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"FORECASTING OF TIME SERIES DATA USING DEEP LEARNING-BASED SYSTEM FOR FINANCIAL MARKET TREND ANALYSIS"

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ABSTRACT

A new way for predicting market trends is becoming very popular in the financial world right now. Many problems still need to be solved, and many studies have already been done on this topic. A lot of attention has been paid to recent study that uses neural networks to predict market trends. The prediction of financial market trends using neural networks is an area that has recently garnered significant interest. This paper looks at both the usual ARIMA and RNN models for predicting financial time series, as well as two deep learning designs known as Bi-LSTM and Convolutional Neural Networks (CNN). The study uses stock data from Apple Inc. (AAPL) from January 2, 2018, to September 14, 2023, to evaluate the predictive performance of each model. To improve model learning, data preparation included choosing which features to use, normalising the data using Min-Max scaling, reducing the number of dimensions, and representing the features. Researchers found that the CNN model was the most accurate and had the lowest RMSE (2.8017). It outperformed Bi-LSTM (5.8554), RNN (10.69), and ARIMA (16.01). CNN did a good job of making short-term predictions, while Bi-LSTM only did well with catching sequential dependencies and less effectively with sudden changes. When looking at changes in stock prices, ARIMA and RNN models performed poorly because trends became more complex and didn't follow a straight line. The results show that the CNN model is very good at finding important patterns and making accurate predictions. This makes it a good way to guess what will happen in the financial markets.

Key Words: *Financial Time Series Forecasting, Stock Price Prediction, CNN, Bi-LSTM, ARIMA, Deep Learning, Apple Inc.*

I. INTRODUCTION

The financial market is an interdependent market that trades on assets such as stocks, bonds, commodities and currencies. It enables the process of capital allocation, creation of wealth and economic growth by connecting the suppliers of capital with the demanders [1][2]. The macroeconomics, corporate performance, geopolitics and investor sentiment all determine the level of market prices. Technological progress, globalisation, and world trade have accelerated market speed, market complexity, and interdependence within the marketplace.

Efficient and proper financial forecasting is essential for optimal trading, risk management [3], and anchoring economic stability. Accurately predicting the market's trend is crucial for traders, investors, policymakers, and businesses to make informed decisions and manage risk. Conventional financial markets, including stock exchanges [4], have historically been a key target of forecasting studies, with precision stock index forecasts providing prospects of trading opportunities and risk management in the portfolio [5]. Cryptocurrencies and specifically Bitcoin have created another set of challenges as they are highly volatile, take place outside of any centralized authority, and display characteristics of speculative trading. On the same note, carbon markets have become popular in dealing with greenhouse emissions

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control and it has become imperative to predict carbon futures prices to enable the environmental policies and industrial needs [6].

Time series data related to finance are highly volatile, lack stationarity, exhibit nonlinearity, and contain noise, which makes their prediction difficult. Although well-known statistical models like GARCH and Auto-Regression Integrated Moving Average (ARIMA) Have Been used for a long time with good results, they don't always have the limitations needed to find complex nonlinear relationships in real financial data. Machine learning models [7][8], e.g. ANN [9], SVR, among others, have a better performance in predictive tasks by automatically learning the patterns in the data, though still requiring manual feature engineering following the initial stages, and they might have difficulties with large-scale data sets [10].

A popular variant of machine learning is deep learning [11][12] which has become a prominent technique of forecasting time series data in the financial sector [13]. It provides sophisticated features to model complex time-varying dependencies, nonlinear dynamics and underlying structures without having to perform elaborate feature engineering. Recent efforts have effectively addressed a range of financial forecasting challenges by utilising attention-based architectures, LSTM networks, CNN, and Temporal Convolutional Networks (TCN) [14]. Such techniques can absorb large quantities of past, historical market data, adjust to dynamic market condition changes, and discover intricate patterns beyond the scope of traditional methods. With a focus on financial time series forecasting—and more especially, market trend prediction—this study examines and discusses deep learning methods in detail [15]. By analyzing the different model architectures, scenarios of application, and comparison with performance rates, the paper present clarity on the existing development, issues to be resolved, and trends of research.

A. Motivation and Contribution of Study

The dynamic volatility of the global financial markets, whether the conventional stock markets or the new age cryptocurrency markets or green carbon trading markets, offers not only opportunities but also threats to investors and policymakers as well as enterprises. To enhance the effectiveness of the trading plans, developing optimal selections of portfolio risks, regulatory compliance, and policy-making, precise market trends forecasting plays a vital role. Nonetheless, the nonlinear, noisier, and very dynamic nature of financial time series presents a big challenge to the traditional machine learning and statistical methods. New developments in DL offer an appealing strategy for dealing with the problem of automatically identifying hidden patterns and intricate temporal correlations in massive volumes of market data. Financial time series forecasting using DL-based models is being pursued because of this, with the goals of improving decision-making in a data-driven industry, enhancing predicted accuracy, and being more adaptable to changing market conditions.

