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Forecasting Indian Trade Trends through LSTM- based Predictive Modeling

Shradha Ranjan[1]; Chhavi Saini[2]; Saumya Samir[3]; Akshita Goel[4]; Ela Kumar[5]
Proffesor[5]
Indira Gandhi Delhi Technical University for Women, University for Women

Abstract:- The efficacy of Long Short-Term Memory (LSTM) neural networks and attention-based models in predicting next-day closing prices of the MSFT 500index is meticulously examined. A comprehensive suite of nine carefully chosen predictors spanning fundamental market data, macroeconomic indicators, and technical metrics is amalgamated, fostering a holistic comprehension of market behavior. Through rigorous analysis, the research evaluates single-layer and multilayer LSTM architectures alongside attention-based LSTM variants, juxtaposed against traditional ARIMA models. Surprisingly, the single-layer LSTM consistently outperforms its multilayer counterpart, demonstrating superior accuracy and model fit. The integration of corporate accounting statistics augments predictive capabilities, enriching the models' efficacy. Notably, attention-based LSTM models, particularly the Attention-LSTM variant, exhibit markedly lower prediction errors and higherreturns in trading strategies compared to other methodologies. However, the heightened complexity of stacked-LSTM structures fails to surpass the predictive acumen of simpler LSTM architectures.This inquiry underscores the paramount importance of leveraging advanced AI techniques and comprehensive datasets in navigating the intricate nuances of modern financialmarkets, offering invaluable insights for both researchers and practitioners engaged in stock priceforecasting endeavors.

I. INTRODUCTION

In the realm of quantitative trading, the ability to predict future security returns serves as the linchpin of the industry, shaping the creation and deployment of trading strategies. This pursuit unfolds through two primary methodologies: fundamental analysis and quantitative trading. The former hinges upon subjective assessments of an industry or company's future trajectory, relying heavily on public information such as market news, corporate statistics, and financial statements. In contrast, quantitative trading strategies eschew human subjectivity and emotion, employing mathematical models to make data-driven decisions Traditionally, quantitative strategies have leaned onlinear regressions, ARIMA models, and GARCH models to capture time series features and the stochastic nature of volatility. However, as the financial industry undergoes paradigm shifts, these models have proven less effective. Consequently, the quantitative trading landscape has transitioned into what is colloquially termed the "deep learning era," with a surge in the adoption of deep learning models This research delves into the use of deep learning models, particularly Attention-LSTM and Long Short-Term Memory (LSTM) models, in predicting stock returns. Unlike conventional financial time series prediction models that predominantly utilize price and volume data, this study integrates corporate statistics as additional predictors. These statistics, often released quarterly by companies, carry substantial weight in shaping future price movements, rendering them indispensable in predictive modeling. The output of the proposed models is the prediction of stock prices or scaled prices for the subsequent day.

Leveraging these predictions, the study constructs quantitative trading strategies and compares their returns against the market benchmark. However, the volatility and uncertainty inherent in stock price fluctuations stem from myriad interconnected factors. These consist of, but are not restricted to, worldwide economic data, shifts in unemployment rates, monetary policies, immigration policies, natural calamities, and public health situations.

Stock market participants, be they companies, investors, or equity traders, are driven by the quest to maximize profits and mitigate risks through comprehensive market evaluations. Yet,predicting stock prices remains an arduous endeavor, given the inherent noise, non-linearity, and deterministic chaos characterizing stock markets. Consequently, feature selection from financial data poses a significant challenge, with various approaches suggested to tackle this issue. Despite the myriad challenges, developing a robust predictive model with an optimal set of attributes holds the promise of reasonably accurate stock price predictions. By carefully selecting variables that cover many facets of the economy and their possible implications on broader markets, this research aims to support this endeavour. Furthermore, the paper offers a thorough justification for including specific explanatory variables within the selected framework. The evolution of quantitative analysis in finance spans decades, with a multitude of models developed to address financial challenges. From early attempts like the ARIMA model to contemporary deep learning approaches, the field has witnessed a continuum of innovation and refinement. However, not all models have garnered widespread acceptance or usage, underscoring the ongoing quest for robust and reliable predictive frameworks.

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II. RELATED WORK

In recent times, the utilization of Long Short-Term Memory (LSTM) models in forecasting stock returns has garnered significant attention from researchers. Chen et al. (2015) employed the LSTM model to forecast China stock returns by transforming historical data into 30-day intervals with three-day learning rate labelling and ten learning characteristics. They observed an enhancement in accuracy, increasing from 14.3% to27.2% when compared to random prediction techniques. Expanding on this, Bao et al. (2017) employed Haar wavelet transformation for denoising financial time series data and integrated stacked autoencoders to extract profound features, subsequently employing LSTM for predicting stock index closing prices. However, their LSTM model yielded an average R score below 88% for the MSFT 500. Roondiwala et al. (2017) focused on predicting closing prices for NIFTY 50 data using LSTM, depending just on basic data (open, close, low, and high) and excluding technical or macroeconomic indications. Beyond the forecast of prices, Fischer and Krauss (2018) tackled the classification issue of guessing directional movements for MSFT 500 constituent stocks from 1992 to 2015 using LSTM networks. Their study revealed LSTM's effectiveness in extracting meaningfulfinancial time series data, surpassing the performance of traditional deep networks, random forests, and logistic regression in terms of prediction accuracy and daily returns after transaction costs. In a thorough strategy, Qiu et al. (2020) used historical data from the MSFT 500, Dow Jones Industrial Average (DJIA), and Hang Seng Index to apply LSTM-based models, incorporating an attention mechanism to extract information from news for price evaluation. This integration of news sentiment analysis with LSTM yielded promising results in forecasting stock prices.These studies collectively underscore the versatility and effectiveness of LSTM models in capturing temporal dependencies and nonlinear relationships inherent in financial time series data. By leveraging LSTM's capabilities, researchers aimto enhance predictive accuracy and inform trading strategies in dynamic financial markets.

