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RESEARCH PAPER

Comprehensive Analysis of Deep Learning Architectures for Temporal Prediction in Financial Markets

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***Abstract*—A set of data arranged by the time of the year is referred to as a time series, and the standard method of the presentation of the changes in the thing during time. To help in decision-making, time series forecasting tries to predict the future values of time series by attempting to predict how these values alter with time. Four large companies on the Nasdaq index are Amazon, Google, Microsoft and Apple. In this work, perform an analysis of architectural deep learning models in the prediction of stock prices on the financial market, based on its stock projections. This included the normalization of data, trimming of outliers and sentimenting of data since getting Ticker Stock via Yahoo Finance until April 2025. Four models were analyzed using traditional measures, including LSTM, GRU, RNN and ARIMA. RMSE, MSE and MAE were performance indicators. It has been shown that LSTM models can perform better than rival models, when required to model the long-term dependencies of time series data. Sentiment analysis and consideration of technology substantially boost the ability of the model to predict. It is also seen that deep learning models have the potential to predict financial time series, and it is possible to propose methods to enhance the present system of predicting market volatility.**

Keywords—LSTM, GRU, RNN, ARIMA, Stock Price Prediction, Financial Time Series, Deep Learning, Sentiment Analysis, Temporal Forecast, Yahoo Finance, NASDAQ, RMSE, MSE, MAE.

I. INTRODUCTION

The most important constituent of any global economy is the financial markets, which also happen to be the major player in the distribution of capital and is also the manager of risks. They provide an energetic platform to buy and sell financial products such as shares and bonds, currency and derivative [1][2][3]. Their stability and effectiveness is paramount with regard to the impact of growth of the economy, investment opportunity and wellness of the global financial system in smooth operation.

Stock price prediction is one of the key activities of financial forecasting because it can present an abundance of useful information to traders, investors, and institutions. The correct predictions result into prudent investment, improved risk mitigation actions, and exposure of trade gains that can be beneficial [4][5]. Still, since much of stock performance is tied to various factors including macroeconomic indicators, geopolitical developments, corporate earnings and investor moods the task of speculating the stock movement is bound to be challenging [6]. All these make the financial markets so non-linear, non-stationary, and highly volatile.

The ARIMA and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models are examples of the statistical models traditionally used to forecast stock prices from historical data [7][8][9]. Though they are effective in describing linear relationships and stationary data these models fail most of the time when faced by sudden market changes and complex non-linear trends. In addition, they involve a lot of manual involvement in choice of features and defining of model architecture.

Machine learning (ML) algorithms, particularly deep learning (DL) models, have demonstrated the ability to autonomously learn complex data structures, in contrast. In contrast to traditional models, deep learning methods allow discovering temporal and non-linear dependencies without making any pre-fixed assumption [10][11]. Some examples of these types of neural networks include RNNs, LSTMs, and GRUs, or Gated Recurrent Units. They perfect for future stock market forecasts because of their ability to learn from sequential and time-dependent data.

An overview of RNN, LSTM, and GRU models is provided in the paper, which compares them when applied to the objective of predicting stock values using real financial data. Their precision, power, and computational speed are given special attention. As an added bonus, the article delves into how several LSTM model variants including vanilla, stacked, and bidirectional LSTM, impact predictive performance [12][13]. A number of important hyperparameters are investigated in relation to these architectural variants. Batch size, periods, optimizers (such as Adam, Adadelta, RMSprop, and SoftMax), activation functions (such as sigmoid and tanh), and network depth are all examples of such parameters. It is very important to learn how to tune hyperparameter settings and architectural decisions to optimize predictive accuracy [14][15]. Even though automatic hyperparameter tuning methods exist, in most cases they lack predictability and do not allow to understand the relative values of parameters and their interaction. By investigating the areas, this paper helps to develop the trend in deep learning-based forecasting techniques and provides financial analysts with better means of working in the conditions of volatile market conditions.