- Empirical analysis on real-world stock market data of Apple Inc. (AAPL) over five years, providing practical insights into market behaviour and price–volume relationships.
- Comprehensive data preprocessing pipeline involving feature selection, dimensionality reduction, normalization, and advanced feature representation techniques to enhance model accuracy and reduce noise.
- Creating a deep learning system that can accurately predict financial time series by combining convolutional neural networks (CNNs) with bi-LSTM architectures.
- Application of denoising techniques to remove high-frequency noise from closing prices, improving the clarity of trends for more reliable predictive modelling.
- Robust performance evaluation using multiple statistical error metrics (MAE, MSE, RMSE) to ensure comprehensive assessment and comparability of model performance.

B. Justification and Novelty

Predicting financial time series remains a continuous challenge, which is why this study is worth conducting. Despite their widespread use, classical models offer limited predicting accuracy due to their inability to capture complex temporal-spatial patterns. To overcome these restrictions, this study developed a DL framework that can learn from raw historical market data without requiring considerable manual pre-processing. Bi-LSTM networks for sequential dependency modelling and CNNs for spatial pattern extraction make up the framework. The novelty lies in the combined use of spatial and temporal modelling techniques, a robust pre-processing pipeline including denoising to reduce market noise, and a comprehensive evaluation using real-world Apple Inc. (AAPL) stock data over five years. The results highlight CNN's superior accuracy in short-term trend prediction, demonstrating its potential for reliable,

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data-driven financial decision-making.

C. Structure of Paper

The following is the outline of the paper: Section II provides a review of the literature on financial time series prediction. Information on data preparation, model designs, and the proposed method is provided in Section III. In Section IV, they show the experimental data and analyse their performance in comparison. Presenting the most important results and discussing potential avenues for further study, Section V wraps up the document.

II. LITERATURE REVIEW

This section presents research on for Forecasting Financial Time Series utilizes diverse machine learning techniques; the summary of these studies is provided in Table I.

Rathi et al. (2025) a variety of ML methods, with a focus on RNN and a tailored LSTM model trained to forecast stock market values based on past stock prices and trading activity. The model's performance is evaluated using a variety of metrics, including the accuracy relative to actuals as defined by training epoch calibration, root mean squared error, and mean absolute error. Results further stress the fact that LSTM models constitute several advantages as predictors because they can seize sequential dependencies of financial time series data and therefore may hold promise for machine learning applications towards forecasting asset values [16].

Money et al. (2024) the issue of limited data in financial time series forecasting; a challenge regularly faced in the context of newly listed companies. While deep learning models excel at learning relevant representations for forecasting, their efficacy is hindered by the need for substantial data. To overcome this limitation, they propose a forecasting model that takes advantage of transfer learning using graph neural networks. The model is constructed based on the assumption that a company's stock price is affected not only by the pertinent economic factors specific to the company but also by the shared class-specific factors within its business sector. The model comprises three neural network modules: i) a module that captures the individual dynamics of a company, ii) a graph neural network (GNN) that captures class-specific dynamics in which the graph is learned from the data, and iii) a module that integrates both the individual and the class-specific dynamics. They propose a novel transfer learning approach to train the GNN, enhancing its efficiency in forecasting time series with limited historical data [17].

Huang et al. (2024) GCN-LSTM-CLUSTING is the foundation of a financial time series risk identification method. Specifically, they use GCN for patch segmentation on MVTS to extract links between patch nodes, LSTM for long-term dependencies, and end-to-end regression models for short-term feature extraction. Finally, clustering methods are used to cluster the potential features of the time series and identify anomalous financial time series [18].

Dandamaev and Sizykh et al.(2023) This study uses the LSTM DL model to apply and evaluate a multivariate multistep forecasting method to the time series of bitcoin prices. After reviewing the many deep learning LSTM implementations of multivariate multistep forecasting, settled on a direct method for creating these forecasts. The input data consists of time series of the price of Bitcoin as well as cumulative stability and drawdowns. Findings suggest that models trained on trading data provide the most accurate short-term predictions. On the other hand, stability provides marginally enhanced accuracy for long-term forecasts [19].

