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ENHANCING STOCK PRICE PREDICTION: A COMPREHENSIVE ANALYSIS UTILIZING MACHINE LEARNING AND DEEP LEARNING APPROACHES

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Abstract

An important tool for assisting businesses and investors in making wise market decisions is stock price forecasting. Frequently, forecasting models are needed as they help investors to make the right decisions depending on the tendencies on the stock exchange. Traders, customers and financial institutions have been equally affected by the financial industry in terms of financial strength. Today's advanced artificial intelligence includes machine learning and deep learning algorithms, which are now recreating the new boundaries of the financier's markets. With a focus on the LSTM model, this research conducts a thorough investigation of machine learning-based stock price prediction. Based on this preliminary analysis, the empirical model used historical stock data from Tesla Inc., which has 1693 observations. Besides, the data is preprocessed here where the data is separated, cleaned and then split into training and testing data. This research also employs the Long Short-Term Memory (LSTM) model for this kind of application because it is capable of capturing long-term dependencies–a characteristic which is desirable for most time-series forecasting applications. These three main parameters of evaluation A three-way test includes the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). the performance of the model. The study reveals here that the proposed LSTM model gives the best prediction by having lower MSE, RMSE, and MAE of 0.08, 0.03, and 0.08 than the other models like ARIMA and Decision tree. Such studies have revealed that LSTM is efficient in identifying temporal patterns of stock prices and further directions.

Keywords: Artificial intelligence, LSTM, and stock price prediction, ARIMA, data preprocessing, predictive modelling.

I. INTRODUCTION

An essential component of the economy is the country's stock market, where the bulk of money is exchanged internationally. Therefore, the economic wellbeing of the nation is in some's way dependent on the performance of the stock exchange.. In order to draw dispersed liquidity and savings via the best routes, it is essential. The most lucrative endeavors and activities might then receive an appropriate allocation of the limited financial resources. The goal of stock market speculators and investors is to increase earnings through the examination of market data. Therefore, if one has the right models to forecast stock price and volatility—which are influenced by a myriad of other factors in addition to macroeconomic ones—one may profit from the financial market[1].

The stock index prices are volatile and have noisy characteristics, predicting stock index prices has long been one of the hardest things to do for people in the finance industry and other relevant fields [2][3]. Enhancing the precision of stock index price predictions is an unresolved issue in contemporary society[4]. Needless to say, a time series is a chronological sequence or sequence of observable data that occurs because of periodic behaviors and actions across many professions or finance, engineering, fields including social science, physics, and economics, among others. Thus, one of the times series with low signal-to-noise ratio includes the stock index price. [5] Our distribution is heavy-tailed and fat-tailed [6][7]. These characteristics are complicated, and that makes it difficult to expect the direction of the directory price. The objective of time sequence prediction is to construct models that will estimate upcoming values of certain variables based on past data[8].

The accurate forecasting of stock prices can aid shareholders in making informed decisions on the purchase or sale of shares [9][10]. SMP refers to the effort of forecasting a stock's future worth. Throughout the years, many different approaches to stock price forecasting have been put out. Four categories have been identified and they are divided into them[11][12]. Fundamental analysis is the first type and is based on financial data that is available to the public. Technical analysis is the second type, in which suggestions are made by utilizing past performance and pricing [13]. The third is using large-scale datasets gathered from various sources through the usage of data mining and ML[14][15].

In modern days Machine learning is essential in time series forecasting. Machine learning systems provide superior predictability in forecasting market prices. Methods like Simple Linear Regression, Lasso, Ridge, SVM, KNN, Random forest and the neural network models SLP, MLP and LSTM are effective engineering tools for predicting stock price.[17].

The demand for enhanced precision in stock price forecasting tools, particularly for volatile equities such as Tesla, Inc., drives this research. Though LSTM, a deep learning model, can better capture these complexity, traditional models have difficulty with the non-linear character of stock variations. By improving prediction accuracy through advanced techniques and robust data preprocessing, this study aims to support investors in making wise choices. Additionally, the comparative analysis of LSTM against conventional models provides insights into the benefits of deep learning, ultimately contributing to enhanced financial forecasting methods.

