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A Novel Hybrid Approach for Stock Market Index Forecasting using CNN-LSTM Fusion Model

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Abstract: Forecasting the path of currency exchange rates in the stock market is a highly investigated and demanding endeavour for investors and researchers in the current dynamic environment. The inherent unpredictability of the market makes it extremely challenging to forecast financial markets with a fair level of confidence. The emergence of artificial intelligence has witnessed intricate algorithms yielding encouraging results in the prediction of stock market trends. Predicting stock prices is essential for formulating a trading strategy and identifying favourable times to purchase or sell equities. Financial time series display heterogeneous time scale characteristics as a result of differing durations of influential variables and distinct trading behaviours of market participants.In order to tackle the difficulty of predicting stock values, we suggest utilising a model called the features Integration LSTM-CNN paradigm. This model combines features acquired from diverse representations of same data, especially, stock time series and stock chart graphics. The fusion neural network, in collaboration with the raw daily price series and the initial and secondary layers of the CNN, extracts diverse characteristics over several interval scales. These qualities encompass the price sequence's short-term, medium-term, and long-term attributes. The hybrid neural network presented incorporates LSTM deep convolution networks to effectively include temporal dependencies across the three categories of information. Subsequently, fully connected layers are utilised to generate complete visual representations for predicting the price trajectory.

Keywords: *Long Short-Term Memory Networks,Multiple Time Scale Features, Stock Forecasting, Share market index, Machine Learning, Neural networks.*

1. Introduction

A stock index, which is frequently used in the stock market, serves as a performance measure for investors, enabling them in trend predictions and aiding in the maximisation of profits. For the purpose of establishing economic estimates and implementing policies, these indicators are absolutely necessary. However, because to the stochastic character of stock indices, it is difficult to accurately estimate how they will perform in the future.

It is common practice to employ the ARIMA model while conducting traditional time series forecasting. Furthermore, a novel "LSTM-CNN feature fusion model" incorporates knowledge from both LSTM and CNN models, resulting in predictions that are superior to those provided by each individual model. Despite the fact that the Efficient Market Theory (EMT) argues that stock prices already incorporate all relevant information, a large number of people still attempt to create profits by projecting stock prices using a variety of different approaches.

The goal of this study is to investigate the application of econometric models for the purpose of predicting stock prices. Some examples of these models include the AutoRegressive Distributed Heteroscedasticity (GARCH) model and the two-factor models created by Fama and French. The ability of neural network models, such as the artificial neural network (ANN) and the Long Short-Term Memory (LSTM), to recognise non-linear correlations in data has contributed to the rise in popularity of these models.

The research that was carried out by Kimoto et al. and Kim et al. highlights the effectiveness of artificial neural networks in predicting stock values, with LSTM models outperforming traditional methods. The accuracy of stock price forecasting is improved by Bao et al. by the utilisation of an innovative methodology that

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incorporates wavelet transform, stacking autoencoder, and LSTM.

The inclusion of Convolutional Neural Networks (CNN) and Long Short-Term Memories (LSTM) into deep learning models demonstrates the effectiveness of these neural networks in capturing long-term dependencies and extracting features. For the purpose of successfully forecasting movements in the stock market at a variety of time intervals, a hybrid model is developed. This model combines the properties of a Convolutional Neural Network (CNN) with learning algorithms that use Long Short-Term Memory (LSTM).

When it comes to predicting Chinese stock indices, the adaptive gradient-based optimisation method known as Adam displays its effectiveness. An approximation of the closing price of the Indian stock market index is generated by utilising a combination of Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) networks, in addition to the Adam optimizer.

Regression models, more specifically linear regression and empirical mode decomposition, are being investigated by a variety of researchers as potential strategies for predicting stock values. Increasing the precision of forecasts can be accomplished through the application of time-sensitive data augmentation techniques, such as wavelet modification.

In the final section of the study, a quick synopsis of the relevant research is presented, followed by an introduction to the proposed methodology, an expansion on the experimental design, and an in-depth analysis of the results.

Author & Year	**Area**	**Methodology**	**Key Findings**	**Challenges**	**Pros**	**Cons**	**Application**
Cowles [1]	Stock Market	Efficient Market Theory (EMT)	Stock prices reflect all relevant information	Difficulty in predicting stock prices	Supports informed investing	Limited ability to outperform the market	Investment decisions
Keim et al. [6]	Econometrics	ARIMA model	Feasibility of predicting stock performances	Assumptions in econometric models	Statistical significance in predictions	Assumptions may not hold in real-life	Stock performance prediction
French et al. [8]	Stock Price Prediction	Autoregressive Distributed Heteroscedasticity	Link between stock's earnings and price	Dependence on fundamental information	Prediction based on volatility and return	Limited consideration of external factors	Stock price prediction
Kimoto et al. [12]	ANN	ANNs	Prediction method for Tokyo Stock Exchange	Successful profits using ANN prediction	Superior performance compared to others	Limited interpretability	Equities forecasting in Tokyo Stock Exchange
Tsang et al. [4]	ANN	ANNs	Purchasing and selling warning system	Aggregate hit ratio over 70%	Effective warning system	Limited discussion on market dynamics	Anticipating Shanghai Stock markets
Yudong et al. [14]	Artificial Neural Networks (ANN)	Enhanced Microbiological Chemotactic Optimisation	Outperformance of proposed model	Comparison with typical ANN performance	Improved forecasting of S&P 500 index	Limited validation on diverse datasets	Forecasting S&P 500 index
Wang et al. [15]	Time Series Data	Waveform Information and Communica-	Outperformance based on statistical	Necessity for denoising	Accuracy in predicting stock prices	Complexity in denoising	Forecasting Shanghai Composite In-