Ma et al. (2022) confirm the BPNN model's predictive capabilities for regression tasks. Using five years' worth of stock composite index data as training data and evaluation metrics like MAPE, MAE, and MSE to evaluate the PEs of the ARIMA and BPNN models, this article concludes that the stock index series accurately represents FTS. This article's BPNN model is more suited for integrated FTS data forecasting, as shown by the results [20].

Kumar and Kumar et al. (2021) The authors propose a stacked LSTM model for reliable stock market forecasting and evaluate it against two additional models, XGBoost and Moving Average (MA). Information derived from the Bombay Stock Exchange in India's historical dataset on Infosys Limited (BSE30) is utilised for the operations. MAPE and RMSE were additional metrics used to assess the model. The proposed stacked LSTM model outperformed the control model, according to the results [21].

Despite significant advancements achieved by DL models such as LSTM, GCN, and hybrid architectures, there are still lots of unanswered questions about financial time series forecasting. Most existing studies focus on specific assets (e.g.,) Bitcoin or a single company’s stock), limiting the generalizability of the models across broader markets. Moreover, while models like GCN and transfer learning offer promising results, their reliance on well-defined

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relational structures or class hierarchies can hinder adaptability to volatile or emerging markets. Additionally, limited attention has been given to integrating external macroeconomic indicators, news sentiment, or high-frequency trading data, which could enhance prediction robustness. Furthermore, few works adequately address data scarcity for newly listed companies or imbalanced datasets, which affects model performance on minority trends. These gaps highlight the need for more generalized, scalable, and explainable models that can handle diverse data sources and varying market conditions.

TABLE I. COMPARATIVE ANALYSIS OF FORECASTING FINANCIAL TIME SERIES USING DEEP LEARNING-BASED MODELS FOR MARKET TREND ANALYSIS

Author	Methodology	Data	Key Findings	Limitation	Future Work
Rathi et al. (2025)	RNN-LSTM model for predicting stock prices based on trade volumes and historical stock prices	Historical stock prices and trading volumes	LSTM effectively captures sequential dependencies in financial time series	Requires large training data and fine-tuning	Extend to other financial instruments and hybrid modelling approaches
Money et al. (2024)	Transfer learning using Graph Neural Networks (GNNs); integrates individual and class-specific data	Limited historical data of newly listed companies	GNN-based transfer learning improves accuracy in low-data scenarios	Relies on well-structured class-based graphs	Explore dynamic graphs and expand to other sectors
Huang et al. (2024)	GCN-LSTM-Clustering for anomaly detection in financial time series	Multivariate financial time series	High anomaly detection accuracy by combining GCN, LSTM, and clustering	Complexity in integration and clustering algorithm	Improve clustering techniques and expand multivariate dimensions
Dandamaev & Sizykh et al. (2023)	Multivariate multistep LSTM forecasting model for Bitcoin prices	Bitcoin price, stability, and drawdown data	Short-term forecasts highly accurate; long-term improved with added stability features	Focus limited to Bitcoin and predefined features	Extend to other cryptocurrencies and add macroeconomic indicators
Ma et al. (2022)	BPNN (Backpropagation Neural Network) model vs. ARIMA for regression forecasting	5 years of stock index historical data	BPNN outperforms ARIMA in predicting financial time series	Limited to single index dataset	Apply BPNN to diversified financial datasets
Kumar & Kumar et al. (2021)	Stacked LSTM model compared with Moving Average and XGBoost	Infosys Limited stock data (BSE30)	Stacked LSTM showed better RMSE and MAPE performance than traditional models	Focused on a single stock (Infosys)	Test on broader stock datasets and integrate external economic indicators

III. METHODOLOGY

The proposed methodology for forecasting financial time series is presented in Figure 1. It integrates data preprocessing, feature engineering, and deep learning models to analyze Apple Inc. (AAPL) stock trends. Historical stock data (2018–2023) undergoes preprocessing, including feature selection (BoW, Word2Vec, LDA, N-grams, and optimization algorithms), normalization using Min-Max Scaler, and dimensionality reduction (PCA, FA, metaheuristics). Boolean encoding, TF-IDF, and embeddings are just a few of the feature representation approaches that can transform selected characteristics into numerical values. The data in a testing set is 20% smaller than that in a training set, which is 80% larger. They provide a CNN-BiLSTM hybrid model In contrast to CNN's ability to extract

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patterns in spatial features, Bi-LSTM can capture sequential relationships in both historical and future contexts. Model performance is evaluated using MAE, MSE, and RMSE, ensuring robust accuracy assessment. This integrated approach enhances predictive capability by combining the strength of convolutional feature extraction with bidirectional temporal learning, aiming to deliver reliable stock market trend forecasts.

