the actual and the predicted stock closing price was used to calculate the RMSE, MSE, R and NRMSE values. The level of the stock-prices modification on the forecasting day was then calculated using the predicted data. A forecasting model, such as a time series analysis or DL approach, is employed to forecast the future values of stock prices. This model takes historical data and potentially other relevant factors into account to generate predictions for future stock prices. The forecasting model produces a set of predicted stock prices for a specific time period, including the forecasting day of interest. These predictions are based on the model's understanding of patterns, trends and other factors observed in the historical stock-price data. To assess the level of modification or change in the stock price on the forecasting day, a comparison is made between the predicted stock price and the actual stock price observed on that day. This calculation aims to measure the difference between the expected value and the actual value. Stock prices may have significant variations in their scales, making it challenging to compare and analyze them directly. Data-normalization techniques, such as scaling or standardization, are applied to transform the data to a common scale, enabling fair comparisons and reducing the dominance of certain features in the prediction model.

Here, we used two different companies' datasets; namely, Apple and S&P 500 stock data. The collected data is processed by data normalization. First, we process S&P 500 stock data. Table 1 shows the comparison between Mobile U-Net V3 and Mobile U-Net V3 with BiLSTM, the hybrid techniques provide higher values for variables and give higher rank correlation values in the training phase. Table 2 illustrates the comparison of techniques for the forecast of closing prices in the testing phase. Figures 9 and 10 demonstrate the future prediction data values of the two datasets. Moreover, Figures 11, 12, 13 and 14 show the squared regression plots of the proposed method on the two datasets. Then, the proposed technique is compared with other recent research prediction techniques and the proposed method achieved higher prediction accuracy compared to other methods.

### 5.4.1 Results of S&P 500 Stock Data

The predictions of the S&P 500 closing price using the Mobile U-Net V3 and Mobile U-Net V3-BiLSTM models are shown in Table 4. The outcomes demonstrate the robustness and dependability of the DL method to forecast the closing price based on training. Based on the RMSE (0.01172) and NRMSE (0.02931) measures, Mobile U-Net V3-BiLSTM had a low prediction error rating.

Table 4. Results from deep learning for training-phase prediction of S&P 500 closing price.

| Approach | MSE | RMSE | NRMSE | R% |
|---|---|---|---|---|
| Mobile U-Net V3-BiLSTM | 0.00098 | 0.02978 | 0.07984 | 99.82 |
| Mobile U-Net V3 | 0.00137 | 0.01172 | 0.02931 | 98.99 |

During the training stage, Figure 5 shows the exact combination between the predicted data of S&P 500's stock price and the actual values. The lack of a discernible difference between the actual and anticipated values serves as a proof of that both Mobile U-Net V3-BiLSTM and Mobile U-Net V3 were prepared to be evaluated during the training phase due to their high R percentages (99.82% and 98.99%, respectively) with extremely low RMSE and MSE values.

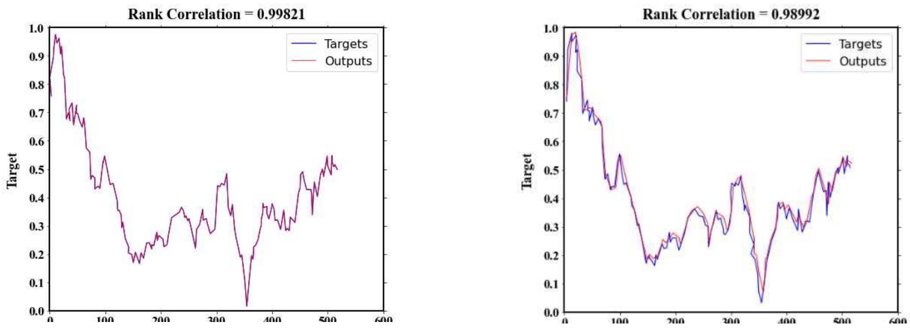


Figure 5. Ranking correlation between two DL techniques for forecasting the closing price of the S&P 500 stock market during the training stage: (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3.

The remaining 30% of the data were utilized, following training, to test the DL approaches' predictions shown in Table 5. The testing stage is crucial for assessing and determining the benefits of the proposed approaches for forecasting Tesla's closing price. The best outcomes were obtained using the Mobile U-Net V3-BiLSTM model (MSE = 0.0001057; RMSE = 0.01126).