		tions Tech	measures	techniques			dex
Chen et al. [16]	Stock Performances in China	Logistic Regression model with LSTM	Accuracy increases with the number of inputs	Use of logistic regression with LSTM	Improved accuracy in stock performance	Limited discussion on external factors	Forecasting stock performances in China
Nelson et al. [17]	Stock Price Trends	Logistic Regression with LSTM	LSTM outperforms other machine learning models	Experimental findings support LSTM	Improved accuracy in trend prediction	Limited comparison with other models	Forecasting future trends in stock prices
Bao et al. [3]	Equity Index Futures	Discrete Wavelet Transform, Stacking Autoencoder	Superior performance of proposed model	Complexity in multi-stage processes	Outperformance of RNN, LSTM, and wavelet-LSTM	Limited discussion on model interpretability	Anticipating equity index futures
Yoshua [18]	Hyper-parameters in Learning	Not specified	Identification of characteristics for large-scale data	Application of findings to learning algorithms	Insightful guidance on hyper-parameters	Lack of specific methodology details	Learning algorithms based on backpropagation and gradient-based optimization
Adam [19]	Stochastic Optimization	Adam (Adaptive predictions of lower-order moments)	Outperformance of Adam in testing	Limited exploration of other optimization approaches	Adaptive prediction of lower-order moments	Dependency on specific characteristics	Stochastic optimization problems
Adam [20]	Chinese Stock Index	Deep Neural Network with Backpropagation and Adam	Estimation of Chinese stock index	Historical data used for training component networks	Utilization of Adam algorithm	Dependency on historical data	Estimating Chinese stock index
MLP and LSTM [21]	Indian Stock Market	Multilayer Perceptron and LSTM with Adam	Approximation of closing price of Indian stock index	Application of Adam optimizer	Combination of MLP and LSTM networks	Limited exploration of alternative models	Forecasting Indian stock market
Author [23]	Stock Price Value	Empirical Mode Decomposition, Hurst Exponent	Computation of stock prices in short-term and long-term	Application of EMD and H analysis	Insightful analysis of time-sensitive data	Limited discussion on model robustness	Forecasting stock prices using EMD and H analysis
Author [24]	Stock Trend Prediction	Time-sensitive data augmentation strategy	Effectiveness of data augmentation in stock trend prediction	Simplicity and effectiveness of the strategy	Enhancement of data in wavelet transformation	Limited discussion on specific datasets	Stock trend prediction using data augmentation

2. Stock Forecasting Methodology

2.1 Long Short Term Memory Networks

The LSTM and MLP algorithms share a notable level of similarities in terms of their mechanism, except for how they handle input from each neuron. Unlike the creation of ordinary neurons, which occurs in a single step, the growth of an LSTM cell occurs through a multi-step approach. In the context of LSTMs, the cell state functions as an additional memory component, storing significant past data that can aid in making predictions. This information can be utilised to aid with prediction. In the next stages, specific mechanisms known as gates are responsible for altering the information stored in the cell state. Initially, the forget gate assesses the need to eliminate any data that is now validly accessible.The user's text is empty. Both the update gate and the tanh activation function would have been responsible for selecting the selection of fresh data to be stored and the exclusion of unnecessary data. The details are once again overlooked or ignored, similar to how they were treated in previous instances. Subsequently, the data is provided to the kernel function, which is then succeeded by the production of the output. This move is undeniably significant.

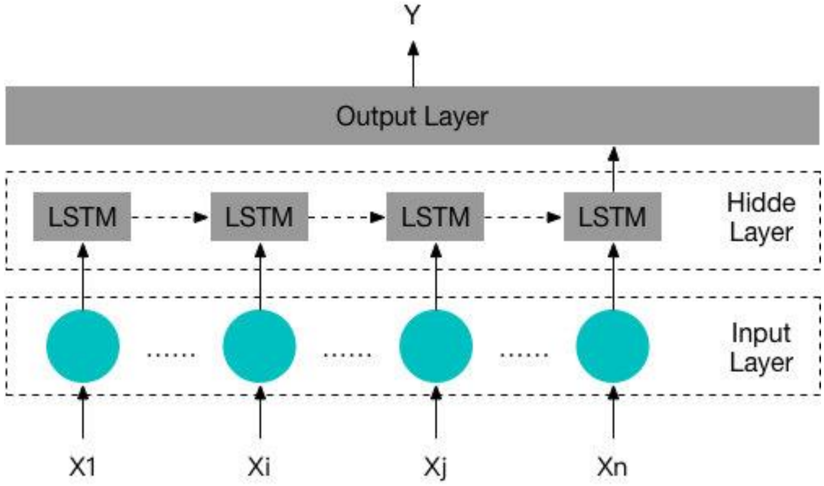


Fig 1. Architecture for LSTM Module

2.2 Convolutional Neural Network

Convolutional Neural Networks (CNNs) execute tasks that are akin to neural networks such as the Perceptron or Multi-Layer Perceptron, but with a notable differentiation. CNNs, unlike traditional networks, do not require the flattening of input images, which results in a significant reduction in the amount of weights. For example, while working with a 112 × 112 input image, conventional approaches would require 12544 operations to acquire weights. On the other hand, Convolutional Neural Networks (CNNs) employ a restricted collection of weights (e.g., 5 x 5 = 25 with a kernel size of 5) that are applied to many small portions of the image, all having the same dimensions.CNNs, in contrast to traditional machine learning methods that examine pixel images, prioritise 'local' characteristics detected in the previous hidden layer rather than pixel-level specifics. In addition, the output layer of a CNN condenses the original image into a vector representation of output values instead of retaining the complete image. The decision to use this design is driven by the nature of the input, which comprises images. This allows Convolutional Neural Networks (CNNs) to organise the information in a more efficient manner.