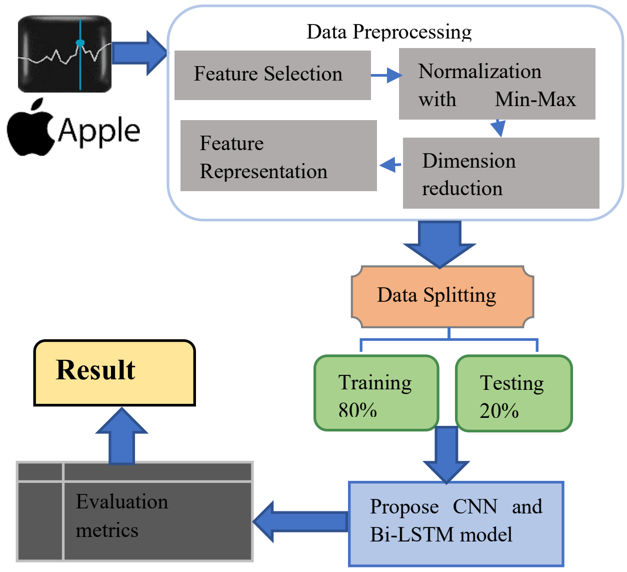

Fig.1. Flowchart of the Forecasting Financial Time Series

The following sections describe each step in detail, as illustrated in the proposed flowchart.

A. Data Collection

This empirical study utilises 1,435 data points derived from AAPL's pricing dataset, including opening price, high price, low price, closing price, adjusted closing price, and volume indicator. The data set encompasses the timeframe from January 2, 2018, to September 14, 2023. Data visualisation aids in comprehending the data:

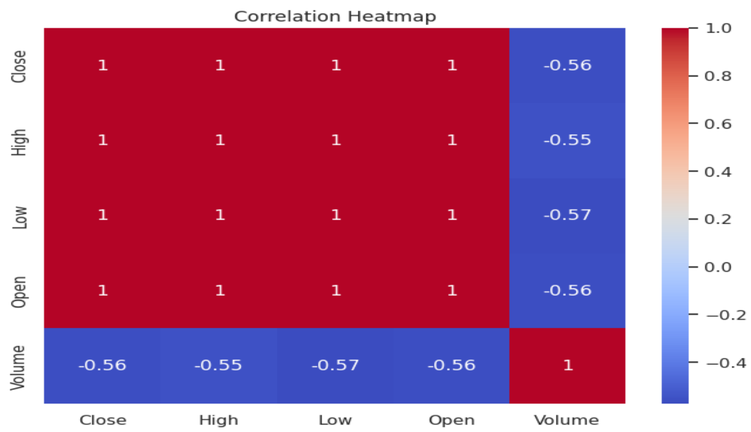

Fig.2. Correlation Heatmap of Apple Data

The correlations among major financial indicators, including Open, High, Low, Close, and Volume, are illustrated in Figure 2, a correlation heatmap of Apple stock data. Due to the interconnected nature of stock market data and the inherent time-series continuity, it is not surprising to see that the Open, High, Low, and Close prices are positively associated with each other (correlation = 1). As a counterpoint, Volume shows a moderately negative connection (-0.55 to -0.57) with all price-related characteristics. Price levels tend to fall marginally in response to rises in trading volume, which may be an indication of selling pressure or market volatility during sessions with a large number of transactions. Overall, the heatmap highlights the strong internal relationship among price features and a noteworthy inverse relationship between price and volume.

Fig.3. Apple Inc. (AAPL) Stock Performance Over 3 Months

Figure 3 displays the 3-month stock performance chart of Apple Inc. (AAPL), showing a consistent upward trend in the stock price from April to the end of July. The stock closed at $384.76 with a 1.21% daily gain and saw a significant after-hours increase to $401.45 (+4.34%), indicating strong market sentiment. The chart highlights key metrics such as a 52-week high of $399.82 and a 52-week low of $192.58, reflecting substantial year-over-year growth. The market cap stands at 1.668T, with a P/E ratio of 30.23 and an EPS of 12.73, suggesting investor confidence and solid earnings.