1.1 Contribution of the paper

The purpose of this work is to design a reliable ML model for predicting stock values of Tesla utilizing the past stock data and to compare it to the existing widely known forecasting methods. The following contribution are discussed as:

- The paper seeks to enhance prediction accuracy by leveraging deep learning techniques, particularly LSTM, to improve stock price forecasts compared to traditional models.
- It focuses on Tesla, Inc. due to its significant market impact and stock price volatility, making it a relevant subject for prediction analysis.
- The focus of the research remains with the approach to be undertaken for data pre-processing since 'garbage in, garbage out' principle cannot be overemphasized.
- It utilizes comprehensive evaluation metrics (MSE, RMSE, MAE) for a rigorous assessment of model performance, facilitating meaningful comparisons.
- The paper provides a comparative performance analysis of LSTM against conventional models like ARIMA and Decision Trees to illustrate the advantages of advanced methods.
- It offers practical implications for investors by providing insights and predictive tools that contribution in creation informed financial choices based on historical data analysis.

1.2 Structure of the paper

The document's lasting sections are organized as follows: Section II talks on relevant literature. The information and techniques, including the general methodology, are provided in Section III. The experimental and comparative results are shown in Section IV. Section V concludes with recommendations for more study.

II. LITERATURE REVIEW

This section provides an overview of a prior study on stock price prediction techniques, highlighting the enhanced performance resulting from the application of deep learning and ML techniques for stock value predicting in various industries.

Moedjahedy et al., (2020), To guess what the stock prices of five phone companies will be, Gaussian Process and SMOreg are used along with two other tools. One is PT. Bakrie Telecom Tbk (BTEL), another is PT. XL Axiata Tbk (EXCL), a fifth is PT. Smartfren Telecom Tbk (FREN), and the last is PT. Telekomunikasi Indonesia Tbk (TLKM). You can get the training sample from December 31, 2019, to January 1, 2017. The study discovered that SMOreg works better than the Gaussian Process, with an RMSE of 0.00005, a MAPE of 1.88%, and an MBE of 0.00025[18].

Liu and Song (2018), proposes a forecasting method for deep residual networks (ResNet) that takes the stock price graph for the image input. This findings suggest that mean accuracy of the ResNet model is 0.40 while that of stochastic benchmark is 0.33 [19].

Kalra and Prasad (2019), A daily forecasting model using the historical price data as well as the news articles is developed to predict shifts in the Indian stock market. To predict the sentiment of news material, a Naïve Bayes classifier is applied with negative and positive as two categories. Different approaches to ML are employed to provide accuracy of between 65.30% and 91.2%. Previous closing prices from consecutive days, standard deviations of such prices for consecutive days, and numbers of positive and negative sentiments in the news items are then used for prediction [20].

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Mathanprasad and Gunasekaran (2022), A computational automated approach has been established to forecast stock market data values utilizing previous data. The machine learning classification method forecasts stock market price and movement fluctuations with an accuracy of 94.17%. This improved prediction helps investors assess current and future stock market values, enhancing their decision-making process[21].

Luo and Hsiao et al. (2022) Examine if a systematic approach exists for identifying purchasable stocks and, more crucially, determining optimal buying and selling times. Subsequent testing revealed that LightGBM has efficacy in predicting and recommending stocks. They compared the coming predictive result and the corresponding recommended investment with two familiar Taiwan ETFs, namely 0050 and 0056. The results furthermore depict that the method outperforms Taiwan ETFs 0050 and 0056, and is practical, effective and successful.(Chang, Luo and Hsiao, 2022).

Reddy and Jaisharma (2022) Better stock prediction through the application of BP and SNLSTM in stocking evaluation for stock price fluctuations. The SNLSTM yields 63.10% accuracy and is relatively accurate when compared with the Back Propagation algorithm which has an accuracy of 61.03%. The outcome showing that, at a $p<0.05$ level of significance, the SNLSTM algorithm outperforms backpropagation with computed $p=0.000$. The SNLSTM demonstrates superior performance in forecasting stock market prices and enhances accuracy levels compared to Back Propagation[22].