In a Convolutional Neural Network (CNN), the arrangement of neurons differs from that of a regular Neural Network. The neurons are structured in three dimensions, namely width, height, and depth. The project will utilise photos with dimensions of 112x112x3 (width, height, depth correspondingly).

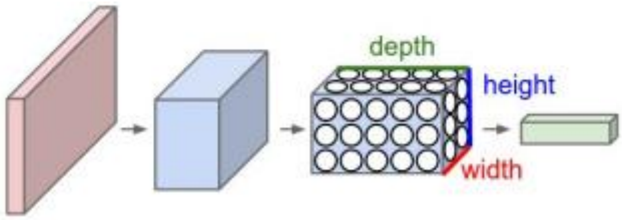


Fig 2. The Layers of CNN

Figure 2 displays a depiction of a conventional 3-layer Neural Network on the left side. In contrast, a ConvNet arranges its neurons in a three-dimensional structure, consisting of width, height, and depth. This may be observed in the visualisations of one of its layers. At each level, every layer in a ConvNet converts the 3D input volume into a 3D sequence of neuron activations. The red input layer in this representation covers the image, matching its dimensions in terms of width and height. The layer's depth corresponds to the three colour channels: red, green, and blue.

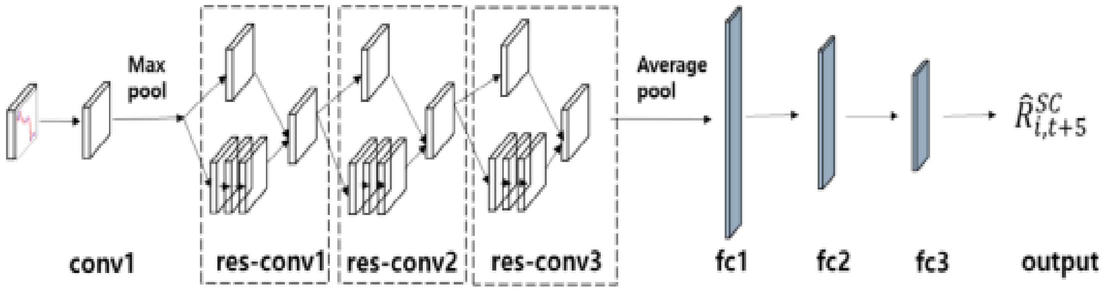


Fig 3. Architecture of CNN

2.3 Feature fusion LSTM-CNN model

We investigate the integration of image and temporal characteristics by combining each feature and every attribute independently, such as image and temporal features. The procedure occurs in three distinct steps. Initially, CNN is trained to minimise CNN loss by comprehending the graphical characteristics of the chart image. Furthermore, LSTM is trained to minimise the LSTM loss function, which allows it to uncover temporal patterns by analysing the time series data of stocks. Ultimately, the feature fusion LSTM-CNN is trained with the objective of minimising the loss resulting from the fusion process. This stage integrates characteristics from CNN and LSTM layers, with parameter sharing occurring within the convolutional layer of CNN and the LSTM layer of LSTM.By integrating several characteristics, such as extracted stock chart images and stock time-series data from the same dataset, we enhance the training model for predicting future stock market trends. Practically, it produces marginally superior outcomes compared to separate models.

This section presents a summary of the proposed hybrid neural network for trend forecasting, which relies on the acquisition of different time-scale features. Subsequently, we thoroughly examine each constituent of the high-performance neural network.The proposed hybrid neural network can be partitioned into three distinct components. To begin with, distinct CNN layers capture features of different temporal scales in the price series. The aforementioned attributes are merged with the initial daily price data to analyse alterations in the value sequence over short, medium, and long timeframes, as illustrated in Figure 1. In the second step, several Long Short-Term Memory (LSTM) models are employed to acquire knowledge of the sequential relationships between characteristics at different time intervals within the dataset. The ultimate stage involves the integration of all the knowledge acquired by LSTMs using a deep convolutional neural network in order to predict the future trend of the closing price. The hybrid neural network, which consists of different network topologies, can be collectively trained using a unified loss function. The hybrid neural network architecture, shown in Figure 4, can be understood as a fusion of three networks derived from individual temporal feature learning, as indicated in Figure 3.