Table 5. The outcomes for forecasting the closing price of the S&P 500 during the testing stage.

| Approach | MSE | RMSE | NRMSE | R% |
|---|---|---|---|---|
| Mobile U-Net V3 - BiLSTM | 0.00010 | 0.01126 | 0.03042 | 99.62 |
| Mobile U-Net V3 | 0.00065 | 0.02624 | 0.07329 | 98.92 |

Figure 6 displays how the DL methods performed during the testing phase. Compared to Mobile U-Net V3 (98.92%), Mobile U-Net V3-BiLSTM has a higher R percentage (99.62%). The next step was to determine whether the prediction values of closing prices were in line with the actual values.

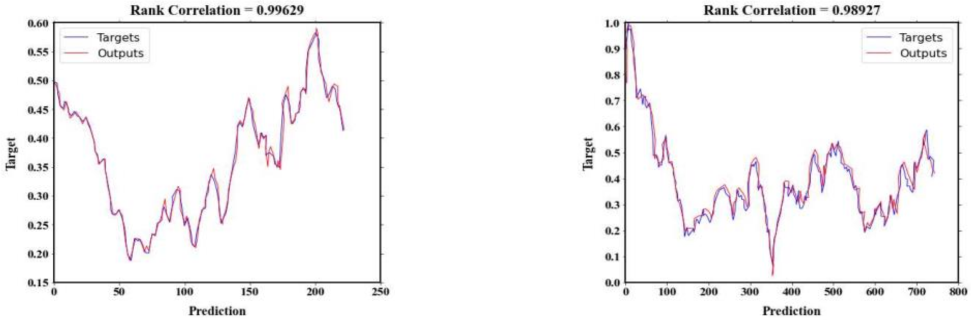


Figure 6. Ranking correlation between two DL approaches for forecasting the closing price of the S&P 500 stock market during the testing phase: (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3.

### 5.4.2 Results of Apple Data

After that, the DL algorithms were used to forecast Apple's stock-market closing price. Table 6 displays the outcomes of the DL approaches throughout the training phase (utilizing 70% of the data). According to the MSE measurements, the Mobile U-Net V3-BiLSTM model had a lower prediction of $3.894 \times 10^{-5}$.

Table 6. The outcomes for forecasting Apple’s closing price due to training.

| Approach | MSE | RMSE | NRMSE | R% |
|---|---|---|---|---|
| Mobile U-Net V3-BiLSTM | $3.894 \times 10^{-5}$ | 0.00549 | 0.01843 | 99.93 |
| Mobile U-Net V3 | 0.0001345 | 0.01075 | 0.0351 | 99.96 |

Figure 7 displays the effectiveness of the Mobile U-Net V3-BiLSTM and Mobile U-Net V3 models. The Mobile U-Net V3-BiLSTM model obtained a better R percentage (99.93%) according to the examination of the correlation metric. This demonstrates that the DL approach is suitable for forecasting future closing prices on the stock market.

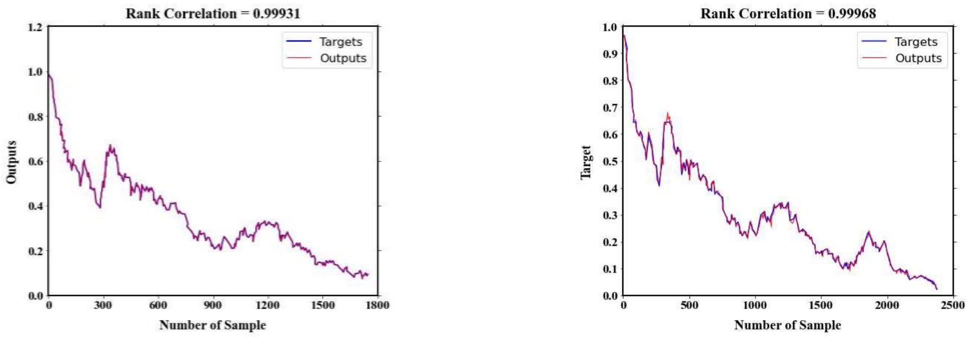


Figure 7. Ranking correlation between two DL techniques for forecasting Apple’s closing price during the training stage: (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3.