Selvin et al. (2017) proposes that stock price prediction based on deep learning should be institutionalized. The stock values of Cipla, Infosys, and TCS were predicted using a model trained on Infosys data. Additionally, the results show that CNN architecture can detect trend changes. The best model for the suggested technique is CNN. For forecasting purposes, it makes use of data provided at a specific time [23].

Patil et al. (2020) A new approach is given by using graph theory. Using data on the temporal and geographical interactions between companies, this approach simulates the stock market as a complex network and helps investors make investment decisions. Both graph-based methods outperform their traditional counterparts, according to their experiments, since they use structural information to construct their prediction models[24].

The table 1 provide the related work summary for the forecasting stock values with the use of ML and DL algorithms.

TABLE I. DETAILED SUMMARY OF THE RELATED WORK FOR STOCK PRICE PREDICTION USING MACHINE LEARNING MODELS

Reference	Methodology	Key Findings	Limitations	Future Work
[18]	SMOreg and Gaussian Process for stock prediction.	SMOreg outperforms Gaussian Process (RMSE: 0.00005).	Limited to five companies.	Explore additional algorithms.
[19]	ResNet model using stock price graphs.	ResNet accuracy: 0.40 vs. stochastic c indicator 0.33.	Extensive data preprocessing needed.	Test different network architectures.
[20]	Naïve Bayes on historical data and news sentiment.	Accuracy: 65.30% to 91.2%.	Limited to sentiment analysis.	Combine with more data sources.
[21]	Employing machine learning methods to predict the	94.17% accuracy in predicting movements.	Depends on historical data	Develop real-time models.

	behaviours in the stock market.		quality.	
[22]	Machine learning in Taiwan stock market.	LightGBM outperforms Taiwan ETFs.	Limited to the Taiwan market.	Expand to other markets.
[23]	Comparison of SNLSTM and Back Propagation.	SNLSTM accuracy: 63.10% vs. Back Propagation 61.03%.	Requires large sample size.	Investigate hybrid models.
[24]	CNN model trained on Infosys stock data.	CNN captures short-term trends; interrelations between companies.	Limited to short-term predictions.	Extend to long-term predictions and compare with other models.
[25]	Graph models using stock correlations and news mentions.	Outperforms LSTM methods by leveraging stock relationships.	Complex graph construction.	Test more graph architectures and features.

III. MATERIALS AND METHODS

Hence, the research targets at developing a machine learning technique that forecast stock prices and key attributes based on historical data. The research methodology is as follows: First, Tesla data is collected, which includes the historical data of the company's share price with 1693 observations and 6 variables of daily data. Then, the data preprocessing is performed on the cleanliness of a given set of data identifying and handling missing values and the removal of redundant features as well as categorical feature mapping. The cleaned dataset is then divided into two sections: 70 per cent goes towards education, and 30 % is used in testing the model. Following that is the LSTM model for stock price prediction. A final three significant areas concern: For assessment of how well this model fits these criteria, the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are the three different forms of errors, which are used in order to evaluate the forecasts' precision and effectiveness. Figure 1 displays the methodology's flowchart.

3.1 Data Collection

Data from Tesla, Inc. was utilized in this research. It is a Palo Alto, California-based American corporation with a focus on renewable energy and electric automobiles. solar roof tiles, electric automobiles, solar panels and other items and services related to this business are now offered by Tesla. Their battery energy storage ranges from household to grid size. The TESLA INC. (TSLA) stock price history is included in this dataset. You may view the information every day. The currency that is utilized is the USD. The datasets have (a) 6 columns and 1,693 rows Data from a single day is shown in each row. When dealing with columns. The information is given below in table 2.