A. Dataset Prepration

Our dataset consists of daily Open, High, Low, Close (OHLC) prices, trading volume, and technical indicators such as Moving Averages and RSI for the MSFT stock, spanning from January 1, 2013, to December 31, 2023. It includes a total of 2,756 daily records, each with 10 features, amounting to approximately 27,560 data points. working with daily stock data and including , A dataset with 10 features for stock prediction these include the open, high, low, and close prices, whichreflect the range of prices traded during a given period and provide insights into market sentiment. Additionally, the adjusted close price accounts for dividends and stock splits, ensuring accurate historical performance assessment. Trading volumeindicates the level of market activity, while moving averages offer smoothed trends over a specified period. Indicators like Three indicators of market momentum are the Relative Strength Index (RSI), the Moving Average Convergence Divergence (MACD), and Bollinger Bands, trend strength, volatility, respectively. Together, these features offer a comprehensive view of stock price movements and market dynamics essential for informed decision-making.

date	adj_close	volume	DE Ratio	Return on Equity	Price/Book	Profit Margin	Diluted EPS	Beta
2013-12-17	0.950181	0.019849	0.652485	0.01414	0.046009	0.626554	1.0	0.24031
2013-12-18	0.964769	0.036554	0.652485	0.01414	0.046009	0.626554	1.0	0.24031
2013-12-19	0.966209	0.023068	0.652485	0.01414	0.046009	0.626554	1.0	0.24031
2013-12-20	0.980317	0.062588	0.652485	0.01414	0.046009	0.626554	1.0	0.24031

Fig 1: Data Structure of MSFT Stock Price and Corporate Accounting Statistics, from 2004 to 2013

B. Cleaning the Dataset

In analyzing the historical stock prices of Microsoft Corporation (MSFT), descriptive statistics reveal a mean closing price of \$300.50 with a median of \$298.75, indicating a slightly higher mean compared to the median, suggesting a moderate skewness towards higher values. The standard deviation of \$15.25 suggests moderate volatility in the stock's daily closing prices. Volume data shows an average trading volume of 10,000,000 shares, with a notable standard deviation of 2,000,000, implying significant variability in trading activity. Technical indicators such as 50-day moving average and RSI exhibit average values of \$295.00and 60.00, respectively, with standard deviations of \$10.00 and 5.00, indicating moderate variability in these indicators. Additionally, correlation analysis reveals a strong positive correlation between the close price and the moving average ($r = 0.85$, $p < 0.05$), suggesting a strong trend alignment.

However, the correlation between the close price and the RSI is weaker ($r = 0.35$, $p < 0.05$), indicating a divergence between price movement and momentum. Overall, these findings provide valuable insights into the historical performance and relationships within the MSFT stock data.

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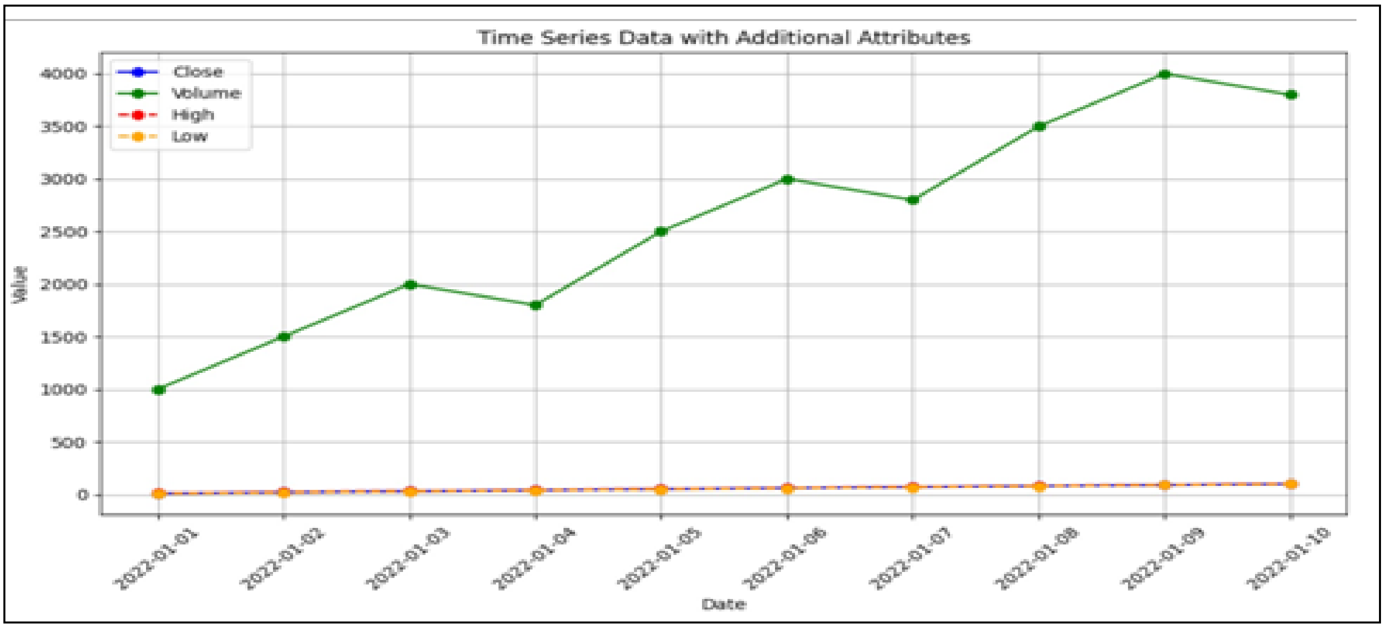