A. *Significance and Contribution*

Efficiently, it tackles the difficult problem of accurately predicting financial time series in extremely volatile stock markets using deep learning models. Model selection for real-world financial prediction tasks is explored in the paper by comparing several architectures, including LSTM, GRU, RNN, and ARIMA. The model's comprehension of quantitative and qualitative market drivers is improved through the combination of sentiment analysis with historical stock data. This research would be practically valuable to investors, analysts, and algorithmic trading systems because it utilizes real-world NASDAQ tech stock data, is subject to intensive preparation, and is subjected to sound evaluation. The use of data-driven decision-making in financial analytics is becoming a trend, and this work is contributing to the literature. The main improvements are:

- This uses a real-world and high-resolution dataset of daily stock prices (AAPL, GOOG, MSFT, AMZN) provided by Yahoo Finance (a complete year, April 2024 April 2025), which guarantees relevance and time-sensitivity to the current trends in the market.
- Performs comprehensive missing value processing and outlier removal, which makes data consistent and minimizes the effects of outliers on model learning.
- Integrates sentiment analysis and Min-Max normalization so the model may learn from quantitative and qualitative market signals.
- Implements and compares multiple DL models, with a focus on LSTM architecture structured with dropout and dual LSTM layers to enhance temporal feature extraction.
- Evaluates models using a comprehensive set of performance metrics including RMSE, MSE, and MAE, providing a robust framework for comparison and validation.
- Offers a quantitative comparison of classical vs. deep learning models, highlighting the superiority of LSTM in capturing long-term dependencies and improving financial forecasting accuracy.
- Provides a scalable and generalizable forecasting framework that can be adapted to other assets, time intervals, and financial indicators, supporting future research and financial system development.

B. *Justification and Novelty*

The rapid fluctuations and inherent volatility of financial markets make accurate forecasting a challenging yet critical task for investors, analysts, and automated trading systems. The non-linear and dynamic patterns found in stock price fluctuations are often not captured by traditional statistical models like ARIMA. This study is justified by its focus on leveraging advanced deep learning architectures specifically LSTM, GRU, and RNN to overcome these limitations. Additionally, integrating sentiment analysis enriches the input space with qualitative insights, reflecting real-world investor sentiment. The use of real-time stock data from major NASDAQ-listed companies ensures practical relevance, while comprehensive model evaluation helps determine the most effective forecasting strategy. This study is therefore crucial for connecting theoretical financial forecasting models with practical financial applications.

C. *Structure of the Paper*

The Structure of the paper is as follows: In Section II, cover relevant research on deep learning architectures for financial market temporal forecasting. Methods, datasets, and preparation procedures are described in Section III. The experimental findings and a comparison of the forecasting models are presented in Section IV. Section V wraps up the research by reviewing the main points and discussing their significance for financial forecasting.

II. LITERATURE REVIEW

This section reviews key research articles on temporal forecasting in financial markets using deep learning approaches. Table I highlights each paper's title, methodology, dataset used (e.g., Yahoo Finance), key findings, and noted limitations or suggested directions for future work.

Sao et al. (2025) makes use of LSTM and combines GAN networks. The LSTM exploits the historical stock price data for temporal dependencies, whereas GAN produces realistic synthetic data to augment model training. The Stock Market Dataset was used, and Python with the TensorFlow and PyTorch frameworks were used to build the suggested model. An RMSE of 0.0125, an MAE of 0.0093, and an R2 of 0.926 showed that the hybrid LSTM-GAN model did better than both LSTM and standard forecasting models. This work greatly enhances the accuracy of forecasting, avoids overfitting, and promotes performance in volatile market environments. The results are extremely useful for investors, financial analysts, and trading platforms because they can make better predictions [16].

Zareeihemat et al. (2025) scope loss function deftly navigates the tension between over-reliance on known data and an emphasis on discovering novel patterns, achieving an optimal compromise between the two extremes. To further enhance the model's robustness and effectiveness across various market circumstances, the hyperparameters are fine-tuned using the custom ABC algorithm. attained an impressive 90.427% accuracy percentage when EWS was evaluated using market data from Korea. This verification shows that the algorithm is capable of making reliable market predictions. By illuminating the dynamics between the stock and housing markets, particularly during bubbles, research contributes to the expanding corpus of information in financial analytics [17].

Islam et al. (2024) current method involves using "predictive analysis," which is similar to predicting future financial patterns. There are a lot of time series data in Financial Aid (FA), but there aren't a tone of historical datasets and financial data is quite dimensional, so it's hard to build good prediction models that are accurate and efficient with runtime and memory. For these difficult jobs, use pre-trained foundation models. Utilizing cutting-edge time series models such as pre-trained LLMs with GPT-2 as its foundation, transformers, and linear models, prove that they can surpass conventional methods, even when fine-tuned "few-shot" or "zero-shot" is completely absent. benchmark study demonstrates the feasibility of employing LLMs for limited financial datasets by combining financial aid with seven additional time series tasks [18].