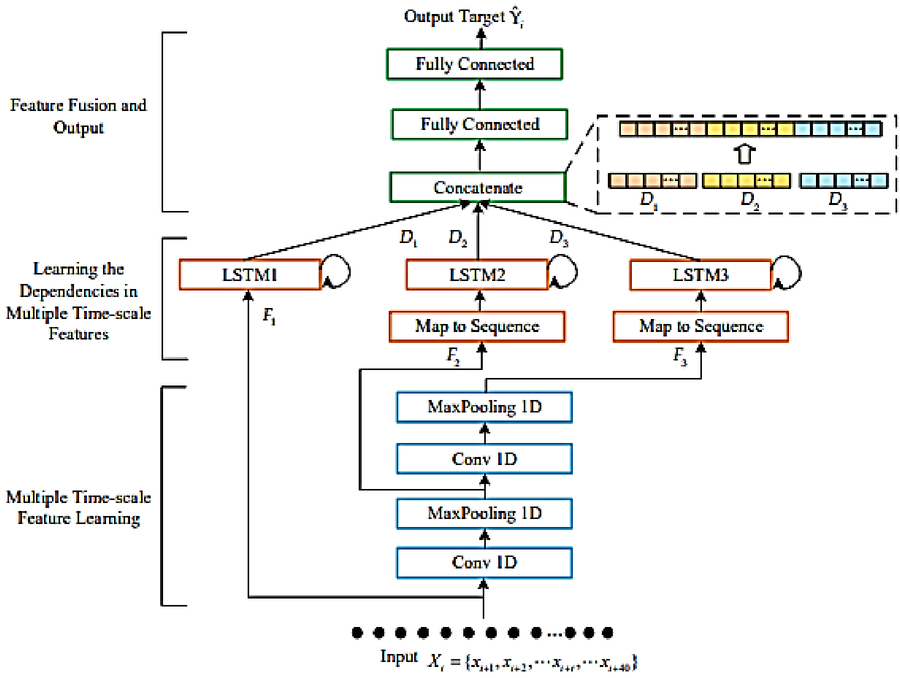


Fig 4. Architecture of Feature Fusion LSTM-CNN

2.4 Datasets and Experimental Setup

The data utilised for this study is obtained from the publicly accessible annual reports of the companies. The experiment was carried out between 19/08/2008 and 04/10/2010, using data from the Yahoo stock market. In this text, numerical formatting is used to communicate the information. Stock data, such as the opening, high, low, and closing values, were gathered on a daily basis and utilised to forecast future stock performance. This analysis incorporated data from over 700 days. The study setting encompassed a GPU, Windows 10 OS, and 8GB of RAM, facilitated by Google Colaboratory, with the primary emphasis on the Tensor Flow deep learning framework.Before normalisation, the dataset was scaled using the minmax feature scaling process, which is an approach used for feature scaling. Subsequently, the processed dataset was partitioned into two distinct subsets: the training dataset and the testing dataset. 80% of the data was used for the training dataset, while the remaining 20% was allocated to the testing dataset.After subjecting the training dataset to three models, specifically LSTM, CNN, and Hybrid LSTM-CNN, with different tuning configurations to predict stock prices, the outcomes were considered successful. An evaluation was conducted to determine the dependability of the projections by comparing the expected dataset with the testing information.

2.5 Performance Parameters

1. RMSE (Root Mean Square Error): To calculate the RMSE, the following equation is used

2. MAPE (mean absolute percentage error): To calculate the MAPE, the following equation is used

Where A_t is the actual value and F_t is the forecast value.

n be the number of fitted points

3. Result Analysis

Through the use of several layers, convolutional nodes with varied unit sizes, and compacted layers, along with the implementation of alternate supervised learning methods between real data and projected data, we have found distinct variations in the root mean square error (RMSE), as evidenced by our research findings. By examining several training epochs for the LSTM model system, it became clear that the choice of learning epochs is vital for efficiently training the model. As shown in TABLE I, the model trained using 100 historical periods demonstrates a smaller root mean square error (RMSE), indicating improved predictive ability in comparison to other models. In this case, the activation function RELU was used to activate all hidden layers, with each hidden layer containing 128 units within the activation function.

Table 1. Analysis of RMSE vs the Number of Epochs wrt Time

No. of Epoch	LSTM RSME	Time
10	0.0011	3
20	0.000725	6
50	0.000493	15
100	0.000493	30
250	0.003198	75

This study chose to utilise one-day advanced indexes data instead of the traditional approach for analysing time series data in order to forecast the price trend of the following trading day. The goal was to create the most efficient forecasting models. This research employed a methodology to assess the fluctuations in commonly utilised technical indicators that are associated with price variations throughout brief timeframes, spanning from one day to one week (equivalent to 5 trading days). After the test was finished, it was seen that the duration of the term shows different levels of sensitivity to the same set of indices, depending on its length.

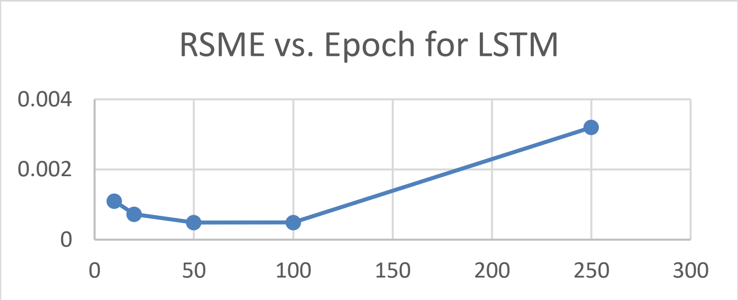


Fig 5. Anaysis of RSME with changing no. of Epoch

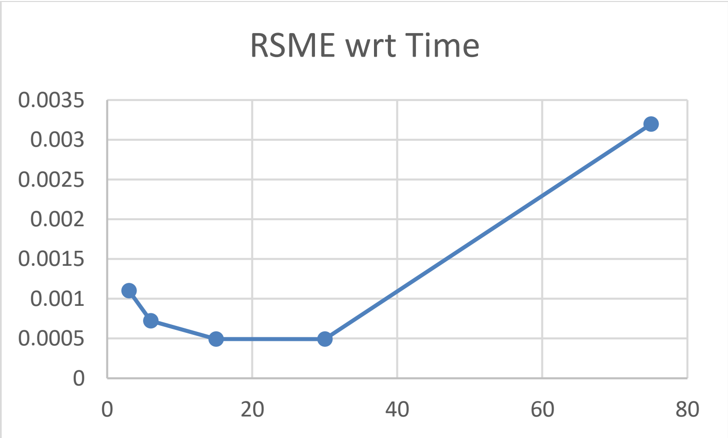


Fig 6. Anaysis of RMSE with Time

Table 2. Analysis of RSME wrt variable hidden layers using LSTM Models

No. of Epoch	RSME with 2 Hidden Layers	Time in mins	RSME with 4 Hidden Layers	Time in mins
20	0.000735	6	0.000985	12

50	0.000536	15	0.000542	35
100	0.000498	30	0.000623	70

The occurrence of this phenomena can be observed in Table I, where a gradual rise in the number of training epochs ultimately results in a problem of proper fitting in the training model, namely at 250 epochs during the LSTM training, as illustrated in Fig. 5. Additionally, the evaluation precision of LSTM appears to diminish with an increase in the number of hidden layers in the model, resulting in a longer training duration, as evidenced by the findings. Table II presents a concise overview of these observations and their sources. To obtain a more comprehensive analysis of the outcomes achieved by employing an LSTM network with two and four hidden layers throughout the course of 50 epochs, please consult Fig. 6 and 7, correspondingly.