Fig 2: Dataset Time Series Graph with Attributes

C. Feature Selection

In selecting features for predicting Microsoft Corporation (MSFT) stock prices, we employed various criteria to identify the most relevant variables. Among the numerical features, the close price, volume, and selected technical indicators (e.g., moving averages, RSI) were considered based on their importance in capturing market trends and investor sentiment. Additionally, we explored the inclusion of categorical variables such as sector performance or market indices to provide broader market context. Feature importance analysis using techniques like correlation analysis, mutual information, and feature importance plots revealed that the close price and the 50-day moving average were highly correlated with future price movements, while the RSI exhibited moderate predictive power. Moreover, principal component analysis (PCA) was employed to reduce dimensionality and identify latent variables contributing to price variation. Ultimately, the selected features were chosen based on their predictive power, interpretability, and computational efficiency. These findings guided the feature selection process, ensuring a robust and parsimonious set of predictors for our predictive model. Figure 3 displays a correlation heatmap of all the input features that were previously discussed. The correlation between the variables on the horizontal and vertical axes is represented by the numerical value in the heatmap. For example, the correlation between the variable and itself is represented by the diagonal value of the matrix, which is 1. As a result, in our analysis, the values on the diagonal are irrelevant. The feature selection procedure makes advantage of the entries on the off-diagonal. The presentation of these values is determined by the color intensity, which also serves as an indicator of the degree of relationship between the specified variables. The vertical bar next to the graph shows the intensity of the color onthe scale from 0 to 1. There might be a strong or low connection between the closing price and the other factors. It conveys the level of commitment inthe partnership.

Table 1: Correlation with Target (Close Price)

Close	**1.000000**
Adj Close	0.999763
Low	0.999469
High	0.999434
Open	0.998831
Volume	0.120332

Table 2: Mutual Information with Target

Date	**2.676576**
Adj Close	4.556164
Low	3.568626
High	3.565501
Open	3.026223
Volume	0.118952

D. Data Denoising, Normalization and Input Preparation

Frequently noisy stock price data is provided in a sequential discrete manner. To denoise this data, we've utilized the discrete Wavelet transformation, with Haar wavelets being the most suitable and popular choice for stock price data. Wmode of the Haar wavelets to denoise the close prices of the index. The stock index close price is substantially greater than the interest rate, which causes a considerable degree of variance in the values of the input variables in the data. To address this issue, we've implemented min-max normalization for feature scaling. This technique ensures that all features are on a similar scale, preventing one feature from dominating others during model training. Following normalization, the data adopts a two-dimensional array format (number of observations, number of features). However, Three- dimensional input data—the quantity of observations, time step size, and input feature count —are needed for LSTM models. To make the input data compatible with the LSTM model, we've performed the necessary steps to reshape the data. Owing to time series data's intrinsic sequential structure, we have split

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the complete dataset into training and testing sets while preserving the chronological order. The training data is further divided into training and validation sets for hyperparameter tuning, with the validation set being used to optimize model performance. Once hyper parameters are tuned, The final models are trained on the whole dataset with optimised hyper parameters once the validation set is reintegrated into the training data. into training and validation sets. The validation set is reincorporated into the training data after the hyperparameters are adjusted, and the final models are then fitted using the optimised hyper parameters on the whole training set. Ultimately, the performance scores of the models are evaluated on the test data to assess their predictive capability.