Irwanto et al. (2024) analysis emphasizes the importance of matching model architectures to data properties. compare models' performance with five-day window for predict one-day prediction output. Interestingly, the single-layer LSTM outperforms the 1D-CNN even with similar hyperparameters, showcasing its strength in capturing long-term temporal dependencies crucial for nickel prices. While the 1D-CNN excels at identifying short-term patterns, its limited receptive field hinders long-term dependence. Taking into consideration the power of each of two models, suggest the exploration of hybrids of LSTM excellence and CNN excellence in being improved in financial forecasting. The finding of the experiment demonstrates that a single-layer LSTM is more efficient as compared to a 1D-CNN with similar parameters [19].

Agarwal et al. (2024) They consider four RNN models, Simple RNN, LSTM, GRU, and BiRNN in this paper according to their result in predicting the values of the Nifty 50 index in the Indian NSE between 2000 and 2021. This big dataset encompasses twenty years of history, and that provides sufficient time to compare each model with three indicators, MAE, MAPE, and MSE. An evaluation of the data available shows that the BiRNN model beats its rivals in terms of MAE, MAPE and MSE among other predictive quality indicators. The main value of the study to the literature on RNN models, and in particular the BiRNN model and its application in stock price prediction, specifically of the Nifty 50 index, lies in its contribution to the body of literature. These findings do not merely confirm the assumption that BiRNN is a promising model in forecasting stock prices, but it also initiates new lines of future research in this area [20].

K et al. (2023) data points are not only the end of day prices but the volume of trading along with numerous technical indicators like momentum, RSI, moving averages. There is ample data given that is necessary to construct and verify the prediction models. An approach to sequence-to-sequence LSTMS has the sole goal of understanding the underlying time dynamics of financial data. The rolling window approach was employed by the researchers to predict the prediction of the end of the next trading day through a given set of observations over a day. LSTMS architecture (with dropout layers in between) has the input layers, multiple LSTMS units, and output layers to mitigate the overfitting issue. They contrasted the LSTMS approach with more conventional approaches such as ARIMA and a simple RNN model in a bid to come up with a compromise [21].

Chandrashekar et al. (2023) An improved financial forecasting tool is achieved by combining ARIMA with Gradient Boosting. The ARIMA model is used to get the time series data ready for extracting the relationship between the variables across time. By putting the residuals of the ARIMA model into the Gradient Boosting method, non-linear functions may be learnt from the data. Their use of actual S&P 500 index data to prove the solution's effectiveness is impressive. When compared to using just ARIMA or Gradient Boosting, the proposed approach outperformed both in terms of accuracy and prediction. Overall, the planned strategy achieved a far higher level of accuracy, at 96.4% [22].

Shabani et al. (2022) capacity to zero in on critical temporal events has led to the recent rise in popularity of a brain layer architecture known as the temporal attention mechanism. To improve the underlying neural network's capacity to concentrate on numerous temporal occurrences concurrently, present a neural layer that draws from the concepts of multi-head attention and temporal attention in this research. Using massive amounts of data from the limit-order book market to predict the future of mid-price fluctuations, prove that method is effective. In comparison to baseline models, experimental results demonstrate that multi-head temporal attention modules improve prediction capabilities [23].

TABLE I. SUMMARY OF BACKGROUND STUDY FOR FORECASTING IN FINANCIAL MARKETS USING DEEP LEARNING ARCHITECTURES

Author	Methods	Dataset	Key Findings	Limitations & Future Work
Sao et al. (2025)	LSTM + GAN	Stock Market Dataset (Yahoo Finance)	Hybrid model improved performance (RMSE: 0.0125, MAE: 0.0093, R^2: 0.926)	Suggests broader validation across more markets
Zareeihemat et al. (2025)	Custom loss function + ABC optimization	Korean market data	Achieved 90.42% accuracy; optimized generalizability	Focused on housing-stock market interactions, may not generalize globally
Islam et al. (2024)	Pre-trained LLMs (GPT-2), Transformers	Financial Aid (FA) + 7 time series tasks	Outperformed traditional models in few-shot settings	Limited historical data; requires further testing on real-time deployment
Irwanto et al. (2024)	Single-layer LSTM vs. 1D-CNN	Nickel price data	CNN excels in short-term patterns, whereas LSTM excels with long-term dependencies	Encourages hybrid LSTM-CNN integration
Agarwal et al. (2024)	RNN, LSTM, GRU, BiRNN	Nifty 50 (2000–2021)	BiRNN outperformed others in MAE, MAPE, and MSE	Suggests extending comparison to global indices
K et al. (2023)	Seq2Seq LSTM, ARIMA, RNN	Stock prices + volume + RSI + MA	LSTMS model with dropout outperformed ARIMA and basic RNN	Further exploration of feature combinations and hybrid setups needed
Chandrashekar et al. (2023)	ARIMA + Gradient Boosting	S&P 500 index	Hybrid ARIMA+GB model achieved 96.4% accuracy	Model performance depends on effective residual extraction
Shabani et al. (2022)	Multi-head Temporal Attention	Limit-order book data	Improved directional prediction of mid-price using temporal attention	High computational cost; scope for efficiency improvements