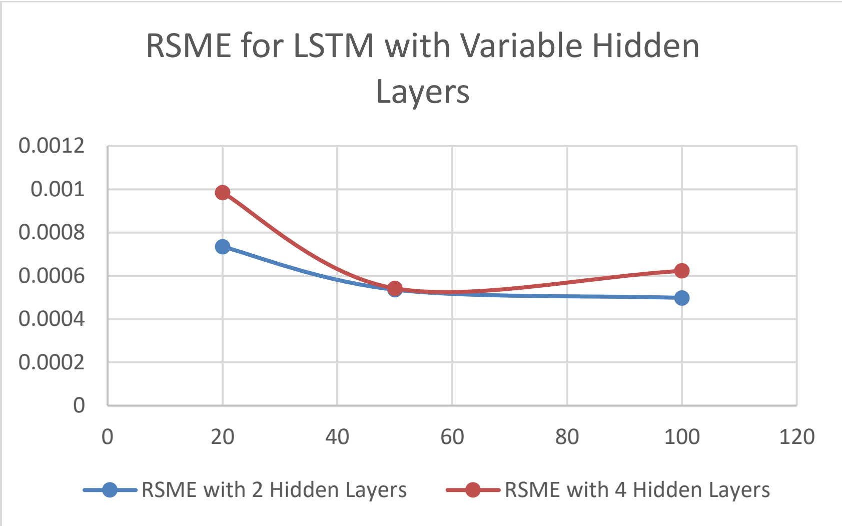


Fig 7. Analysis of RSME for LSTM with Variable Hidden Layers

Additionally, the Training and Validation loss for the Convolutional Neural Network (CNN) is calculated and plotted, encompassing epoch values that span from 0 to 500 with exponential increments. Furthermore, the Mean Absolute Percentage Error (MAPE) for CNN is computed and graphically represented with different epochs. The results are depicted in figures 8 and 9, correspondingly.

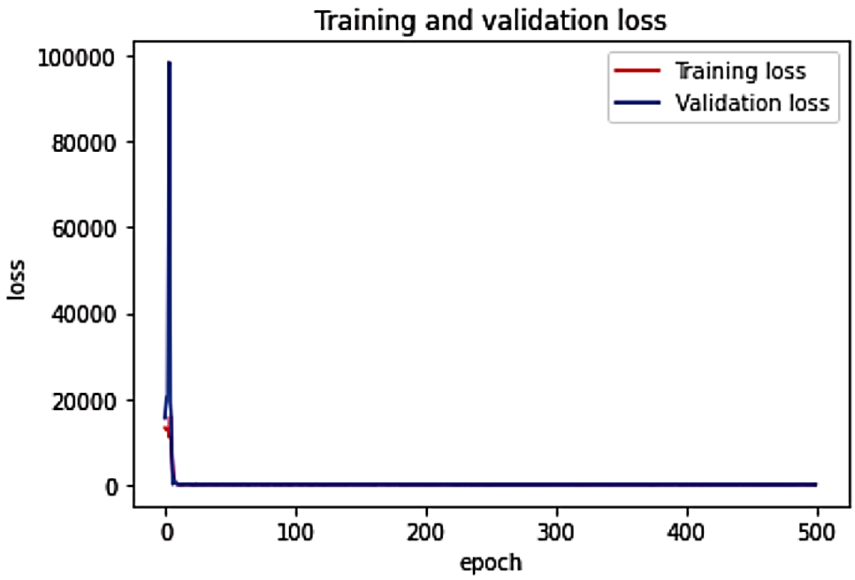


Fig 8. Analysis of RSME for CNN with Variable Epochs

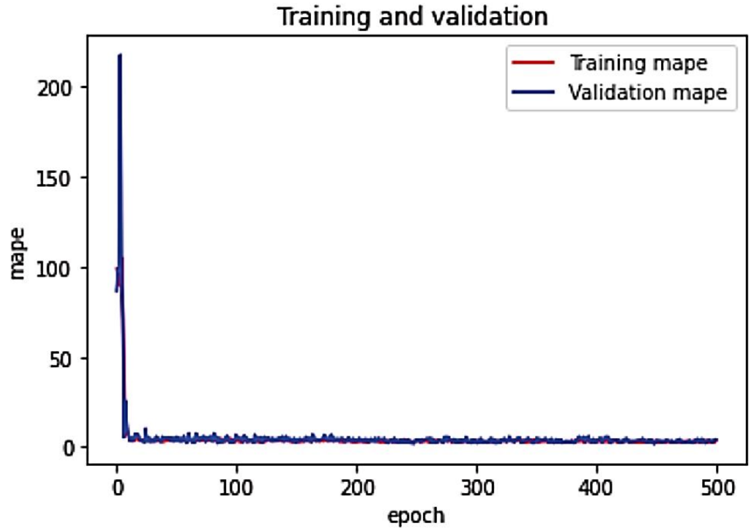


Fig 9. Analysis of MAPE for CNN with Variable Epochs

For our proposed hybrid LSTM-CNN model also, we calculated the same RSME and MAPE values. Here we opted for 100 Epochs. The obtained results are plotted and presented in figure 10 and 11 respectively.