The RMSE and MSE of the DL algorithms for forecasting the closing price of Apple due to the testing period are shown in Table 7 and Figure 8. The R percentage (99.87%) of Mobile U-Net V3-BiLSTM was relatively close to 100 even if the RMSE and MSE were the lowest feasible values. In this research, Mobile U-Net V3-BiLSTM had lower MSE and RMSE than Mobile U-Net V3. The R percentage for

Mobile U-Net V3 was 99.63% or nearly one. The results were somewhat better for Mobile U-Net V3-BiLSTM than for Mobile U-Net V3.

Table 7. The outcomes for forecasting Apple's closing price due to testing.

| Approach | MSE | RMSE | NRMSE | R% |
|---|---|---|---|---|
| Mobile U-Net V3 -BiLSTM | $3.894 \times 10^{-5}$ | 0.00549 | 0.01843 | 99.87 |
| Mobile U-Net V3 | 0.0001345 | 0.01075 | 0.0351 | 99.63 |

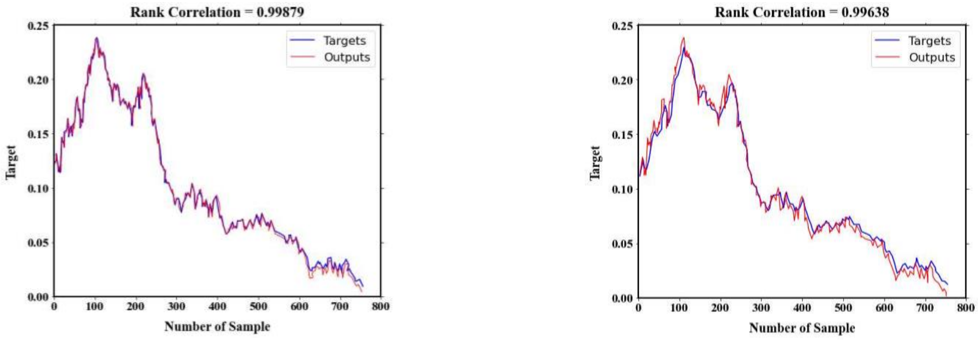


Figure 8. Ranking correlation between two DL approaches for forecasting Apple's closing price during the testing stage: (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3.

### 5.4.3 Predicting Future Values of S&P 500 and Apple Data

We predicted future values for S&P 500 and Apple from 28 February 2020 to 29 April 2020 to evaluate the performance of the Mobile U-Net V3-BiLSTM and Mobile U-Net V3 models (60-day period). Figure 9 demonstrates predicting the values of the S&P 500 Corporation utilizing the DL approach. Figure 10 shows the forecasting values for the Apple Corporation that were obtained using the deep-learning model.

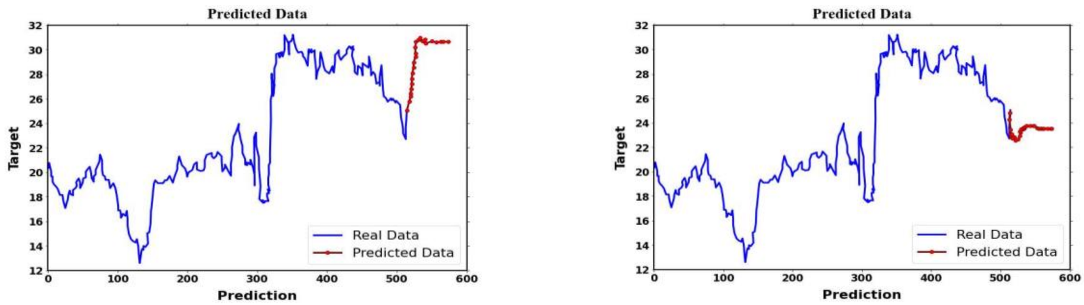


Figure 9. Predicting the future values of S&P 500 utilizing (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3.