III. METHODOLOGY

A thorough pipeline for predicting stock prices using DL models is depicted in the methodology flowchart. To begin, it collect stock data from Yahoo Finance that covers the past several years. It targets technologically based firms listed on NASDAQ which include Amazon, Google, Microsoft and Apple. Next, the Min-Max scaling occurs to normalize the data in order to make neural networks a more efficient learner, which exerts all data values into a shared range. The second step involves applying sentiment analysis on the data to ensure that the data is able to capture both numerical and qualitative market signals. The second step is the engineering, which involves extraction and organization of the pertinent features to enter the model. Then, split the data into half and test it on 80 percent of the data (training) and 20 percent of the data (testing) to analyze the model prognosis. In particular, the

LSTM network should be used for the bulk of the modelling because of its famed capacity to capture the temporal correlations of financial time series. Last but not least, the data is examined to determine how reliable and accurate the model's predictions are. Common metrics utilized in this assessment comprise RMSE, MSE, and MAE. Figure 1 shows the Flowchart for Temporal Forecasting in Financial Markets Using Deep Learning Architectures.

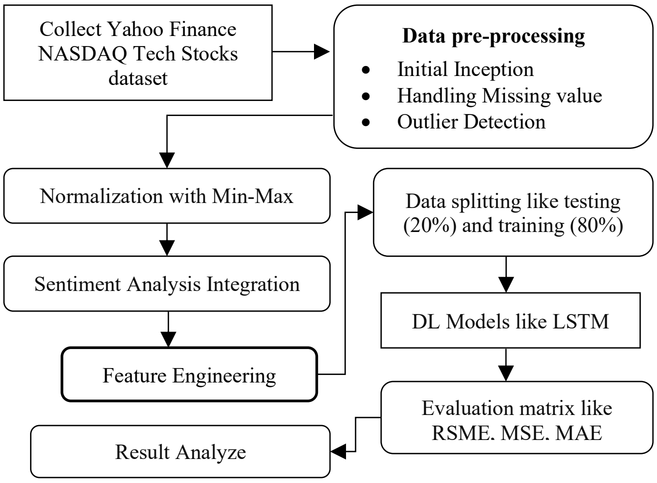

Fig. 1. Flowchart for Temporal Forecasting in Financial Markets Using Deep Learning Architectures

The following steps of proposed methodology are briefly discussing in below:

A. Data Collection

This dataset compiles NASDAQ-listed tech giants Apple, Google, Microsoft, and Amazon's market data from the past. The python module yfinance, which offers easy access to current and extensive financial statistics, was used to extract the from Yahoo Finance. From April 2024 through April 2025, the dataset covers an entire trade year and contains the following important information for every trading day:

- **Open:** The initial valuation of a digital stock on a specific trading day.
- **High:** The session's peak price before the market closed.
- **Low:** This is the session's lowest pricing.
- **Close:** This is the trade's closing price.
- **Volume:** The sum of all share trades made all day.

The consensus value of the stock as of each trading day's end is reflected in the closing price, thus that is the one predicting. The consistency and informativeness of this variable about daily market mood make it a popular choice for financial forecasting.

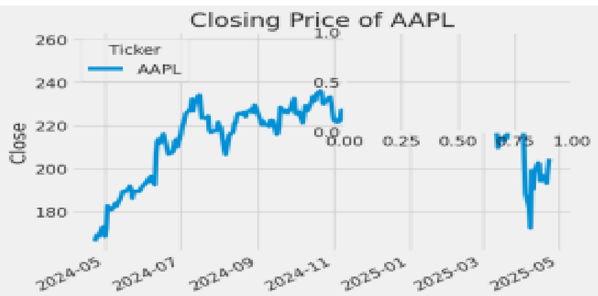

Fig. 2. The Apple Stock Market's Final Price Movements from April 2024 to April 2025.