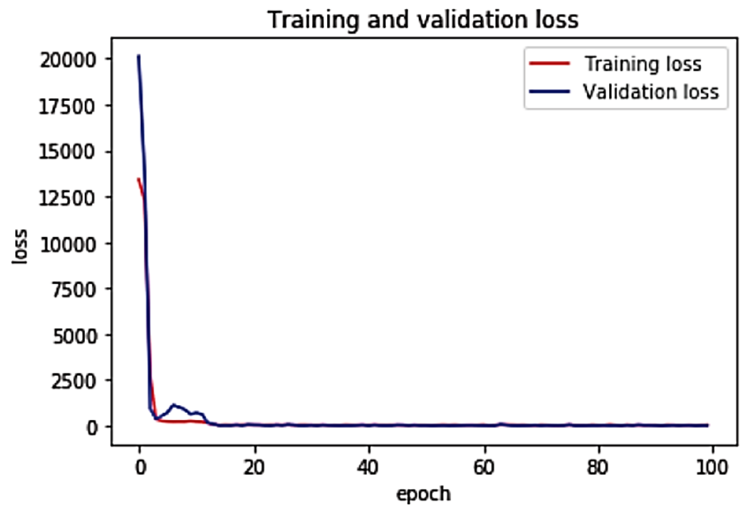


Fig 10. Analysis of RSME for Hybrid LSTM-CNN with Variable Epochs

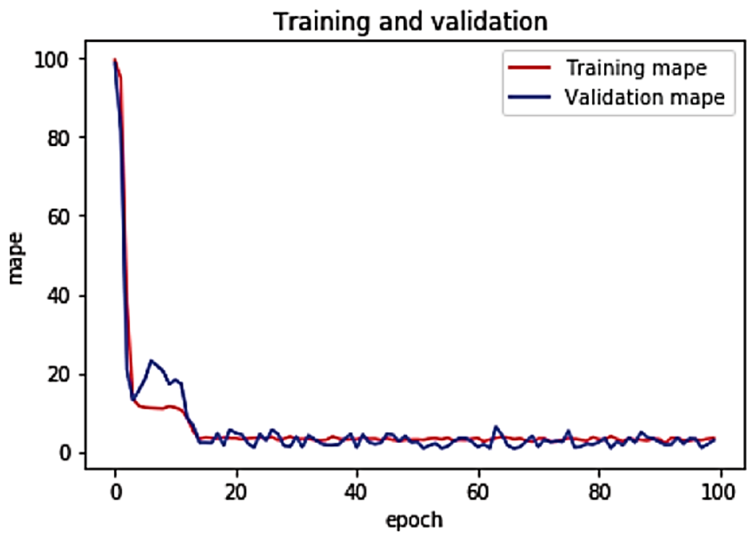


Fig 11. Analysis of MAPE for Hybrid LSTM-CNN with Variable Epochs

We implemented the three models and tried to predict the stock prices for coming days. The prediction has been made and compared as taining data, validation data and dev prediction data. The results obtained are shown in following figures.

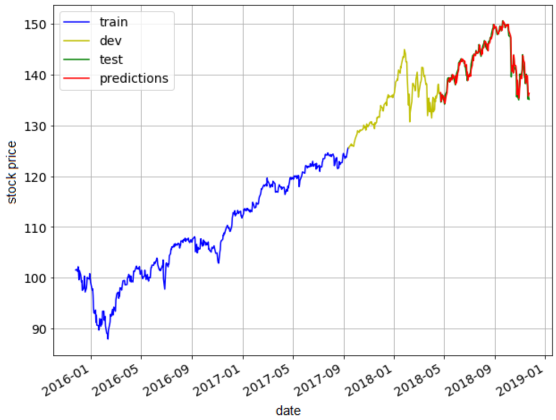
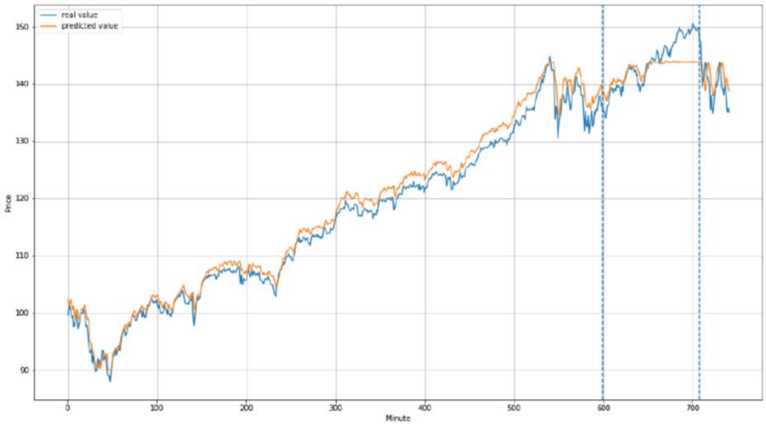
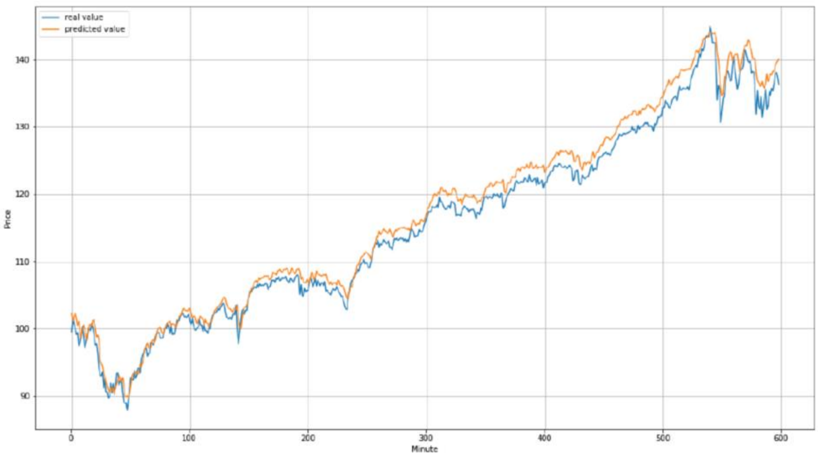