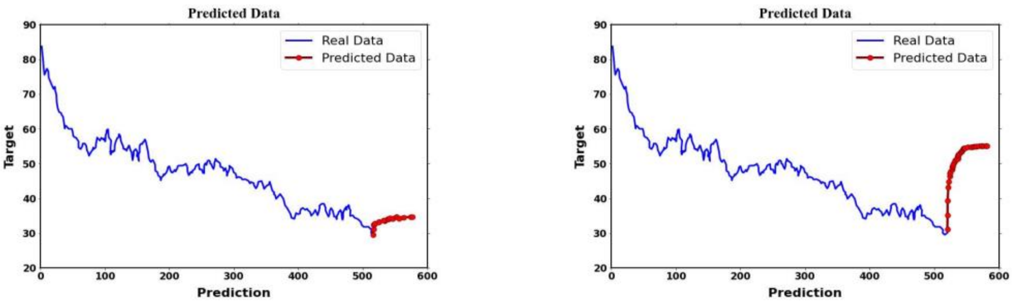


Figure 10. Predicting the future values of Apple utilizing (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3.

Investors have very simple access to more equities and stand to gain significantly from dividends paid as part of the corporation's shareholder-incentive strategy. On the stock market, investors desire to buy equities the values of which are anticipated to rise and sell those the values of which are anticipated to decline. Stock traders must therefore be able to effectively predict the basic stock behavior before deciding to purchase or sell. The more accurate their prognosis of a stock's behavior, the more money they will profit from it. To help traders maximize their earnings, it is crucial to create an autonomous algorithm that can accurately predict market moves.

As a result, the capability of the DL techniques Mobile U-Net V3 and hybrid Mobile U-Net V3-BiLSTM to forecast S&P 500 and Apple stocks was examined in this paper. Figures 11 and 12 show, respectively, how these models performed throughout the training and testing phases for S&P 500. Both the training (Mobile U-Net V3-BiLSTM: R2 = 99.79%; Mobile U-Net V3: R2 = 98.76%) and testing (Mobile U-Net V3-BiLSTM: R2 = 99.31%; Mobile U-Net V3: R2 = 96.53%) stages of the evaluation saw higher Mobile U-Net V3-BiLSTM performance than Mobile U-Net V3. In comparison to Mobile U-Net V3, Mobile U-Net V3-BiLSTM thereby achieved more accuracy.

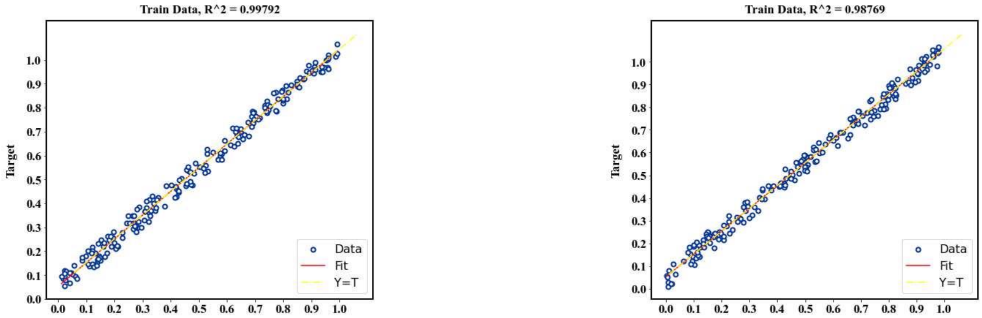


Figure 11. The squared regression plot of the proposed methods (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3 due to training for S&P 500.

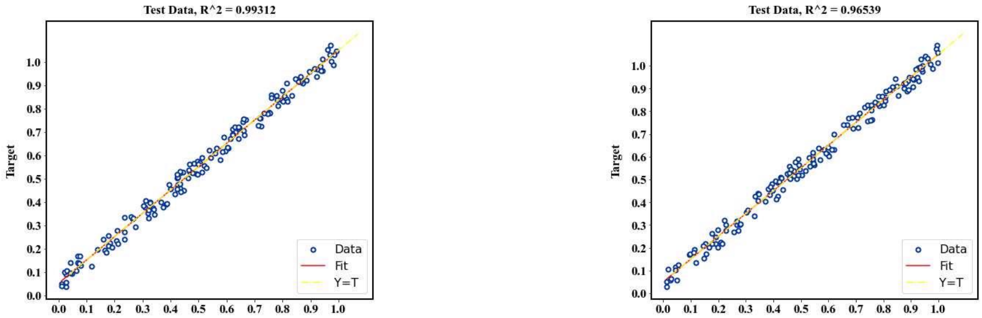


Figure 12. The squared regression plot of the proposed methods (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3 due to testing for S&P 500.