Figure 2 shows the closing price trend of Apple Inc. (AAPL) from May 2024 to May 2025. The initial rise of the stock price demonstrates healthy growth as it reaches more than $240 after being about 170 dollars. Then it goes up and down and falls sharply at the beginning of March 2025, which may be as a result of the market being volatile or caused by external factors. An incomplete recovery is witnessed in April- May 2025. Also, in the graph there were some unplanned labels on the Y-axis (0.0 to 1.0) probably during normalization or a plotting detail. Generally, the chart portrays normal stock market activities including an upswing, fluctuation and correction.

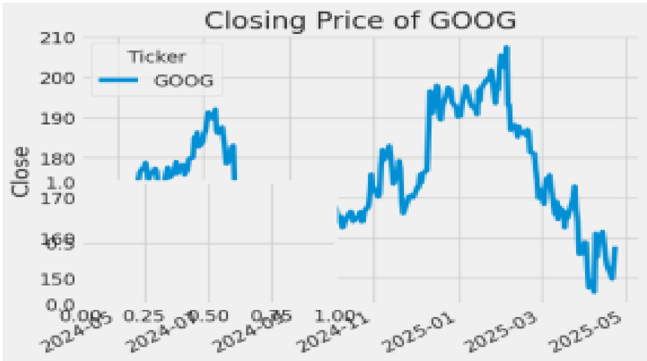

Fig. 3. Closing Price Trends for Google Stock (April 2024–April 2025).

Figure 3 illustrates the trend of the closing price of the stock of Google (GOOG) between May 2024 and May 2025. Its price starts an increment by approximately making the price shoot up to about 200 dollars by early 2025, with some signs of growth till late 2024. It then dips with an appreciable volatility rising to the highest point in early 2025 and then abruptly and steadily drops to just below $150 by May 2025. In the x-axis, there are a few mis abstracted or replicated tick labels probably because of a plot problem. Overall, the chart reflects a rise-fall pattern with high volatility, suggesting a potentially unstable market period for Google stock.

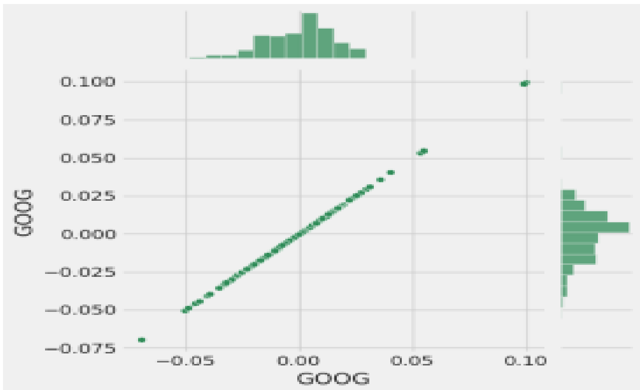

Fig. 4. Daily return scatter plot comparing Google with Google.

Figure 4 is a combined distribution graphic that shows how actual and expected returns on Google (GOOG) stock relate to one another. The scatter points lie almost perfectly along the diagonal, indicating a strong correlation and highly accurate predictions. The top and right histograms represent the distributions of the actual and predicted values respectively, both appearing centred around zero, which is typical for daily stock returns. Overall, the plot demonstrates that the model predicts GOOG returns with high precision and minimal bias.

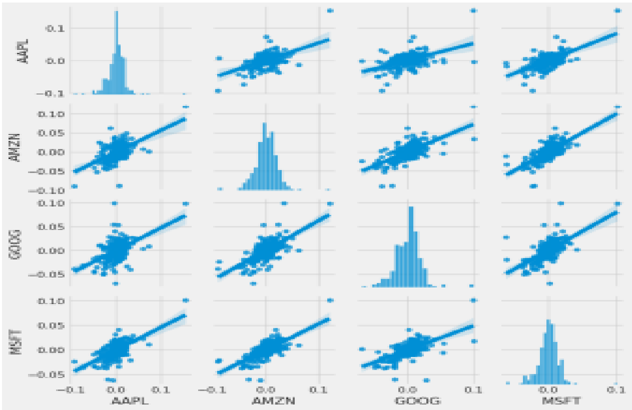

Fig. 5. Pairplot of daily returns for Apple, Google, Microsoft, and Amazon, with regression lines showing trends.