Table II. Data Set Information

	Open	High	Low	Close	Adjusted Close	Volume
mean	183.274022	187.265251	178.941224	183.351102	183.351102	4.441050e+07
std	227.979867	232.845126	222.443374	227.987027	227.987027	3.035737e+07
min	36.220001	36.945999	35.397999	35.793999	35.793999	8.297500e+06
25%	54.985001	55.930001	53.929001	54.994501	54.994501	2.478255e+07
50%	66.602002	67.950001	65.445999	66.756000	66.756000	3.498150e+07
75%	165.516998	168.243504	161.504005	163.856503	163.856503	5.211238e+07
max	891.380005	900.400024	871.599976	883.090027	883.090027	3.046940e+08

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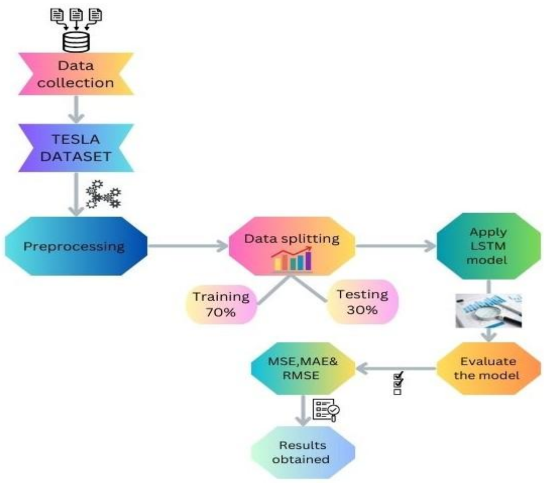

Fig. 1. Methodology flowchart for Stock price prediction

3.2 Data Preprocessing

Data processing are the most necessary aspects needed for training of the model. since every column and row may not be important to the design and set of available datasets are not in a way that could be used to the training of the machines[26]. It involves searching for category values and removing superfluous information from the dataset, as well as examination for lost values and removing them from the data collection [27][28]. The following table presented the Min-Max Normalization of this dataset. Min-Max normalization: if you recall, this method rulers a feature to ensure it falls within a specific range, commonly 0 to 1, the use the following method equ.1:

$$X' = \frac{x - \min(x)}{\max(x) - \min(x)} \ldots\ldots\ldots(1)$$

where x means the starting point and min(x) and max(x) means the smallest and extreme points of the set correspondingly.

3.3 Data Splitting

The dataset used in this study has been split into two sections: test data and training data. The detail 30% has been established for the testing purpose while the remaining 70% of the data has been designated for training purpose.

3.4 Deep learning Classification Models

Since the advent of artificial intelligence, several algorithms have been employed to predict fluctuations in the stock market. To predict a stock's starting price for the subsequent day or to understand the long-term market, a synthesis of statistical analysis and deep learning methodologies is employed [7]. The deep learning classification model uses a multi-layered Perceptron by which features from input data are learned while the data itself is classified into certain classes. They are often used when they require large data sets for training and strong

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computational resources to meet required high accuracy [29]. The following paper offers and explanation of the LSTM model which was applied in this paper for stock price prediction.