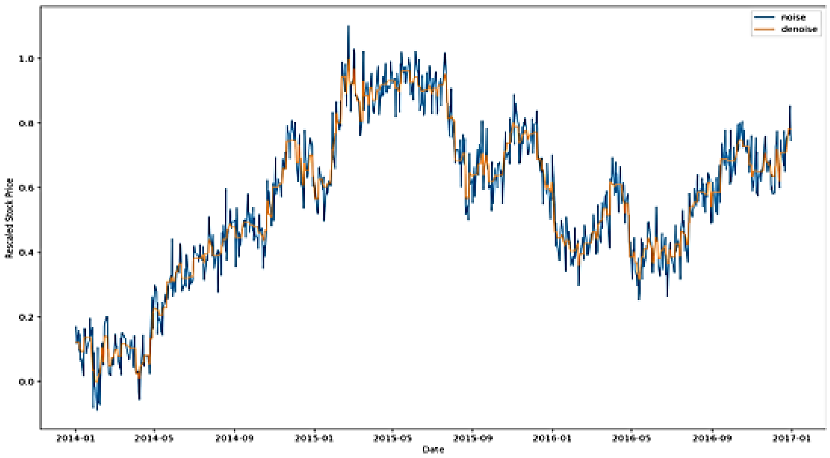

Fig.4. Plots of Apple Closed Price Before and After Denoising

Figure 4 illustrates the comparison between the original noisy Apple stock closing prices and the denoised version over a period spanning from 2014 to early 2017. The blue line represents the raw (noisy) data, which contains short-term fluctuations and volatility typical in stock prices. The orange line shows the smoothed or denoised series, which effectively filters out high-frequency noise while preserving the overall trend and major turning points. To prevent financial time series forecasting algorithms from being fooled by market noise and instead concentrate on fundamental trends, denoising is an essential step.

B. Data pre-processing

The term "data preprocessing" refers to the steps taken to get raw data ready for model training. These steps include cleaning, transforming, normalising, dimensionality lowering, and representing features. The data preprocessing phase was made of several processes in order, or sequences on the basis that they refine the data and prepare or prime it to make it useful to analyze:

1) Feature Selection

Selecting the most useful textual features for making predictions, to reduce noise and increase accuracy, is what feature selection is all about. Some well-known examples include Bag of Words (BoW), Word2Vec for contextual embedding capture [22], Latent Dirichlet Allocation (LDA) for topic generation, N-gram for word local order retention, and

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optimisation methods like GA and PSO.

2) Data Normalization

All the feature values were scaled within the range (0-1) using the MinMaxScaler class of the scikit-learn library's preprocessing library. This normalization prevents the likelihood that the features based on large ranges of numbers overshadow the ones based on small ranges letting all variables play an equal role in the learning process [23]. The data rescaling makes the process of training more practical and stable, accelerates the convergence of machine learning models and increases their overall predictiveness.

$$n = \frac{n - minimum(n)}{maximum(n) - minimum(n)} \qquad (1)$$

Equation (1) is the formula of Min-Max normalization, which data is normalized to the same range (commonly 0 to 1) by subtracting the maximum value and dividing by the range. This aligns all features so that they can be on an equal footing, enhancing model performance and training consistency.

3) Dimension Reduction

The curse of dimensionality can occur where high-dimensional features are inefficient, and less accurate. Metaheuristics like GA or Firefly Optimization (FO) as well as PCA and FA techniques lower the complexity of a data set whilst still maintaining crucial information which not only increases the speed of training but also the quality of prediction.

4) Feature Representation

The chosen characteristics are transformed into values suitable for the machine learning models. While Boolean representation has the word presence in binary form [24], TF-IDF uses term-based weights depending on the term significance, and embeddings, such as Word2Vec or GloVe can derive semantic and relative sense to use in more effective training of the model.

C. Data Splitting

The dataset was divided into two sections: the training set and the testing set. The former was utilised to train the models, while the latter was utilised to evaluate their performance. The ratio of the two sets was 80:20 Most models learn from a big amount of the data using the 80/20 split, which leaves enough data for testing while still allowing the model to learn from a large portion.

D. Propose Convolutional Neural Networks

CNNs are a special kind of DL model developed for handling and understanding data that is grid-like, like images. They have changed the game for picture classification and other computer vision applications since they can automatically detect hierarchical patterns from raw pixel data [25]. The three main layers of a typical CNN are the fully connected, pooling, and convolutional layers. Every layer is displayed collectively in Figure 5.

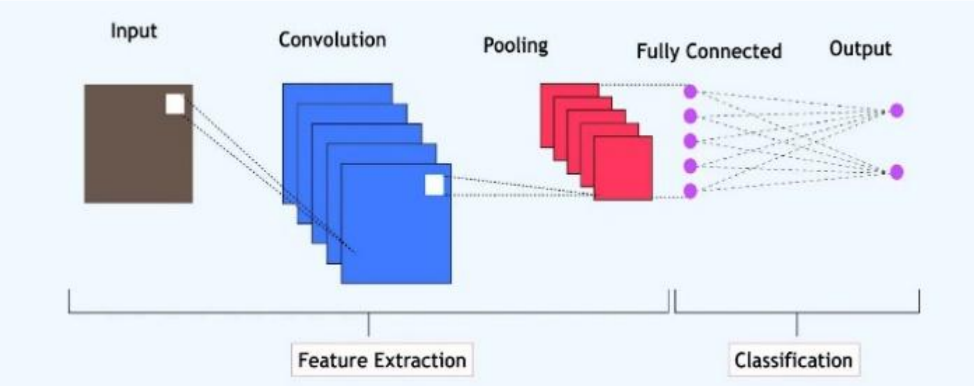

Fig.5. CNN Architecture

Figure 5 shows a CNN architecture that uses convolution and pooling layers to flatten the input image before dense layers process it to get the final output prediction. The following CNN layers are:

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- The convolutional layer creates an activation map by filtering thousands of pixels at a time in the images [26]. Mathematically, the convolution operation for the k-th feature map can be expressed as given in Equation (2):

$$y_{i,j}^{(k)} = f\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} x_{i+m,j+n} \cdot w_{m,n}^{(k)} + b^{(k)}\right) \qquad (2)$$

- This is where the activation at location (i, j) The k-th feature map is represented by $y_{i,j}^{(k)}$, Where x is the input, w is the filter weight, b is the bias, and f (·) is the activation function like ReLU.
- Pooling layer: decreases the convolutional layer's output data to make storage more efficient.

The preceding layers' output is "flattened" into a single vector and conveyed to the stage below using the Fully Linked Layer, which is another term for the fully linked input layer. The first fully connected layer takes feature analysis inputs with weights to get the right label prediction. A fully connected output layer provides the final likelihood of each label.

E. Propose Bi-Long Short-Term Memory

One hidden layer in Bi-LSTM sends data from the past into the future, and the other uses the reverse direction of data flow [27]. Within the framework of DL architectures, Bi-LSTM offers better data representation capabilities than conventional LSTM trees. In light of Equations (3-5), the Bi-LSTM's output is:

$$h^f{}_t = LSTM(x_t, h^f{}_{t-1}) \qquad (3)$$

$$h^b{}_t = LSTM(x_t, h^b{}_{t-1}) \qquad (4)$$

The output layer is then computed as:

$$y_t = W_{hy}^f h_t^f + W_{hy}^b h_t^b + b_o \qquad (5)$$

W_{hy}^f represents the weights that are transferred from the forward layer to the output layer, W_{hy}^b represents the weights that are transferred from the backwards layer to the output layer, and b_o stands for the bias vector of the output layer. By integrating h_t^f and h_t^b, get h_t. At time t, Bi-LSTM learns by merging knowledge from the past and the future, using both sets of data simultaneously.

F. Evaluation Performance Matrix

Regression measures are frequently used to evaluate the efficacy of forecasting models. These measures measure various aspects of the family of errors- some measure the average size of errors, some larger range, and some scale the errors to match the original data such that it is easier to interpret. The combination of using them provides a balanced and satisfactory picture of model performance.

1) MAE

The MAE is an easy indicator of the average of absolute errors in forecast versus actual. This measure directly gives us a measure of the mean size of forecast errors [28], its direction not being relevant. Simply speaking, the MAE is the average of the absolute forecast error (Equation (6)) and the lower the absolute error the better forecast.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} y_i - x_i \qquad (6)$$

2) MSE

Standard deviations between actual and anticipated values are averaged to get the MSE, which is a useful statistic for evaluating regression models. The large outliers are more favoured in this measure than the slight ones because the errors are squared before averaging acts upon them, and as a result, this metric is sensitive to outlier values (Equation

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(7)).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \qquad (7)$$

3) *RMSE*

The RMSE, a version of the MSE, was still used. An indicator of the normal magnitude of prediction errors proportional to real values, the RMSE is obtained by taking the square root of the MSE. A popular statistic, the root-mean-squared error (RMSE) can be expressed as a percentage of the predictability of a forecast and is easy to understand and use (Equation (8)). Being measured on the same scale makes it easy to interpret and compare the RMSE to the actual values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^p)^2} \qquad (8)$$

All of these metrics added together give the impression of a more complex evaluation system for the prediction models' precision and consistency.

IV. Results and discussion

Deep learning-based models transform how market trends should be described through forecasting financial time series, as these models enhance the predictive analytics precision and power. This research work offers comparative analysis of CNN and Bi-LSTM models in the framework of financial market forecasting to determine their effectiveness in recognition of complex temporal patterns peculiar to financial records. During the research, all experiments were run using Python with TensorFlow and Keras frameworks, utilising a high-performance computing environment optimised for large-scale time series. Table II shows the comparison of the CNN model with the Bi-LSTM. The CNN has a lower MAE of 2.0988, MSE of 7.9001 and RMSE of 2.8017 in contrast to Bi-LSTM 3.9967, 34.2865 and 5.8554 respectively. These results prove that the CNN model has a better ability to extract valuable characteristics in the time series financial data to achieve more accurate market trend forecasts. The results highlight the possibility of deep learning models based on CNN as a method to improve financial decision-making.