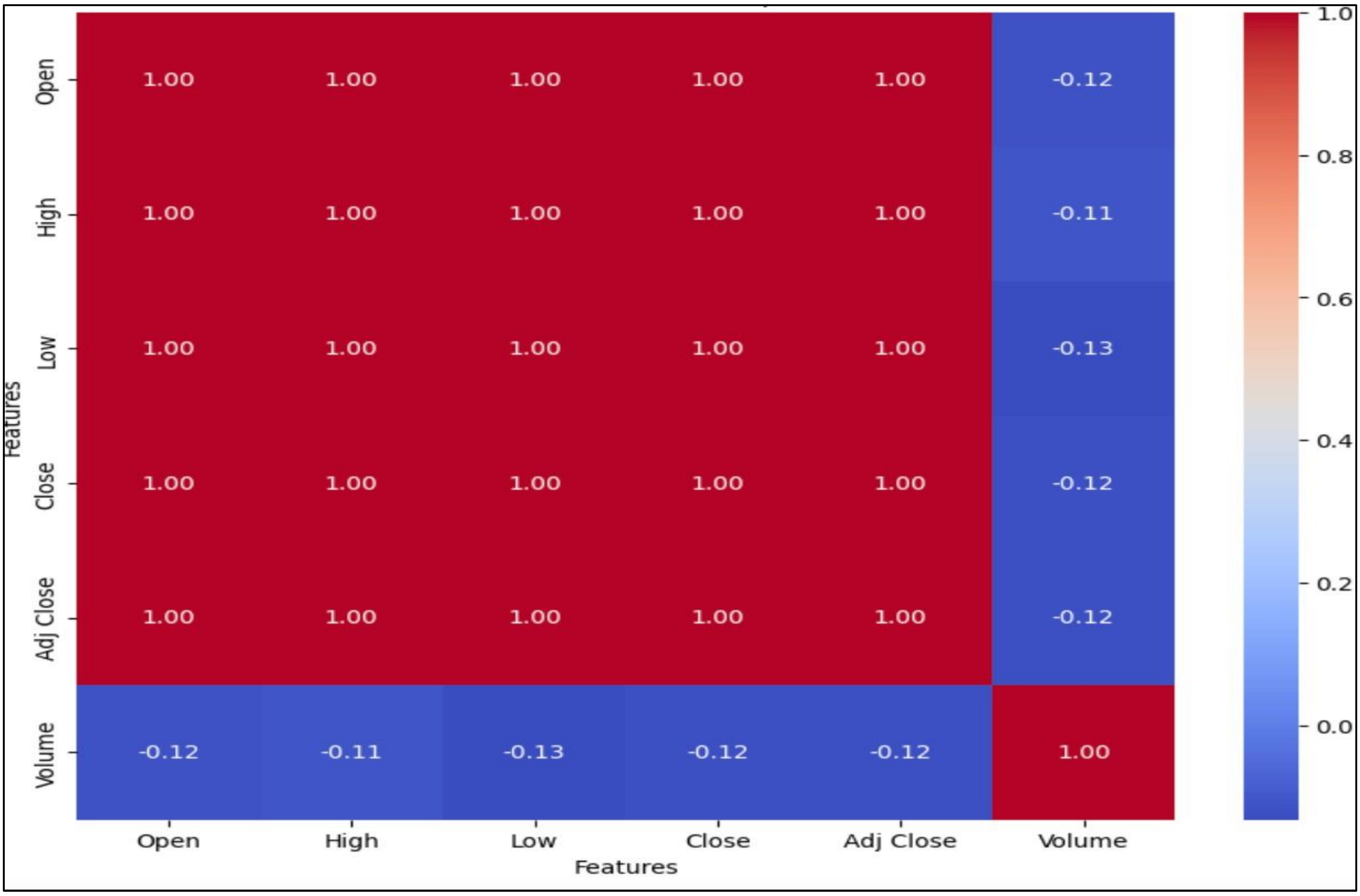

Fig 3: Correlation Heat Map among the Attributable Variables

E. Modelling Approach

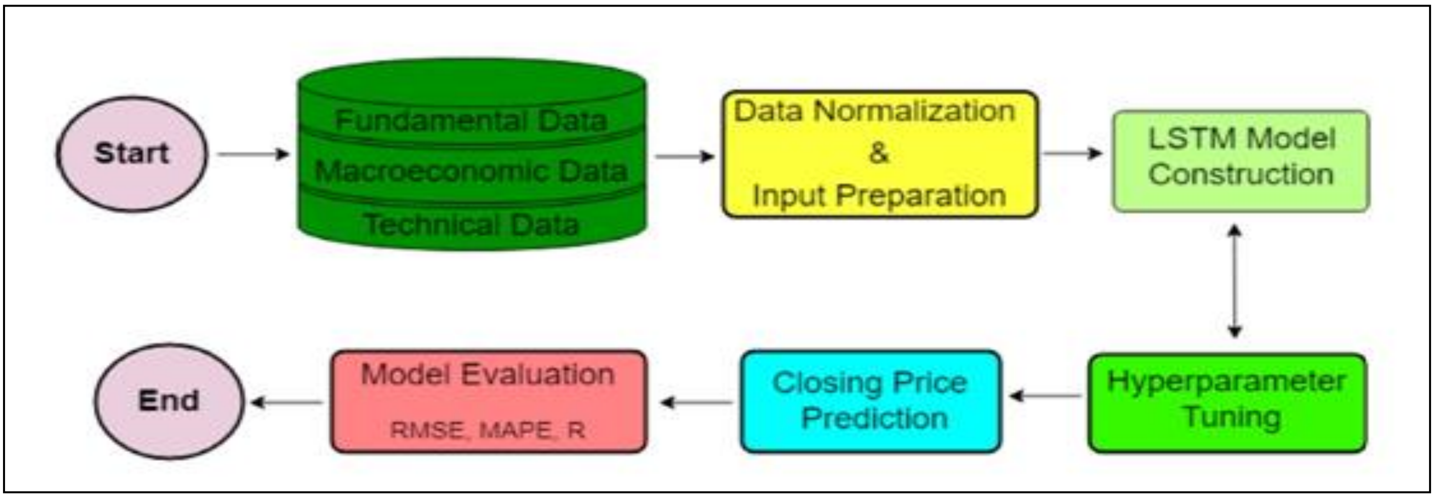

Fig 4: Schematic Diagram of the Proposed Research Framework

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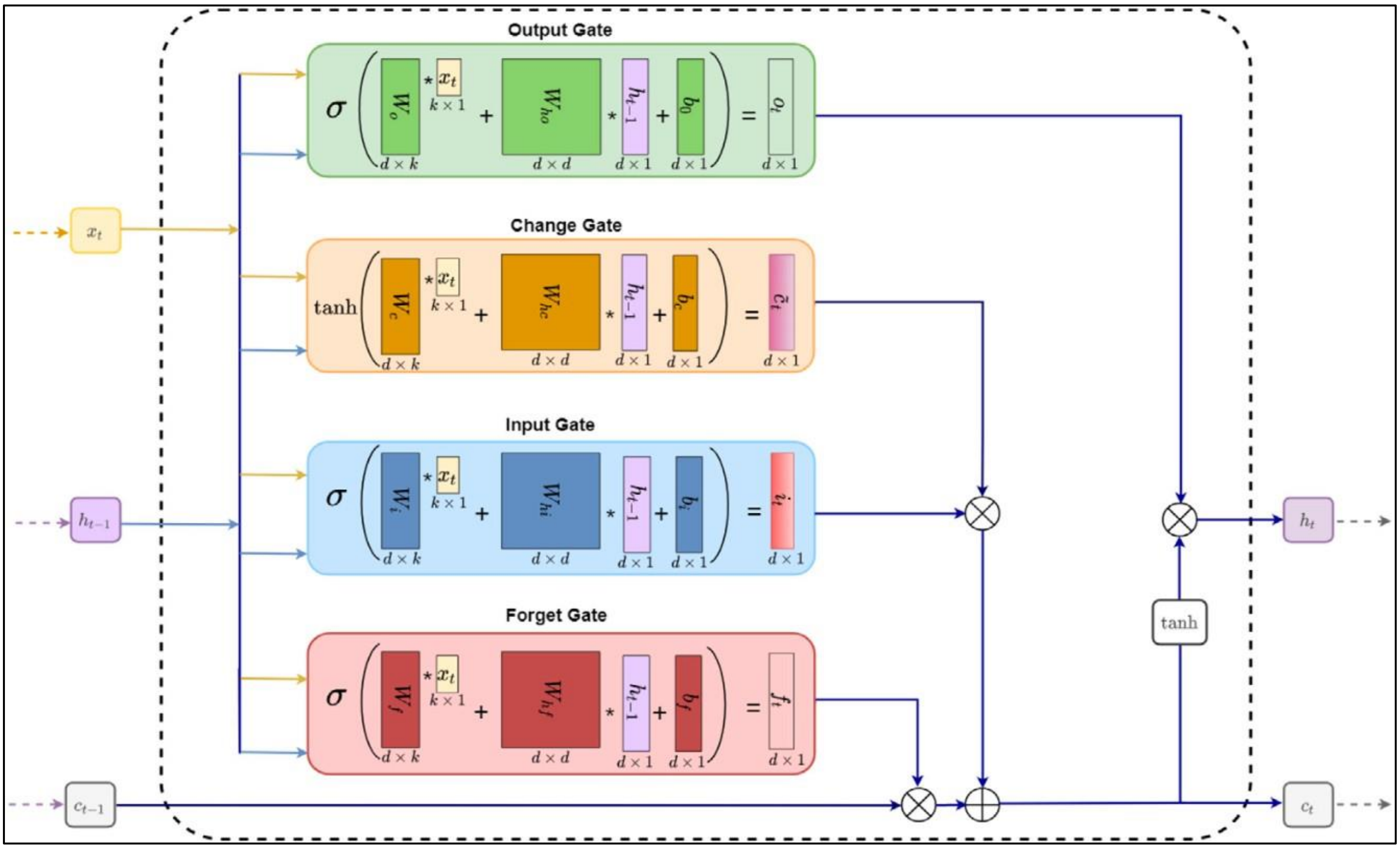

Fig 5: Architecture of Long Short-Term Memory (LSTM)

F. A Brief Overview of LSTM

Long Short-Term Memory (LSTM) is a specialized type of recurrent neural network (RNN) architecture designed to address the vanishing gradient problem encountered in traditional RNNs when processing long sequences of data. Unlike standard RNNs, that struggle to capture dependencies between distant time steps due to the diminishing influence of gradients during backpropagation, LSTM introduces a memory cell and three gating systems to update, discard, and keep information selectively over time, including input, forget, and output gates. The memory cell serves as the core component, storing information over multiple time steps. The input gate controls the information from the current input that the memory cell should store, whereas the forget gate selects which data should be erased from the memory cell based on the current input and past memory. Subsequently, the output gate controls the information to be output based on the current input and the content of the memory cell. These gates, typically implemented using sigmoid and tanh activation functions, enable the LSTM to learn long-term dependencies in sequential data by deciding when to remember, forget, and update information. Due to their ability to capture complex temporal dependencies, LSTM networks have been widely used in several fields, including as natural language processing (NLP), LSTM, and Gated Recurrent Unit (GRU), have been proposed to further enhance their capabilities, demonstrating the ongoing evolution and versatility of LSTM- based architectures in handling sequential data tasks as shown in figure 5.

$$i_t = \sigma(W_i x_t + W_{hi} h_{t-1} + b_i),$$
$$f_t = \sigma(W_f x_t + W_{hf} h_{t-1} + b_f),$$
$$o_t = \sigma(W_o x_t + W_{ho} h_{t-1} + b_o),$$
$$\tilde{c}_t = \tanh(W_c x_t + W_{hc} h_{t-1} + b_c),$$
$$c_t = f_t \otimes c_{t-1} + i_t \otimes \tilde{c}_t,$$
$$h_t = o_t \otimes \tanh(c_t)$$