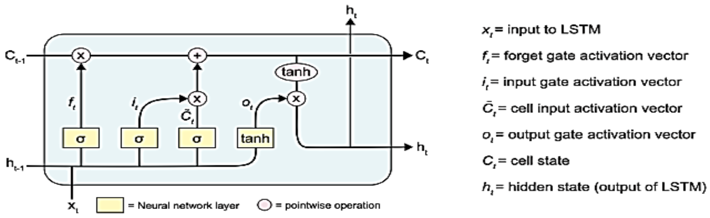

Fig. 2. LSTM model architecture

ANN also have RNN as a subset which has the additional capacity to get a glimpse of long sequence pattern recognition; there is also LSTM networks. The first people to utilize them were Hoch Reiter and Schmidhuber in 1997and later developed further by other authors. The memory structure of the LSTM architecture is its main advantage as it can control how long the learning process takes to reduce long-term biases.[30]. Figure 2 illustrates the primary architecture of a generic LSTM network. It is noted that there are three main variables: Ct, ht, and xt. The LSTM network's memory (Ct), output (ht), and input (xt) are represented by the variables. Within the structure, three main processes are carried out. By multiplying elements-by-elements, the first operation sets up the memory unit (ft) for the second step. Through the use of a neural network layer known as the forget gate, the previous output and the current input determine this structure. The next step is to evaluate the cell state, which is determined by a neural network and is affected by the input gate, current input, and previous output. This module combines the current input with the previous memory to prepare the cell state for the next gate. Finally, we have the final unit, which employs a neural network to evaluate the current output in respect to the prior output, current input, and cell state [31].
In the current study, the used LSTM architecture is presented in Figure 2 below. It is the input gate it, the change gate ct˜ and the forget gate ft which the memory cell ct employs to update information for the input xt. The memory cell ct and the output gate ot are employed to transition from one hidden state ht.key points. When the output gate (OT) and memory cell (CT) are switched on and off, this hidden state is altered. The functions containing parameters define LSTM working activities as shown in the equations 2 to 7.

$$i_t = \sigma\left(W_{ix_t} + W_{{h_i}^{ht-1}} + b_{i,}\right), \ldots\ldots (2)$$

$$f_t = \sigma\left(W_{fx_t} + W_{{h_f}^{ht-1}} + b_{f,}\right), \ldots\ldots (3)$$

$$o_t = \sigma\left(W_{ox_t} + W_{{h_o}^{ht-1}} + b_{o,}\right), \ldots\ldots (4)$$

$$\tilde{ct} = tanh\left(W_{cx_t} + W_{{h_c}^{ht-1}} + b_{c,}\right), \ldots (5)$$

$$f_t \otimes c_t + i_t \otimes \tilde{ct} \ldots\ldots (6)$$

$$h_t = o_t \otimes (c_t) \ldots\ldots (7)$$

Trials & Tune v2 includes the use of the hyperbolic tangent as the tanh layer and the sigmoid function as σ layer. Element-wise product is represented by the ⊗ operator, weight matrices are represented as W and Wh and bias vectors represented simply as b.[32]

1. Autoregressive Integrated Moving Averages (ARIMAs)

Since financial time sequence data is characterized by complexity and dynamics, autoregressive integrated moving average (ARIMA) is suitable for stock price forecasting [33]. The first question that is usually answered through econometric analysis is whether the behavior of stock prices is stationary or non-stationary The behavior of stock prices is typically non-stationary and ARIMA models are effective in demeaning the series to obtain stationarity which is the precondition for modeling. Indeed after establishing that the series is stationary, the first step of modelling an ARIMA is to first differ the time series data in order to achieve stationarity and therefore remove trends as well as seasonality. They then utilize MA parts in order to explain effects of prior disturbance or so-called white noise, then AR segments to illustrate the relationship between the current value and previous values. The number and difference of AR and MA components are indicated by the model's parameters p, d, and q, in that order. required respectively. These parameters are computed by the ARIMA model, which then matches the model to the data. To predict future data points, forecasting makes use of model parameters and prior observations [34].

2. Decision tree

Decision tree is commonly used in the stock trends a review based on this study's findings. A model that is based on artificial intelligence and which constructs a decision tree produces sets use the instructional models to develop a set of guidelines. It repeatedly splits by itself to diagnose which descriptor – normally 'attack' or 'normal' – applies to the stream under analysis. One example towards the use of this approach in the cybersecurity is the identification of the DoS attacks through the analysis of traffic volume, intensity and time duration. If the flow amount is low but the traffic period is high then this must be an attack and it will be lumped in this class. By categorizing variables like CPU utilization, network traffic, and data write volume, decision trees may be used to detect command injection risks in autonomous automobiles. This approach is favored for its intuitiveness, as the developer is aware of what the AI identifies as aberrant traffic and what it does not [35].

IV. RESULTS AND DISCUSSION

This section outlines result and discussion of stock price prediction focusing on LSTM, ARIMA and decision tree model. Additionally, the models for evaluating the performance are MSE, RMSE, and MAE, which point out the best model in the context. The following chapters and sections will give the details of exploratory data analysis of Tesla dataset, performance metrics and outcomes of LSTM model and comparison.