A pair plot displaying the correlations between the daily returns of four big stocks: AAPL (Apple), AMZN (Amazon), GOOG (Google), and MSFT (Microsoft) is visualized in Figure 5. Returns for each stock are shown by diagonal histograms, which show normal behaviour with most of the distribution centred around zero. The scatter plots below the diagonal show that the stock returns are positively correlated with one another, and the trend lines indicate that these tech stocks tend to move in the same direction. This provides data for co-movement analysis and portfolio diversification that points to high inter-stock correlation.

B. Data Preprocessing

In the context of Temporal Forecasting in Financial Markets pre-processing plays a crucial role due to the inherent noise, volatility, and inconsistencies in financial time series data. The most crucial procedures are the preliminary examination of stock price dynamics, the treatment of the missing data with dropna () and forward-fill functions, and outliers' identification and elimination to reduce the influence of the market abnormalities. Moreover, irrelevant features had been eliminated in order to trim the data. The dimensionality reduction was implemented using such methods as the clustering of correlated assets or indicators so that they lowered the number of dimensions to generalize the model better. These pre-processing comply with the best literature in making financial predictions. These are measures in accordance with current knowledge articles to improve model performance and applicability:

- **Initial Inspection:** The dataset was then analysed with the. head (), info () and. describes () functions to provide insights into the structure and data types of the dataset and their summary statistics.
- **Missing values:** The initial stage in cleaning up the data include managing the missing values. The function, isnull (). sum () was used to identify missing data. Null values were excluded in the records using the dropna () method to ensure validity of data [24].
- **Handling Missing Values:** Any occurrence of missing values is dropped by the use of dropna () function in the pandas library. A complete and clean dataset is used to train the model, which reduces the chances of biased learning or inaccurate prediction.
- **Outlier Detection and Treatment:** An outlier's presence can greatly affect the accuracy of a learning process. use a z-score thresholding method to fix this. data points with z-scores exceeding ±3 standard deviations from the mean should be removed or capped as they are deemed outliers and their influence is diminished.

C. Normalization with Min-Max Scaler

Using Min-Max normalisation on the emotion score and closing price elements improves the efficiency of gradient-based optimisation and ensures that all features are used equally during learning. Within equation (1), find the normalization formula in use.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

D. Data Splitting

Two subsets are created from the combined dataset in order to test the generalizability of the model:

- **Training Set (80%):** Used to train the LSTM model; spans April 2024–January 2025.
- **Testing Set (20%):** Includes the months of February through April of 2025 and is set aside for testing how well the model predicts using new data.

E. Feature Engineering

Traders and analysts often utilize moving averages (MAs) as technical indicators to supplement raw closing prices and sentiment ratings in their datasets [25]. The purpose of moving averages (MAs) is to reveal long-term price trends by smoothing out short-term variations. Apple, Google, Microsoft, and Amazon's stock prices are tracked in this paper using moving averages:

- The 10-day moving average (MA10) is a useful tool for capturing short-term momentum and measuring how prices have changed recently.
- The MA20 or 20 Day Moving Average gives a less dramatic image of the trends within the upcoming 20 days.
- The 50-Day Moving Average (MA50) is a handy indicator of market mood and change of trend over the long-term.

F. Classification with LSTM Model

The research uses a LSTM NN, a type of prediction model, implemented using the DL package of Kera. LSTM networks are better in time-series prediction than RNNs since they can retain the relationship over time and are not prone to vanishing gradient problem [26]. A significant amount of recent research in the field of financial time-series forecasting has focused on LSTM networks because it has been demonstrated to be exceptionally useful in reducing the dependence on market data in the long run. To enable the long-term gathering of vital information, the distinctive mechanism and specific architecture of LSTM enable one to control the flow of information within the network in finer detail. This is made possible by the incorporation of memory cells and special gates like input, forget and output gates. According to research, LSTM outperforms other approaches as it can process numerous criteria including market risk premium, size, and book-to-market ratio and intricate time trends in ETF returns on a daily basis [27][28]. LSTM design suggests a memory cell with long-term memory capability [29]. There are three gates in each LSTM cell:

- **Input Gate:** Sets the rate at which data can be inserted into the memory cell.

- **Forget Gate:** Selects which memories to keep and which to erase based on their previous states.
- **Output Gate:** Adapts the output to the current state of the cells.