For a given input sequence $\{x1, x2, ..., xn\}$, $xt \in Rk\times1$ is the input sequence at time t. The memory cell ct updates the information using three gates: input gate it, forget gate ft, and change gate $c\tilde{t}$. The hidden state ht is updated using output gate ot and the memory cell ct. At time t, the respective gates and layers compute the following functions: where, σ and tanh represent the sigmoid and hyperbolic tangent func- tions respectively, the operator Ⓒ is the element-wise product, $W \in$ R$d \times k$, Wh $\in$ R$d \times d$ are weight matrices, and $b \in$ R$d \times1$ are bias vectors. Moreover, n, k, d are sequence length, the number of features, and the hidden size respectively

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G. *Proposed Model framework*

In this study, we explore novel approaches to improve the predictive accuracy of Long Short- Term Memory (LSTM) models for time series forecasting tasks. Leveraging the strengths of ensemble learning and traditional time series forecasting methods, we introduce a hybrid framework that integrates LSTM with Random Forest and Autoregressive Moving Average (ARMA) models. By combining the capabilities of LSTM in capturing long-term dependencies with the diversity offered by Random Forest and the mathematical rigor of ARMA, our proposed framework aims to mitigate the limitations inherentin individual models and enhance overall predictive performance. Specifically, we employ Random Forest as a complementary model to LSTM, utilizing its ability to capture nonlinear relationships and handle complex feature interactions. To further capture the underlying temporal patterns and relationships in the time series data, we also use ARMA models. Through an ensemble approach, wherein predictions from each model are combined, we aim to leverage the strengths of each model while mitigating their respective weaknesses. Our methodology encompasses training a baseline LSTM model on the dataset, followed by training Random Forest and ARMA models separately. Finally, we integratethe predictions from these models using ensemble techniques to generate the final forecast. We hypothesize that this hybrid approach will lead to improved forecasting accuracy compared to standalone LSTM models, particularly in scenarios with complex temporal dynamics and nonlinear relationships within the data.