4.1 Exploratory data analysis (EDA)

Data visualization refers to the graphical depiction of data. It comprises all pertinent procedures and techniques utilized in the communication channels of data or information presented in an illustrated manner that is readily identifiable, analyzable, and responsive to enquiries [36]. This dataset has a total of seven variables. The main variables are used to visualize the data which are mentioned below in the following figures.

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Fig. 3. Plot Opening price graph

Figure 3 graph plots the opening price from 2017 to 2021, showing a stable trend until early 2020. From then, the "Open" line shows a sharp increase until peaking in early 2021, with fluctuations but a significantly higher overall trend.

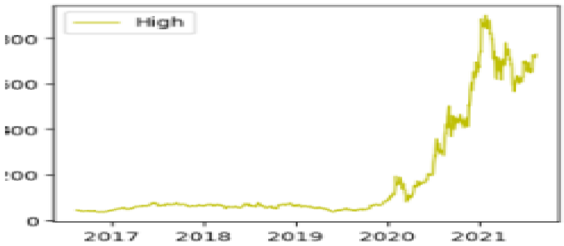

Fig. 4. High price graph

Figure 4 shows a plot of high price from 2017 to 2021. The graph starts flat, rises sharply, and peaks in early 2021. The y-axis shows scale and years from 2017 to 2021.

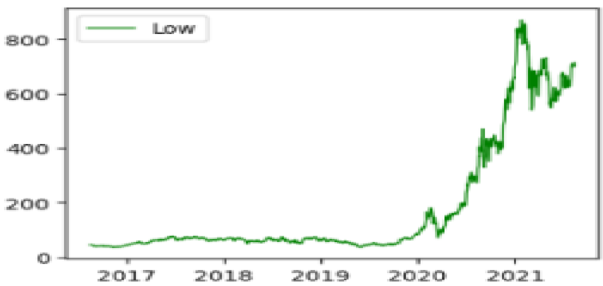

Fig. 5. Low price graph

Figure 5 shows a line graph from 2017 to 2021, with a 'Low' line, rising sharply until early 2020, reaching its peak in 2021, suggesting a significant change or event during this period.

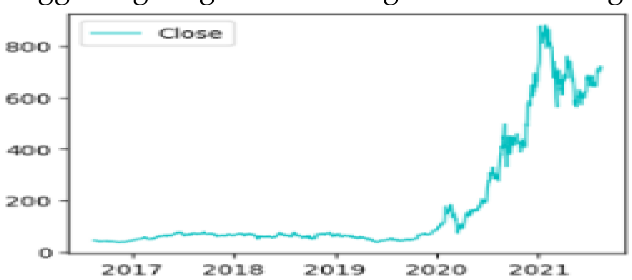

Fig. 6. close price graph

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Figure 6 depicting the 'Close' values of the market index from 2017 to early 2021. The market index's 'Close' values showed a stable trend until late 2019, then a gradual increase, culminating in a sharp spike in values in 2020 and 2021.

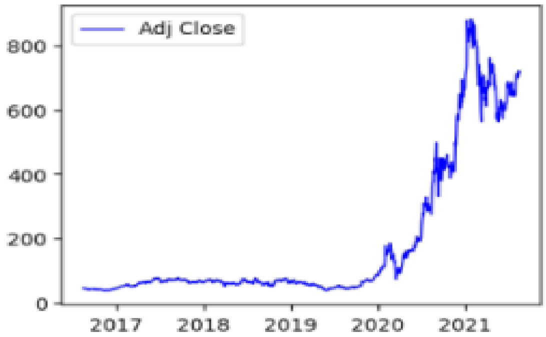

Fig. 7. Plot Adj price graph

Figure 7 shows Plot Adj price graph. It represents that a significant increase in value over time, particularly after 2020, indicating a sharply increased.