Figures 13 and 14 show that the predicted and actual values have a significant degree of agreement. Also, incredibly high R percent values were recorded in the training (Mobile U-Net V3-BiLSTM: 99.96%; Mobile U-Net V3: 99.82%) and testing (Mobile U-Net V3-BiLSTM: 99.72%; Mobile U-Net V3: 98.71%) phases. These values show that for the Apple data, the Mobile U-Net V3-BiLSTM model was more accurate and dependable than the Mobile U-Net V3 model.

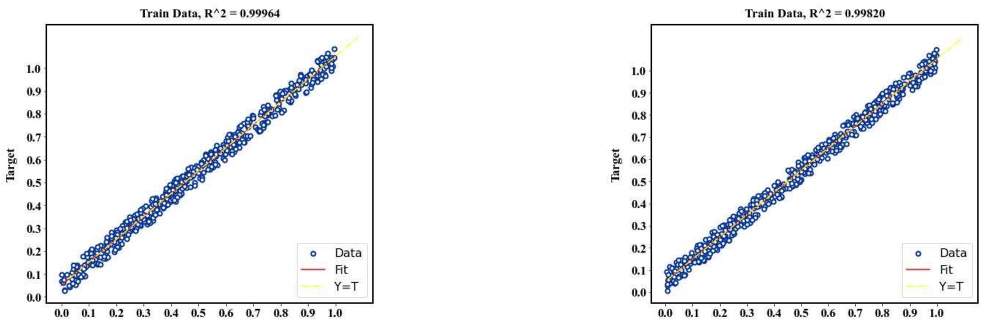


Figure13. The squared regression plot of the proposed methods (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3 due to training for Apple.

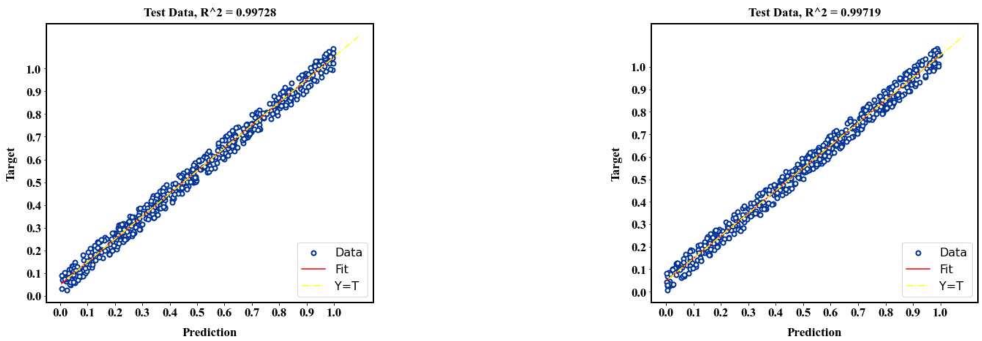


Figure 14. The squared regression plot of the proposed methods (a) Mobile U-Net V3-BiLSTM and (b) Mobile U-Net V3 due to testing for Apple.

We compared the outcomes of this proposed deep-learning framework with those of previous research to demonstrate Mobile U-Net V3's efficacy. Table 8 displays the outcomes of the Mobile U-Net V3 model provided in this work in comparison to the models used in earlier works. According to the MSE metric, the Mobile U-Net V3 model is superior to the models used in other research studies.