The fundamental component of prediction model is a typical LSTM cell, whose internal architecture is shown in Figure 6. The following is the organizational framework of the model [30][31]:

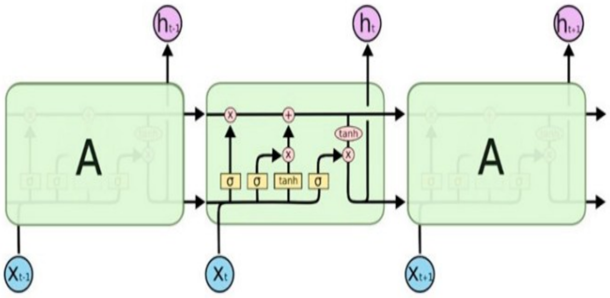

Fig. 6. The internal structure of an LSTM

Mathematically, the hidden state h_t at time step t is computed as Equation (2):

$$h_t = tanh(W_{xh}X_t + W_{hh}h_{t-1} + b_h) \tag{2}$$

In this case, Xt stands for the input at time t, h_{t-1} for the hidden state from the prior time step, W_{xh} and W_{hh}, for the weights and bias terms, and bh for the reverse.

G. Evaluation Metrics

Several commonly used regression criteria in financial forecasting were employed to assess the deep learning models' performance: The following are some measurements of performance: [32]:

1) Root Mean Squared Error (RMSE)

RMSE is a way to measure error in the original scale of stock prices. It is often used in financial uses because it is easy to understand (see Equation (3)).

$$\text{PMΣE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2} \tag{3}$$

2) Mean Squared Error (MSE)

MSE is more susceptible to outliers, which can have a big impact on stock price forecasts, because it prioritises bigger errors (see to Equation (4)).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2 \tag{4}$$

3) Mean Absolute Error (MAE)

MAE gives a simple way to evaluate accuracy since it takes into account both big and little errors equally when measuring the average magnitude of prediction errors. The following (refer to Equation (5)) gives the MAE:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

These matrices are utilized to determine the machine and DL models.

IV. Result Analysis and Discussion

This section shows the outcomes of tests using Deep Learning design to guess when the financial markets open and close. A 3.6 GHz Intel Core i7 processor, 32 GB of RAM, and Windows 11 were used to train and test this system. MAE, MSE, and RMSE were used to measure performance. Using past data from Yahoo Finance, Table II shows how well different deep learning models, such as LSTM, did at predicting stock prices.

TABLE II. Performance of Deep Learning Models on Financial Time Series Data for Stock Price Forecasting

Model	RMSE	MSE	MAE
LSTM	7.22	52.14	5.89

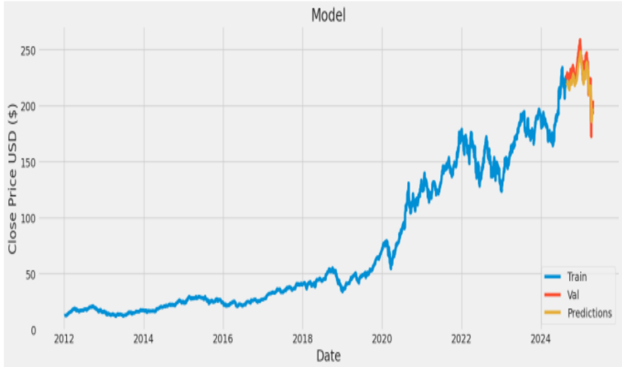

Fig. 7. Comparison of Actual vs. Predicted Closing Prices for Apple Stock.

Figure 7 illustrates the stock price forecasting performance using a deep learning model, visualized across three phases: training (blue), validation (red), and prediction (orange). On one side, have the time series (Date) from 2012–2025, while on the other, and have the closing price in USD. The algorithm catches both short-term volatility and long-term positive tendencies in stock prices by training on historical data. The predicted values provide strong evidence of successful temporal learning and generalization, closely matching the validation data. Such a plot demonstrates that the model can work on non-stationary time series and learn price momentum to be able to deliver an accurate financial prediction.

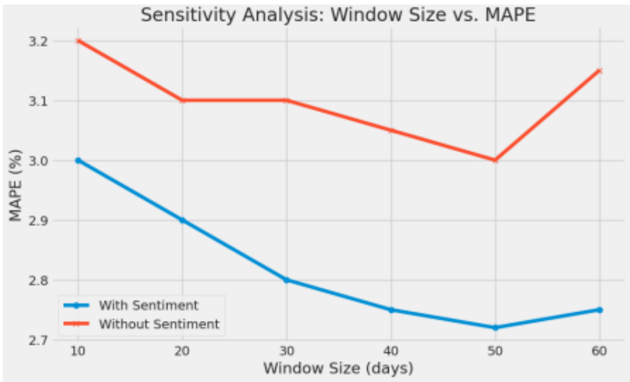

Fig. 8. Effect of Window Size on MAPE for Apple Stock with and without Sentiment Integration.