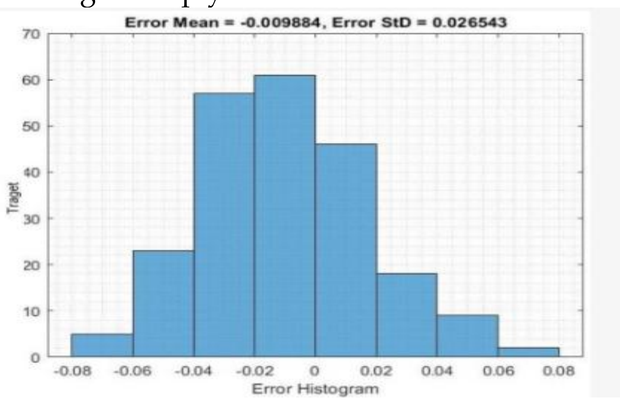

Fig. 8. Histogram Tesla stock market closing price

In Figure 8 below, the accuracy histograms of the deep learning models are used to predict the closing amount of Tesla stock during the testing period are depicted. The differences between the real and expected data were obtained using histograms discrepancies. Mean error for LSTM model is -0.00988.

4.2 Model Evaluation Matrix

This section covers the actual tests that was done in the course of the forecast. In order to evaluate the presentation of different models, the data collected is analyzed using MSE, MAE, and RMSE. The model chosen as exhibiting the best fit was therefore tested to establish how well it would perform if applied on a similarly behaving market index as the training stocks.

1. Mean absolute error

The name for mean absolute error is calculated by using the abbreviation MAE. It can be more accurate with the real situation of the expected inaccuracy. The MAE is calculated by eq.8:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\text{Yi} - \hat{\text{Y}}\,\text{i}| \ldots\ldots (8)$$

2. MSE

What is important to say here is that the Mean Squared Error (MSE) is a measure that reflects the difference between the estimator and the estimated value. The square of the Euclidean distance yields Mean Squared Error (MSE). It follows equation 9.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} |\text{Yi} - \hat{\text{Y}}\,\text{i}|^2 \ldots\ldots (9)$$

3. RMSE

RMSE may effectively minimize computational demands and facilitate a more comprehensible conclusion when the dataset is too large. It is following equation 10.

The Tesla dataset's machine learning models' performance in predicting stock prices is assessed using the following metrics.

$$\text{RMSE} = \frac{1}{n}\sum_{i=1}^{n} |\text{PredYi} - \hat{\text{Y}}\,\text{i}|^2 \ldots\ldots (10)$$

4.3 Results of LSTM model

The following Table 3 delineates the LSTM model's ability to forecast stock market performance (using the Tesla dataset) using the MSE, RMSE, and MAE.

Table III. LSTM Model Performance For Stock Prediction

Model	MSE	RMSE	MAE
LSTM	0.08	0.03	0.08

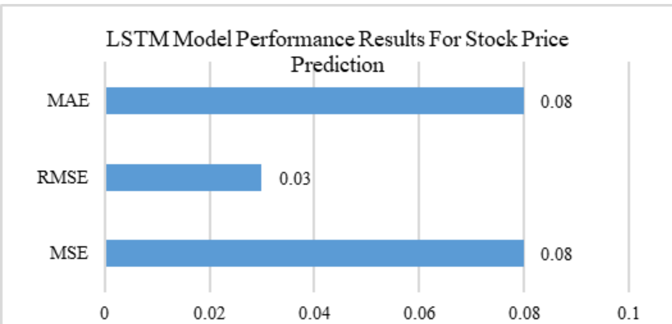

Fig. 9. Bar graph of LSTM model performance for stock price prediction

Figure 9 shows the performance of an LSTM model with the following values: RMSE of 0.03, MSE of 0.08 and MAE of 0.08. These results suggest that the proposed model makes accurate predictions of the target variable with minimal deviations in terms of the analyzed measures.

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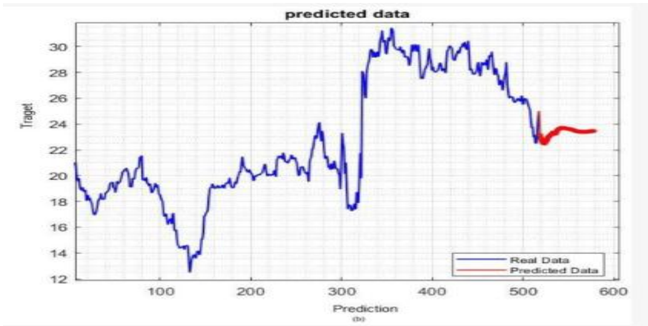

Fig. 10. Predicted and actual values graph prediction based on LSTM model

Figure 10 The predicting of Tesla's values using a deep learning model indicates that the closing price was $25.14, while the forecasted value for the previous days is $30.51. Additionally, the LSTM projection for October 18, 2017, is $23.46.