Table 8. Comparison of prediction outcomes of the proposed Mobile U-Net V3-BiLSTM system with the results of previous studies.

| Source | Model | Dataset | MSE | R | RMSE |
|---|---|---|---|---|---|
| Aldhyani & Alzahrani [16] | CNN-LSTM | Tesla, Inc. | 0.0001308 | 0.9926 | 0.01143 |
| | CNN-LSTM | Apple, Inc. | $5.725 \times 10^{-5}$ | 0.9973 | 0.00756 |
| Yu & Yan [17] | LSTM | S&P 500 | - | 0.952 | |
| Lu et al. [18] | CNN-BiLSTM-AM | Shanghai Composite Index stock | - | 0.9804 | 31.694 |
| Pang et al. [19] | ELSTM | Shanghai A-share composite index | 0.017 | - | - |
| Liu & Long [20] | LSTM | S&P 500 | - | - | 0.0075 |
| Proposed Model | Mobile U-Net V3 – BiLSTM | S&P 500 | 0.000108 | 0.9962 | 0.9962 |
| | Mobile U-Net V3 – BiLSTM | Apple, Inc. | $3.894 \times 10^{-5}$ | 0.9987 | 0.9987 |

The proposed approaches may offer effective future prediction because of the possible benefits, which have long been a desire of most economies and people. Learning how to predict price changes in stocks might be helpful for those who are interested in studying stock-market forecasting. Predictions will be available to researchers that are more accurate than they have ever been because of artificial intelligence. Also, as technological advancements and algorithmic accuracy rise, its precision will rise with time. Our proposed method achieved higher accuracy value compared to other techniques. It is predict the closing price with less computation time complexity.

## 5.5 Evaluation of Training and Testing Set

As the number of iteration steps grows, graphs of loss value and prediction accuracy are shown in Figures 15 and 16. The graphs demonstrate the advantages results of implementing the study's proposed convergence technique. During the training phase, the proposed methods are trained for 200 iterations using the prepped training set. Currently, there is a 0.1 learning rate.

The training and testing accuracy, along with testing and training loss functions, are represented in Figures 15 and 16. 0.53 second is used for training the proposed model and 0.24 second is used for testing the proposed approach. During the training phase, the proposed method is trained for 200 epochs using the prepped training set. A learning rate of 0.1 has been established.

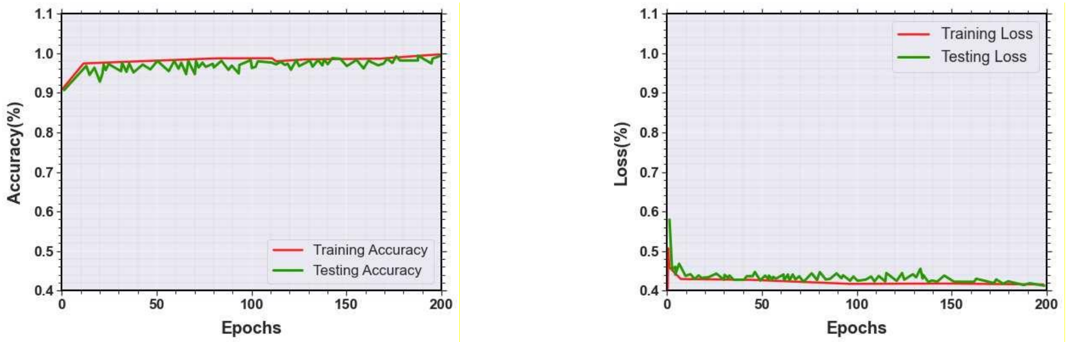


Figure 15. (a) Training and testing accuracy and (b) Training and testing loss for the Apple dataset.

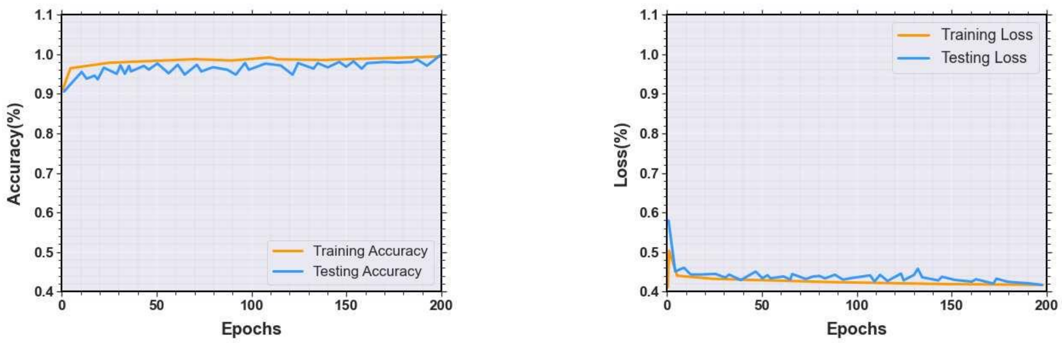


Figure 16. (a) Training and testing accuracy and (b) Training and testing loss for S&P 500 Stock dataset.