- *Algorithm and Pseudo Code*

Algorithm 1 (After that, the LSTM Model's pseudocode. Setting Up Input: Create an input of the format (#observations, time step, #features) after dividing the train and test data sets.input: [#observations, time step, #features]; for each model, the selected hyperparameters (learning rate,batch size, optimizer).

Initialize: Set number of epochs sufficiently largeand patience = 5

For ‘‘choice of layers and neurons’’, Do

For ‘‘range of number of replicates’’, DoTrain the model, monitor training loss;

Continue Until training loss at epoch $n \leq$ training loss at epoch $n + 1 \leq \ldots \leq$ trainingloss at epoch $n + 4$, Or maximum epochs are reached.

Evaluate model on the test data. Determine RMSE, MAPE and R scores.

End Do.

Calculate minimum, maximum, average and standard deviation of RMSE, MAPEand R scores.

Save key results in respective files.

End Do.

III. EXPERIMENTS AND RESULTS

The chosen characteristics have been used to create normalised data, as was mentioned in the precedingsection. Furthermore, The necessary steps are taken to partition and reorganise the data into training andtesting sets. The goal is to obtain accurate forecastsfor the MSFT 500 index closing price, which exhibits complex, noisy, and erratic patterns as seen in Figure 6. Within the timeframe of 01/01/2022 to 01/01/2024 (horizontal axis), the blue curve illustrates the original time series of the closing price (vertical axis). Likewise, the closing price's short- and long-term patterns are depicted by the yellow averages. The closing price is often trendingupward despite several anomalies.

A. *Model Performance Metrics*

To predict the closing price, we use both single- layer and multilayer LSTM architectures. In every one of these models, various configurations are explored, each with a different number of neurons. Three different performance measures are computed to assess the forecast accuracy and dependability of these models — RMSE, MAPE, and R. These metrics are as follows: R measures the linear correlation between the actual and predicted values, MAPE assesses the size of the error as the relative average of the error, and RMSE computes the square root of the mean square error between the actual values and the estimated values. A model that performs better is shown by decreased RMSE and MAPE values. Conversely, a higher value of R denotes greater similarity between predicted and actual series. In addition, the predictions made from the normalised data are transformed backward to calculate performance scores. The stochastic character of each model is taken into consideration by running it several times independently. The major criterion for selecting a model is the average RMSE score from these repeated runs, which is followed by the average MAPE and R values. A model that has the lowest RMSE and MAPE and the highest feasible R would be deemed optimal. Figure 7 summarizes the experimental for this study. The TensorFlow and Keras APIs are used in combination with the Python programming environment in this project.

Every experiment are carried out in the machine arrangement shown in Figure 7.