TABLE II. Performance Of CNN And Bi-LSTM Models On Apple Data

Matrix	CNN	Bi-LSTM
MAE	2.0988	3.9967
MSE	7.9001	34.2865
RMSE	2.8017	5.8554

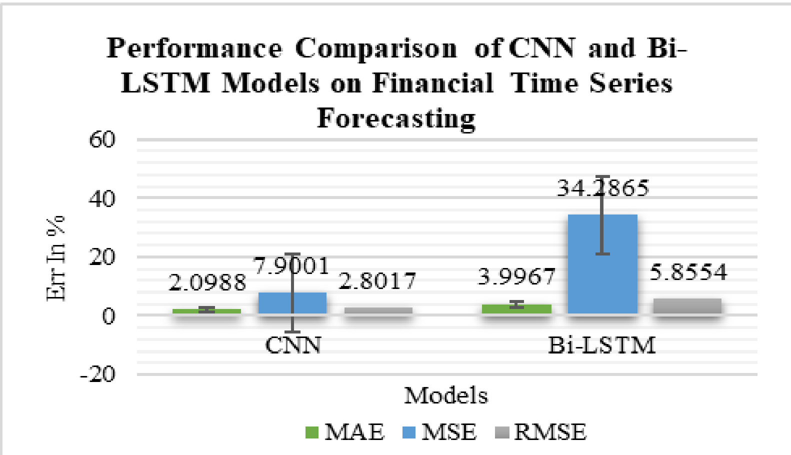

Fig.6. Performance Comparison of CNN and Bi-LSTM Models

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Figure 6 is a bar chart that compares CNN and Bi-LSTM, two deep learning models, in terms of their forecasting accuracy of financial time series. Measures such as MSE, RMSE, and MAE are used to compare the models. The Bi-LSTM model has higher error rates in all three metrics than the CNN model, with an MSE of about 34.2. This implies that CNN model can make better predictions and is more applicable to the task of market trend analysis because it induces a smaller error in predicting the model.

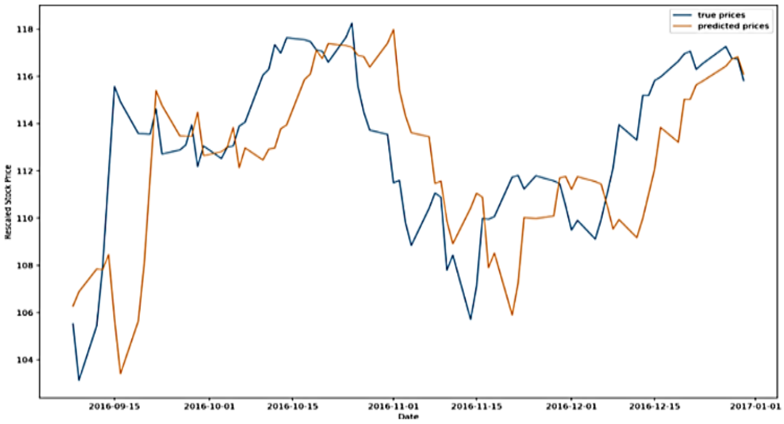

Fig.7. Plots of Predicting Stock Prices for CNN Model

Figure 7 shows the graph of the predicted prices of the company's stock in the CNN model versus the real stock price of Apple in a given period of time within mid-September to early January 2017. The blue line represents the real prices, whereas the orange line represents the forecasted ones. In general, the CNN model can track the general trend of the stock, representing two major tendencies, namely, the up and down trends. Nonetheless, a few deviations can be observed between the predicted and the obtained (actual) prices particularly around high rates of change, where the model lags or overshoots. Irrespective of these variations, the CNN model shows a sensible predictive correlation with the real price movement, and it could hence be a forecaster in the near-term prediction of stock price.