## 6. Conclusion and Future Works

The performance of companies, investor expectations, the geopolitical climate, investor perceptions and financial reports are just a few of factors affecting the stock market's behavior. When determining whether the stock price has increased or decreased, a company's profits are a crucial component to be considered. Also, predicting how the market will act for an investment can be challenging. To anticipate the stock-market analysis in this research, we used novel DL techniques. To normalize the input data given in the preprocessing stage, we are employing the min-max normalization approach. The stock-market analysis should then be predicted. Using of hybrid Mobile U-Net V3 and BiLSTM approaches, we predict the stock-market analysis using stock data from Apple, Inc. and S&P 500. The closing prices of these two firms are predicted. Our proposed method achieved a higher accuracy value compared to other techniques. Also, it is predicting the closing price with less computation time complexity. The evaluation of this research achieved a higher R-square value compared to other existing techniques. Further research will look at how well the model fits into various time-series prediction application fields, including forecasting gold prices, oil prices, earthquakes and weather, among others, based on AI techniques.

## REFERENCES

[1] N. Jing, Z. Wu and H. Wang, "A Hybrid Model Integrating Deep Learning with Investor Sentiment Analysis for Stock Price Prediction," Expert Systems with Applications, vol. 178, no.1, pp.11-50, 2021.

[2] H. Rezaei, H. Faaljou and G. Mansourfar, "Stock Price Prediction Using Deep Learning and Frequency Decomposition," Expert Systems with Applications, vol. 169, no. 3, p. 114332, 2021.

[3] S. Mehtab, J. Sen and A. Dutta, "Stock Price Prediction Using Machine Learning and LSTM-based Deep Learning Models," Proc. of Symposium on Machine Learning and Metaheuristics Algorithms and Applications (SoMMA), pp. 88-106, Chennai, India, October 14–17, 2020.

[4] J. M. T. Wu, Z. Li, N. Herencsar, B. Vo and J. C. W. Lin, "A Graph-based CNN-LSTM Stock Price Prediction Algorithm with Leading Indicators," Multimedia Systems, vol. 23, no. 5, pp. 1-20, 2021.

[5] M. Vijh, D. Chandola, V. A. Tikkiwal and A. Kumar, "Stock Closing Price Prediction Using Machine Learning Techniques," Procedia Computer Science, vol. 167, no. 2, pp. 599-606, 2020.

[6] S. Mehtab and J. Sen, "A Time Series Analysis-based Stock Price Prediction Using Machine Learning and Deep Learning Models," Int. J. of Business Forecasting and Marketing Intelligence, vol. 6, no .4, pp. 272-335, 2020.