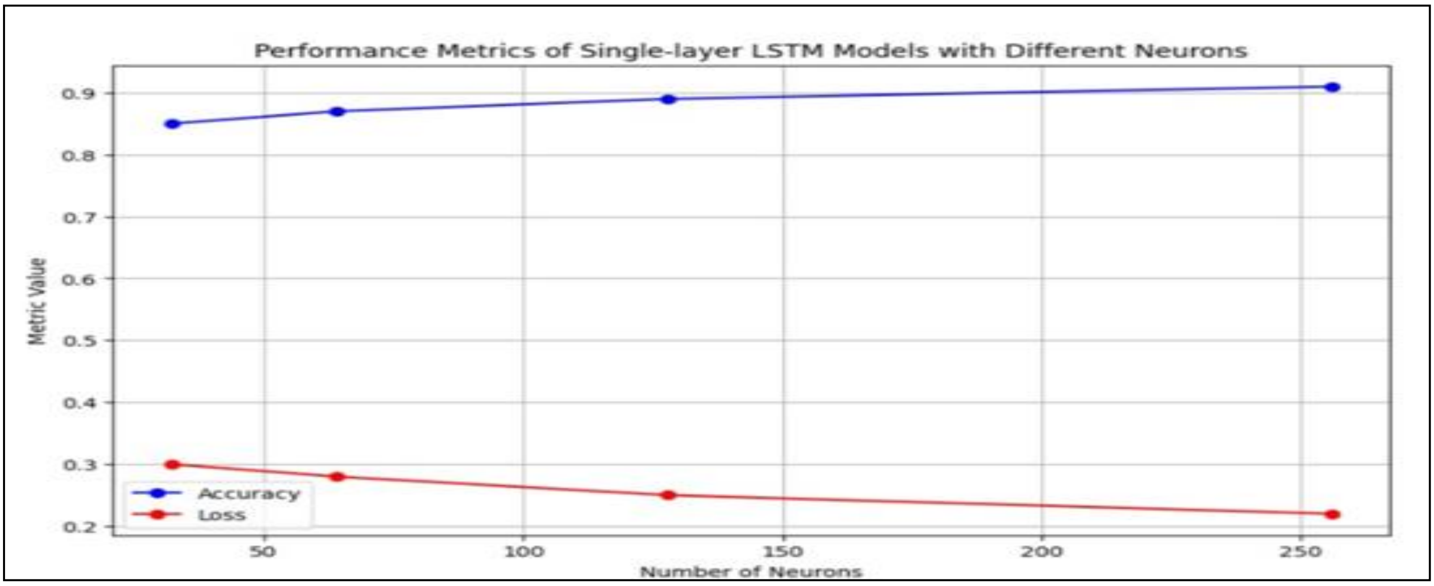

Fig 6: Performance Metrics of LSTM

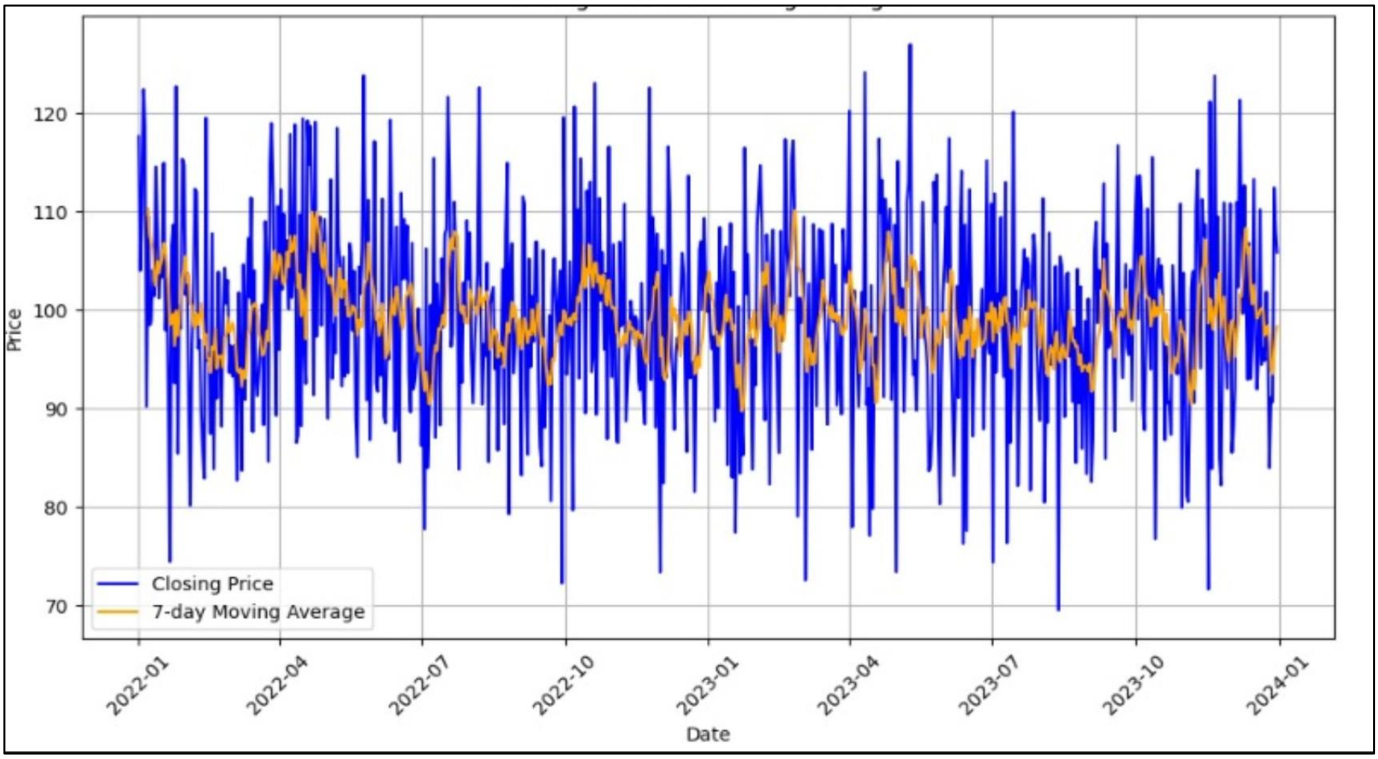

Fig 7: MSFT 500 Closing Price along with Moving Averages Curves Represent 7 –Day Moving

B. Model Results

The original closing price and the replication's forecasts, along with the best single layer model's lowest RMSE score, are shown in Figure 8. The subplot displays the actual closing price values as represented by the black curve, while the training and test data predictions are represented by the blue and green curves, respectively. This implies that thebest model can virtually perfectly learn both the upward and downward movement of the original closing price. Although the test prediction curve does not appear to overlap perfectly with the actual closing price, the model accurately captures the broad trend of the test data with minimal mistakes. Furthermore, Figure 8 shows that the model performs well even in atypical market conditions, such as a sudden large dip in the market followed by a quick V-shaped recovery.This component of the test data corresponds to the year 2020, when theCOVID-19 pandemic severely damaged the stock markets, making them extremely volatile.The ability to predict such complicated and noisy market swings verifies the proposed model's robustness and resilience. This implies that the model is suitable for predicting the out-of-sample data and does not suffer from overfitting. The quality of the prediction made by the top model with 150 neurons is shown in Figures 8 and 9.