4.4 Comparative Analysis

In this section, performance measures employed in evaluating the sincerity of the LSTM model include, MSE, RMSE, and MAE.

Table IV. Comparison Between Various ML Models For Stock Prediction

Model	MSE	RMSE	MAE
LSTM	0.08	0.03	0.08
ARIMA [37]	0.07	0.26	0.2
Decision tree[38]	0.09	4.5	0.29

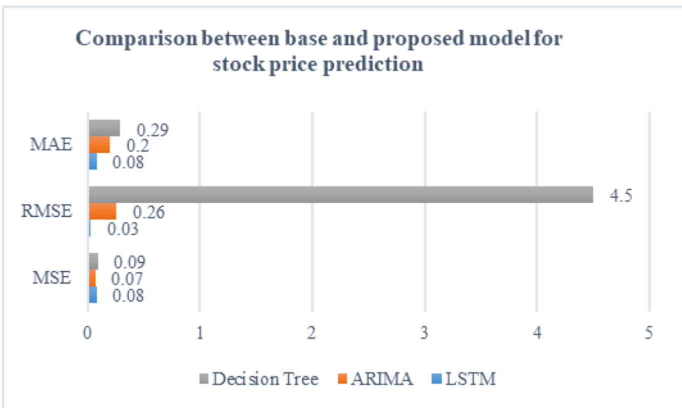

Fig. 11. Comparison between the base and proposed model

Figure 11 Comparison of the baseline and suggested models, which incorporate LSTM, ARIMA, and Decision Tree, utilizing three assessment metrics: MSE, MAE and RMSE. The proposed LSTM model achieved good prediction accuracy with a MSE of 0.08, RMSE of 0.03 and MAE of 0.08. When comparing the proposed model with LSTM, the ARIMA model has shown somewhat better accuracy but with higher errors, with MSE equal to 0.07, RMSE equal to 0.26, and MAE equal to 0.2. The Decision Tree model has an MSE of 0.09, a significantly higher RMSE of 4.5, and an MAE of 0.29, indicating it performs the worst in terms of prediction accuracy. Based on these values, LSTM is the most effective model in comparison to the baseline models.

V. CONCLUSION AND FUTURE SCOPE

Stock prediction is an essential element of financial markets because correct stock price forecasting impacts investments and overall decisions about financial resources. This assessed the performance of three distinct predictive models in forecasting stock prices: decision tree models; autoregressive integrated moving averages; and LSTM. This paper also presented three types of prediction methods, where the authors established that the best potential was realized by the LSTM approach. Explaining the results, the LSTM model received a MSE, RMSE, and MAE of 0.08, 0.03, and 0.08, respectively, therefore it was more accurate and reliable. The low error values suggest that the model is most suitable for time series data because it can measure the temporal connections within a given set of data. Therefore, this research delivers the possibilities of LSTM as a most stable method in forecasting even when the appreciation of time indexed data is essential. This supports previous ideas suggesting that complex models, such as the neural network models like LSTM provide higher levels of forecast precision than more conventional models such as ARIMA and Decision Trees.

The possible directions for future research, which may help to improve predictive accuracy and the range of the models' application, can be set as follows: As for further development, there might be research on how to integrate features of LSTM with other models of time series forecasting, including ARIMA, or using features of ensemble learning. This could be because the temporal relationships of LSTM and the linear trends of ARIMA jointly utilized in this work may boost the model's performance. Furthermore, it could be possible to involve other datasets with more complex spatial and temporal patterns or with other properties in order to confirm the applicability of the findings. Finally, the application of feature engineering and hyperparameter tuning might improve LSTM model performance even if only slightly, thus allowing for practice-applied predictions with higher accuracy.

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