[7] Z. Jin, Y. Yang and Y. Liu, "Stock Closing Price Prediction Based on Sentiment Analysis and LSTM," Neural Computing and Applications, vol. 32, no. 5, pp. 9713-9729, 2020.
[8] S. Kumar Chandar, "Grey Wolf Optimization-Elman Neural Network Model for Stock Price Prediction," Soft Computing, vol. 25, no. 6, pp. 649-658, 2021.
[9] Y. Li, H. Bu, J. Li and J. Wu, "The Role of Text-extracted Investor Sentiment in Chinese Stock Price Prediction with the Enhancement of Deep Learning," Int. J. of Forecasting, vol. 36, no. 4, pp. 1541-1562, 2020.
[10] P. Gao, R. Zhang and X. Yang, "The Application of Stock Index Price Prediction with Neural Network," Mathematical and Computational Applications, vol. 25, no. 3, pp. 53-70, 2020.
[11] J. B. Awotunde, R. O. Ogundokun, R. G. Jimoh, S. Misra and T. O. Aro, "Machine Learning Algorithm for Cryptocurrencies Price Prediction," Proc. of Artificial Intelligence for Cyber Security: Methods, Issues and Possible Horizons or Opportunities, pp. 421-447, 2021.
[12] A. Tsantekidis, N. Passalis, A. Tefas, J. Kanniainen, M. Gabbouj and A. Iosifidis, "Using Deep Learning for Price Prediction by Exploiting Stationary Limit Order Book Features," Applied Soft Computing, vol. 93, no. 23, pp. 106-401, 2020.
[13] S. Mehtab and J. Sen, "A Robust Predictive Model for Stock Price Prediction Using Deep Learning and Natural Language Processing," arXiv preprint arXiv: 1912.07700, 2019.
[14] A. Ghosh, S. Bose, G. Maji, N. Debnath and S. Sen, "Stock Price Prediction Using LSTM on Indian Share Market," Proceedings of 32nd Int. Conf. on Computer Applications in Industry and Engineering, vol. 63, no. 33, pp. 101-110, 2019.
[15] X. Liang, Z. Ge, L. Sun, M. He and H. Chen, "LSTM with Wavelet Transform Based Data Preprocessing for Stock Price Prediction," Mathematical Problems in Engineering, 2019.
[16] T. H. Aldhyani and A. Alzahrani, "Framework for Predicting and Modeling Stock Market Prices Based on Deep Learning Algorithms," Electronics, vol. 11, no. 19, pp. 31-49, 2022.
[17] P. Yu and X. Yan, "Stock Price Prediction Based on Deep Neural Networks," Neural Computing and Applications, vol. 32, no. 3, pp. 1609-1628, 2020.
[18] W. Lu, J. Li, J. Wang and L. Qin, "A CNN-BiLSTM-AM Method for Stock Price Prediction," Neural Computing and Applications, vol. 33, no. 8, pp. 4741-4753, 2021.
[19] X. Pang, Y. Zhou, P. Wang, W. Lin and V. Chang, "An Innovative Neural Network Approach for Stock Market Prediction," The Journal of Supercomputing, vol.76, no.7, pp. 2098-2118, 2020.
[20] H. Liu and Z. Long, "An Improved Deep Learning Model for Predicting Stock Market Price Time Series," Digital Signal Processing, vol. 102, no. 11, pp. 102-741, 2020.
[21] X. Jin, J. Zhang, J. Kong, T. Su and Y. Bai, "A Reversible Automatic Selection Normalization (RASN) Deep Network for Predicting in the Smart Agriculture System," Agronomy, vol. 12, no. 3, pp. 55-91, 2022.
[22] P. Singla, M. Duhan and S.Saroha, "An Ensemble Method to Forecast 24-h Ahead Solar Irradiance Using Wavelet Decomposition and BiLSTM Deep Learning Network," Earth Science Informatics, vol. 15, no. 1, pp. 291-306, 2022.
[23] A. Alsenan, B. Ben Youssef and H. Alhichri, "MobileUNetV3—A Combined UNet and MobileNetV3 Architecture for Spinal Cord Gray Matter Segmentation," Electronics, vol. 11, no. 15, pp. 23-88, 2022.
[24] Apple, Inc. Stock Data, [Online], Available: https://www.kaggle.com/datasets/meetnagadia/apple-stock-price-from-19802021.
[25] S&P 500 Stock Data, [Online], Available: https://www.kaggle.com/datasets/camnugent/sandp500.

**ملخص البحث:**

نقترح في هذه الورقة نظاماً هجيناً يقوم على التّعلُّم العميق لتوقُّع الأسعار المستقبلية للأسهم. فقد حظيت تقنيات التّعلُّم العميق في الآونة الأخيرة بقدْرٍ كبيرٍ من الاهتمام؛ لأنّها أحرزت نجاحاً ملحوظاً في القدرة على التّعامل مع البيانات. ويستخدم النّظام الهجين المقترح بيانات السّوق من أجْل توقّع سعر الإغلاق. ولتجريب النّظام المقترح، تمّ تطبيقه على قاعدتي البيانات لشركة .Apple, Inc وشركة S&P 500. كذلك تمّت مقارنة النّظام المقترح بعددٍ من الأنظمة التي اقترحتها دراسات سابقة من خلال مجموعةٍ من المؤشّرات. وقد أثبت النّظام المقترح نجاعته وتفوُّقه على الأنظمة الأخرى من حيث الدّقّة في التّنبُّؤ بأسعار الأسهم.