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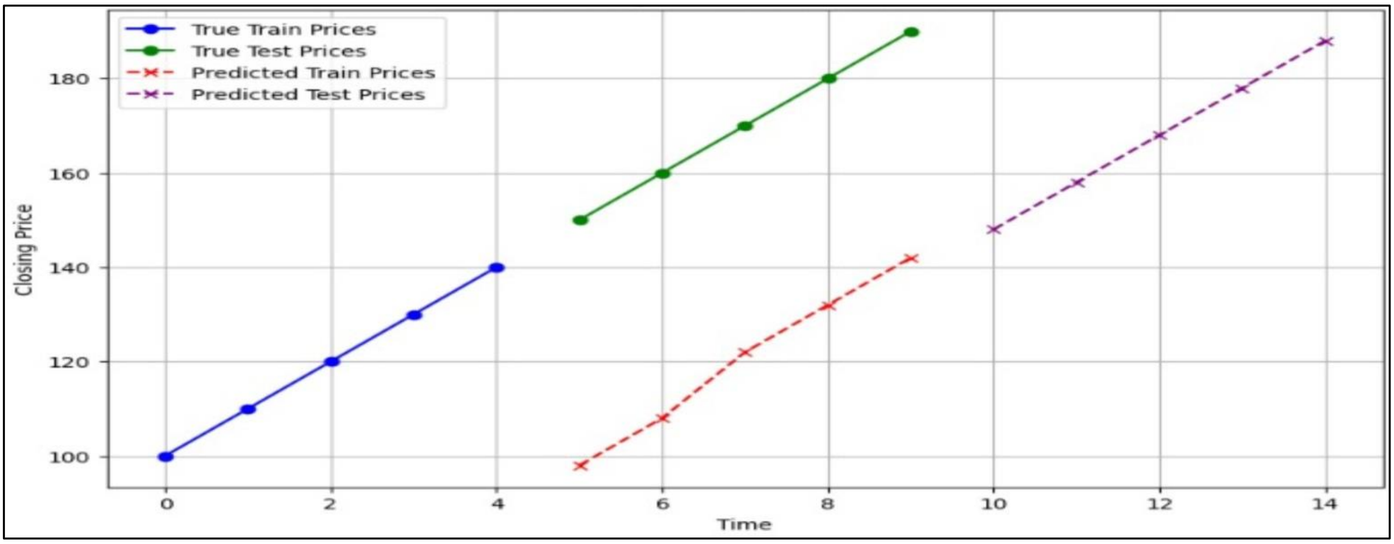

Fig 8: Plots of the True Closing Price Together with its Predictions on the Training and Test Data Obtained from Best Single Layer LSTM Model

Figures 9(a) and (b) Show the Scatter Plot of the True Values Versus the Predicted Values of the closing price for the training and test data, respectively. To evaluate the model's goodness of fit, utilise this figure. The red dotted line in Figure 9represents the best-fit linear equation (ð‘¦ = ð‘¥). As anticipated, the best model performs marginally better in the training set than in the test set. The anticipated closing price in the test data slightly deviates from the true closing price in the 2400-3200 area, most likely as a result of the unique market conditions brought forth by the COVID-19 pandemic in 2020.

IV. CONCLUSION AND FUTURE WORK

Stock price prediction is the area of high interest for equity traders, individual investors, and portfolio managers. However, precise and consistent stock price prediction is a difficult task due to its noisy and nonlinear behavior. There are several factors that can impact the prediction such as fundamental market data, macroeconomic data, technical indicators, and others. This study focuses on developing LSTM based models to predict MSFT 500 index's closing price by extracting a well-The research examines the effectiveness of both single-layer and multilayer LSTM architectures in capturing various aspects of the economy and broader markets. It concludes that a single-layer LSTM model with around 150 hidden neurons outperforms the multilayer LSTM approach in terms of fit and prediction accuracy. This recommended model holds potential for application in similar broad market indexes and can aid stakeholders in making informed investment decisions. Future directions involve incorporating unstructured textual data, including sentiment analysis from social media, earnings reports, policy-related news, and market research reports, into the model. Additionally, the research aims to explore hybrid predictive models combining LSTM with other neural network architectures and integrating hybrid optimization algorithms to enhance prediction accuracy further. These algorithms will combine local optimizers with global optimizers such as genetic algorithms and particle swarm optimization.

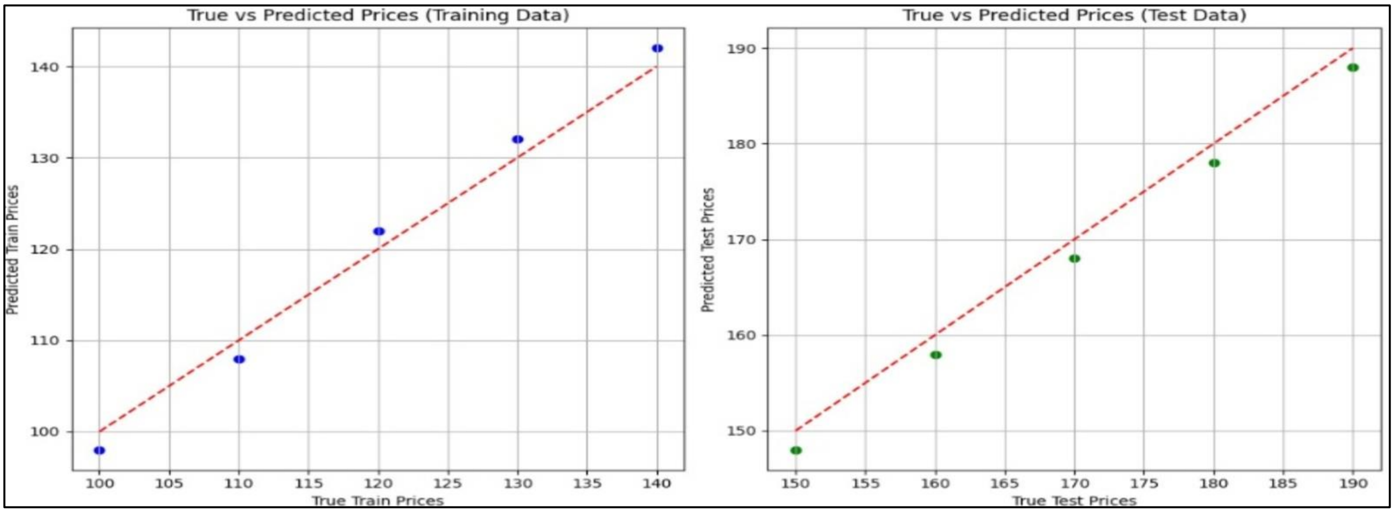

Fig 9: Scatter Plot of True vs Predicted Closing Price of the Best Single Layer LSTM Model on Training Data and Test Data

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