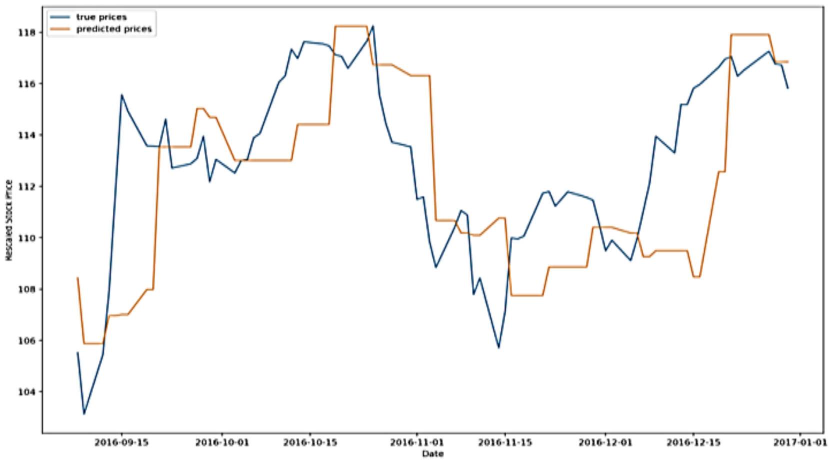

Fig.8. Plots of Predicting Stock Prices for Bi-LSTM

Figure 8 shows the results of the Bi-LSTM model for predicting the yearly stock price of Apple from mid-September 2016 to early January 2017. The stock's actual prices are shown in blue on the graph, while the model's predicted values are shown in orange. Predicted values are less smooth and more step-like than observed trend, suggesting that Bi-LSTM model failed to capture the data's rapid and frequent changes as well as its finer-grained patterns. Though the direction of the general trend is followed to some extent, the forecasts are not accurate in times of volatile prices. This is an indication that the Bi-LSTM model might not have performed well when identifying short-term volatility in this case scenario and that this could be as a result of excessive smoothing or shortcomings of sequence learning setup.

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A. Comparative Analysis

RMSE is used as an evaluation metric in this section to compare the deep learning models for financial time series prediction utilised in market trend research. According to Table III, the CNN model had the lowest RMSE of 2.8017, which suggests that it is very good at extracting complicated spatial features and patterns from financial data in order to make accurate predictions about market trends. The second model with quite impressive levels of performance is the Bi-directional LSTM (Bi-LSTM) model, which had an RMSE of 5.8554, and thus, performed well in modelling sequential dependencies in the time series as compared to other methods; however, the prediction is not as precise as the CNN model. Other conventional statistical (ARIMA) and neural network (RNN) models presented a relatively large value of RMSE 16.01 and 10.69, respectively, possibly due to their inability to capture non-linear and temporal patterns in the market data as compared to SNN. Such findings further support the applicability of CNN-based architectures in deep learning methods to the forecasting of financial time series data, enhancing the knowledge base for analysing market trends and strategies to inform effective investments.

TABLE III. COMPARISON OF DEEP LEARNING MODELS FOR FORECASTING FINANCIAL TIME SERIES

Models	RMSE
CNN	2.8017
Bi-LSTM	5.8554
ARIMA[29]	16.01
RNN[30]	10.69

The CNN and Bi-LSTM models, both suggested to be used in financial time series forecasting and market trend prediction, showed different advantages in their predictions. The CNN model performed very well in the extraction of complex spatial features that are precise and reliable forecasts of strategic investments. In the meantime, the Bi-LSTM model performed well by providing the sequential dependence on the information and supplying great predictive power. These deep learning techniques were more effective than conventional ones, such as ARIMA and RNN, since they captured nonlinear and time-varying dynamics in financial markets and consequently were the most effective means of predicting trends in the market.

V. CONCLUSION AND FUTURE SCOPE

Financial time series are particularly difficult to predict because of volatility and noise, as well as nonlinear dependencies. The architecture of DL, such as CNN and Bi-LSTM, can overcome these problems because they still automatically recognise spatio-temporal patterns without much manual feature engineering. In this article, that is, a systematic pre-processing pipeline (that is, feature selection, normalization, dimensionality reduction, and denoising), was implemented on the data of the AAPL stock from 2018 to 2023. The CNN model demonstrated a good predictive performance: it has MAE: 2,0988, MSE: 7.9001, RMSE: 2.8017, indicating that the model can recognise short-term market trends rather well. The Bi-LSTM model (MAE 3.9967, MSE 34.2865 and RMSE 5.8554) proved to be effective in capturing sequential dependencies but it was not accurate when there was the need to fluctuate swiftly. Conventional ARIMA and RNN models were not as appropriate in complex, nonstationary nature of the financial data.

In the future, research must explore a combination of CNN with other branches of LSTM, a hybrid CNN-Bi-LSTM, to extract spatial features with long-range temporal modelling. Robustness may be enhanced with the addition of macroeconomic indicators, opinion analysis, and an alternative set of datasets. Testing across multiple assets, sectors, and time horizons would help assess generalizability, while explainable AI tools could enhance transparency, enabling more informed and trustworthy decisions in data-driven financial strategies.

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