Fig 12. Stock price prediction after fine tuning of LSTM

From figure 12 we can observe the training, validation and dev prediction values for LSTM algorithm. Similarly, the same for CNN is shown in figure 13.



(a)



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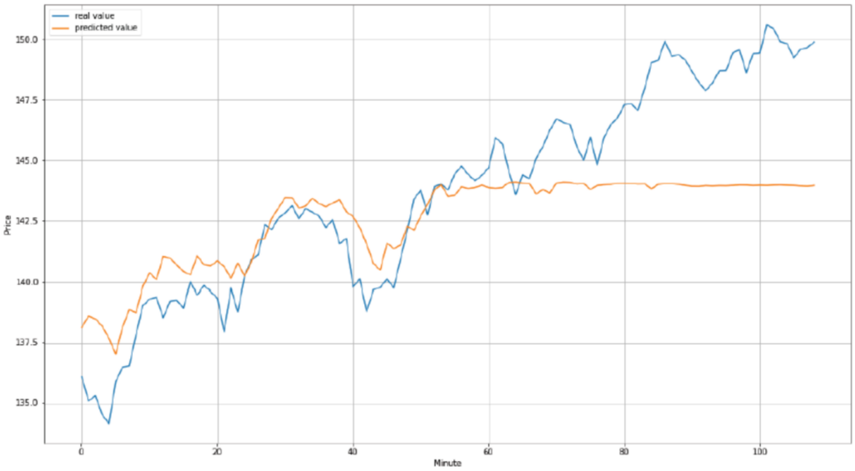
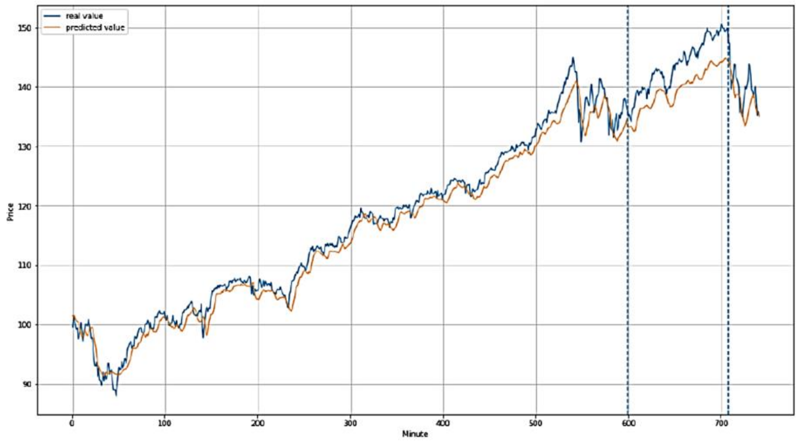


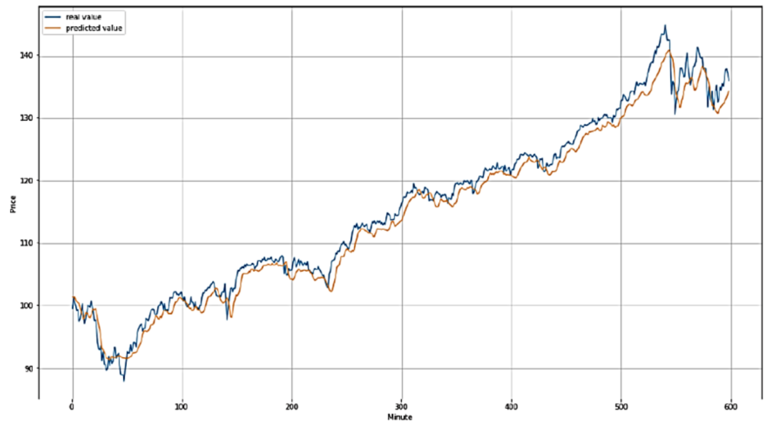
(c)

Fig 13. (a) Training Prediction Values (b) Validation Prediction Values (c) Dev Prediction Values for CNN Model

Based on the given results, it was observed that the CNN model demonstrates more effectiveness in forecasting stock prices in comparison to the LSTM model. Thus, we proceeded to assess the efficacy of the feature fusion LSTM-CNN model. The obtained and shown performance of the feature fusion hybrid LSTM-CNN model for stock price forecasting. Figure 14 depicts the performance of the feature fusion hybrid LSTM-CNN model.