The stock price forecasting models are subjected to a sensitivity analysis in Figure. 8, which considers the MAPE and window size (in days). One case involves sentiment analysis (blue line), whereas the other does not (red line). The sentiment model always has better values of MAPE in the model thus has better predictive performance. More importantly, the best results are achieved when the window is 50 days, and the model based on sentiment achieves minimum MAPE of about 2.7%. The significance of adjusting the window size and including sentiment traits into financial time series modelling for improved forecasting accuracy is highlighted in this discussion.

A. Comparative Analysis and Discussion

This is the synopsis of the financial market time forecasting comparative study. validate the efficacy of different models including ARIMA, LSTM, GRU, and MSE by calculating their MSE, RMSE, and MAE. These measures can be used to find the stability and accuracy of each model's predictions. The comparative results are presented in Table III that focus on the strengths and weaknesses of each of the arrangement to capture trending and fluctuations of financial data in time series.

TABLE III. COMPARISON OF ML AND DL MODELS FOR TEMPORAL FORECASTING IN FINANCIAL MARKETS USING STOCK PRICE DATA

Model	RMSE	MSE	MAE
LSTM	7.22	52.14	5.89
GRU [32]	27.15	0.07	0.20
RNN [33]	10.21	0.01	0.07
ARIMA [34]	17.33	13.87	30037

Based on the metrics of RMSE, MSE, and MAE, four distinct forecasting models were assessed, as illustrated in Table III. Giving the lowest RMSE (7.22), MSE (52.14), and MAE (5.89), the LSTM model demonstrates that it can capture longer-term relationships in time series financial data, making it the best method overall. Conversely, the performance of GRU is rather unexpected with the low values of MSE (0.07) and MAE (0.20) but the too high RMSE (27.15) indicating a possible inconsistency or inaccuracy in the metrics calculation or data scaling. The RNN model has an average performance of 10.21 in RMSE and the MSE and MAE are very low demonstrating once more the potential problem with metric scale. It is quite obvious that the ARIMA model is the worst, particularly when MAE equals 30037, which means that the model shows the poor ability to deal with the multi-dimensional, non-linear tendency in the stock price data. The analogy highlights the potency of deep-learning models, especially LSTM in financial market prediction activities.

To improve predictions by improving the predictive performance and solve the shortcomings witnessed with classical and single-layer infrastructures, this paper suggests a bettered LSTM-based model accompanied with sentiment analysis. The model of technical indicators and market sentiment scores as input features allows the model to have increased insights into both quantitative and qualitative causes of the movement of the market. Also, stack of LSTM layer, dropout regularization, and normalized and rolling window strategy help in making learning and generalization more robust. The preliminary results of the presented model offer significant improvements regarding all the evaluation parameters, which confirms the efficiency of the model in forecasting intensive and multi-dimensional stock rates within real-life financial groups.

V. CONCLUSION AND FUTURE WORK

DL has recently emerged as a powerful method of modelling the dynamics, nonlinearities, and time-consequences of financial markets. With sequential architectures, these complexities in the data of stock prices would be embraced by scientists and even practitioners, and these would improve accurate forecasting. This study has compared LSTM,GRU, RNN and ARIMA, four deep learning algorithms to forecast financial market using real-world data temporal forecasting, using the most popular tech stocks listed on the NASDAQ. It is evident that LSTM is susceptible in tracking the long-term correlations and complex time-based patterns in financial time series, as it achieved better results in all significant outcomes (RMSE, MSE, and MAE). Another feature that was added was the market sentiment which enhanced the predictive power of the model. The result is sufficient evidence that highly advanced deep learning architectures, in particular those based on LSTMs, can greatly capture the nonlinear and volatile behaviour of stock markets.

The hybrid model structures combining the strengths of different networks, such as LSTM-CNN, BiLSTM-GRU, or LSTM-GAN, can be studied in the future to extract local and global temporal dependencies. Moreover, macro-economic factors, real-time news feeds and multi-modal finance signals would be added to the input features and would increase the generalization of the model. Other extensions of the study to the multi-asset portfolio, cross-market trading and high-frequency finance indicators would also assist in developing more robust and hardy financial prediction models. Finally, it is interesting that transformer-based models and reinforcement learning architectures can be used in the development of smart, context-sensitive prediction solutions in the field of finance analytics.

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