(a)



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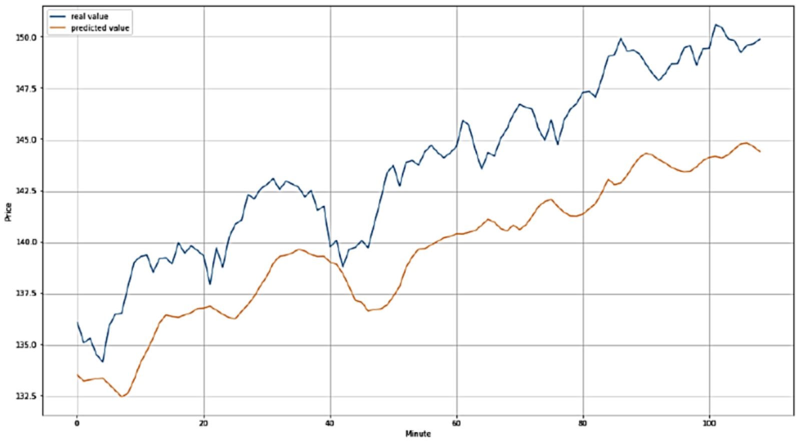

(c)

Fig 14. (a) Training Prediction Values (b) Validation Prediction Values (c) Dev Prediction Values for Feature Fusuion Hybrid LSTM-CNN Model

TABLE 3 LSTM, CNN and Hybrid LSTM-CNN result comparison after applying tuning parameters

Algorithm	RMSE	MAPE
LSTM	1.3605	0.9785
CNN	2.9920	1.9999
Hybrid CNN-LSTM	1.0539	0.7529

When compared to the corresponding of LSTM and CNN, the findings of Hybrid LSTM-CNN indicate a superior outcome in terms of performance. In the feature fusion LSTM-CNN model with candle bar graphs and company time series as inputs, the out-of-sample loss was reduced by 18.18 percent (root mean square error) and 17.56 percent (RMSE) (MAPE). Experiments with different connectivity charts and market time series revealed that the LSTM model performed significantly better than the others. Our three models are compared in terms of their prediction errors in Fig 15, which is based on stock chart pictures as input. Results demonstrate that the neural network based Presented method has been the most accurate model for predicting the stock prices in this study.

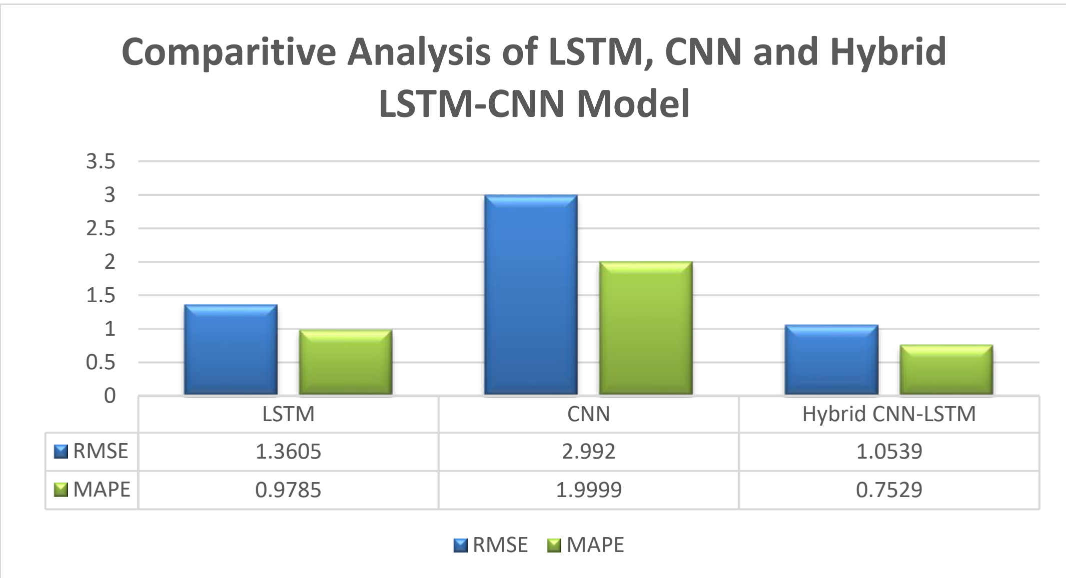

Fig 15. LSTM, CNN and Hybrid LSTM-CNN Algorithm Comparison

4. Conclusion

This research work presents a hybrid neural network that is used to model and predict stock market indices. The network combines several time scales to extract features and train the model. Considering the various scales included in financial time series data, it is reasonable to aggregate these elements in order to forecast future trends. The suggested system streamlines the model by employing a single Convolutional Neural Network (CNN) to extract various time scale variables. This is in contrast to existing models that utilise multiple networks for the same purpose. As a result, the proposed system offers predictions that are both more comprehensible and precise. Three Long Short-Term Memory (LSTM) models are utilised to capture temporal relationships on various time scales, and the knowledge obtained from these models is combined through fully connected layers to forecast the direction of price trends.The experimental findings demonstrate that the hybrid network effectively improves prediction accuracy in comparison to benchmark networks. Comparing our models to those based on F1, F2, and F3 demonstrates that including different time scale variables enhances the accuracy of predictions. Our recommended model has superior capability in acquiring substantial knowledge about the environment when compared to the Simplistic Model. LSTM, CNN, and Hybrid LSTM-CNN algorithms are capable of extracting features from financial time series data. However, their effectiveness is hindered by the varying sizes of financial time series. The hybrid neural network streamlines the model by utilising solely a CNN to extract multi-scale data, hence augmenting prediction accuracy.

Nevertheless, the proposed methodology demonstrates erratic trend prediction for specific datasets, presenting a difficulty. There are two potential reasons for this problem: either the underlying price series rules were not adequately covered by the three successive scale features, or there were negative effects from unexplained factors such as governmental policy, industrial expansion, environmental conditions, and so on.This work establishes a fundamental basis for future endeavours. Utilising a multi-layer Convolutional Neural Network (CNN) to extract additional scale characteristics and integrating various information sources such as macroeconomic data, news, and market sentiment could potentially improve forecasting abilities.

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