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Tesla Stock Price Prediction: A Hybrid Approach using Machine Learning Techniques and GRU Models

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Abstract— A nation's stock market plays a vital role in providing the necessary financial framework for its economy by facilitating the efficient utilisation of both financial and social capital. While marketing models enable market participants to select companies with high dividend payments while minimising investment risk, reliable equity market models provide investors with reasonable options for making decisions. Share market prediction has improved with technological advancements. Using statistical techniques like exploratory data analysis and machine learning performance measures like RMSE, MSE, MAE, R2 score regression, Random Forests, MGD, and MPD, this paper investigates strategies for predicting the closing prices of Tesla stock. For future projections, neural networks with gated recurrent units (GRUs) are employed. As machine learning techniques can prevent overfitting, jamming and are better at predicting stock prices, for high-volatility stocks like Tesla, this makes them appropriate.

Index Terms— Close Stock Price, Deep Learning, Future Price Prediction, High Stock Price, Low Stock Price, Machine Learning, Open Stock Price, Stock Market, Tesla.

I. INTRODUCTION

The fluctuating nature of global financial markets has been reflected through the stock prices that get affected by such a wide range of factors, including economic indicators, company performance, geopolitical events, and market sentiment of investors. For traders, investors, and financial institutions seeking a return on investment and minimizing risk, stock price prediction has become a prerequisite in this volatile era.

Tesla Inc. has been an exciting subject for analysis and prediction from among the many stocks that are available for trading. Tesla was founded in 2003 by Martin Eberhard and Marc Tar penning and has since been led by CEO Elon Musk. Eco-friendly and disruptive, Tesla has dominated the production of electric vehicles and renewable energy sources in the automotive industry.

Owing to Elon Musk's inspirational leadership, the company's rapid growth, and its bold expansion plans, Tesla's stock prices have become the subject of aggressive speculation and scrutiny. Owing to its volatility and sensitivity to sudden changes, the stock is an ideal candidate for study in stock price prediction, which uses sophisticated methods of analysis to predict future price movements.

Because of recent developments in data science, machine learning, and deep learning, sophisticated predictive modelling techniques are all capable of capturing sophisticated complex patterns and trends in financial data. By critically analysing past stock price data and weaving in multiple factors, for example, trading volume, technical indicators, and market sentiment, the scholars can create prognostic models of future stock prices, more or less.

A strong understanding of the candlestick chart is required when working with OHLC (Open, High, Low, Close) data. For the purpose of this study, we analyse and forecast Tesla's stock prices using historical stock price data in the OHLC (Open, High, Low, Close) format. The four essential components of a candlestick chart are: opening price (Open), the highest price (High), the lowest price (Low), and the closing price (Close). Candlestick charts present data of a single trading period, usually a day. The body of the candlestick shows the actual range of prices between open and close prices; an empty (green or white) body indicates closing price is higher than opening price, and a filled (red or black) body indicates closing price that is lower than opening price[1].

Moreover, the shadows or wicks—thin lines that extend above and below the actual body—describe the highest and lowest prices achieved in that period. Longer wicks reveal greater price ranges and possible market indecision. Such wicks are very helpful when trying to understand price volatility and trading activity. Analysts and traders can find trends, reversals, and the most effective levels of support and resistance in the stock prices within the patterns and formations made by candlesticks in succession. Analysts gain important insights into investor sentiment and market trends, and possible price movements by scrutinizing these candlestick patterns.

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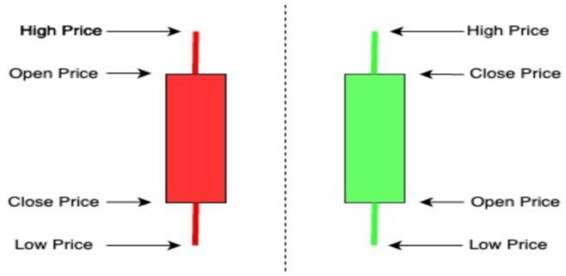

Fig 1. Candlestick chart in Stock Market

II. MOTIVATION

The motivation for choosing the project on Tesla stock price prediction comes from a mix of personal interests in finance and technology, coupled with a strong desire to apply machine learning techniques to the actual field of financial data. Tesla, with its innovations and dynamic stock price movement, gives an interesting challenge to perform predictive modelling. Using machine learning algorithms and deep learning techniques like Gated Recurrent Unit (GRU), the project breaks down the complexities in Tesla's stock price dynamics and develop a sound predictive model.

It also offers an opportunity to deepen the understanding of market trends, test the efficacy of predictive models, and to add to the understanding of stock price forecasting. In addition, predicting Tesla's stock prices with accuracy can lead to very valuable insights for investors, traders, and financial analysts because this allows them to make informed decisions and manage risks in the fast-paced world of stock trading.

III. LITERATURE SURVEY

One of the most significant contributions is the use of different models, including Linear Regression, Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Bidirectional LSTM (Bi-LSTM) to predict stock prices. It also emphasizes the need for the performance evaluation with the help of metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R2). Furthermore, training and fitting of models were discussed, including the use of Graphic Processing Unit (GPU) computing and tuning the parameters of the model. This study was conducted without any financial support and was affiliated with Bina Nusantara University, Indonesia. Ethical considerations, including conflicts of interest and plagiarism, were also addressed.[2]

As recent technology advances, machine learning algorithms get more popular, due to their capability to analyse the historical data, find the trends, and make future predictions, such algorithms are increasingly used in making the stock market forecasts. The study concludes with an analysis of long short-term memory models used for stock price prediction and testing various machine learning algorithms and approaches used in sentiment analysis. The document also strives to show the importance of the evaluation of the model in terms of metrics like mean absolute error and mean square error. The findings suggest that the proposed strategy performs significantly better than the standard statistical approaches in terms of stock value forecasts for Tesla and Apple. The paper concludes by pointing out that deep learning algorithms and sentiment analysis may help improve stock price prediction to an extent, and traders and investors can use the research to make investments wisely.[3]

Furthermore, in [4] The authors are comparing the performance of four models: linear regression, super vector regression, random forest regressor, and long short term memory. The study uses a particular dataset and evaluates the models based on a variety of parameters. The result has shown that linear regression is the best method that could predict Tesla's stock prices. It stresses that the right prediction of the stock is important in the stock market for the investors and traders. In the study, it is found that linear regression was the best machine learning model to predict the stock prices of Tesla. This was concluded by comparing four models, i.e., linear regression, super vector regression, random forest regressor, and LSTM. The study highlights that linear regression has the highest R-squared value for Tesla from 2020 to 2022 compared to the other three models, and therefore, it is performing best in predicting Tesla's stock market performance.

In conclusion, new trends formed the basis of employing deep learning techniques such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) even though the linear regression, support vector regression, and random forest regressor models have all been critically studied. Nevertheless, it is clear that deep learning models like Gated Recurrent Unit must be introduced in order to get the correct stock price predictions since those that depend on traditional machine learning models might be flawed in and of themselves. Such models are very reliable and deliver better forecasting powers with the incorporation of GRU along with careful analysis using metrics such as Mean Squared Error (MSE), Root Mean Squared Error, and Coefficient of Determination (R2). This paper, focusing on the prediction of Tesla stock prices based on the last 30 days and forecasting the next 15 days, argues for the incorporation of deep learning techniques, such as GRU, along with traditional machine learning models in order to increase the accuracy and efficiency of predicting stock prices.

IV. ABOUT THE DATASET

The dataset covers the period of Tesla stock, from the year 16-08-2016 to 13-08-2021. It consists of the trading volume for each day together with the opening, high, low, and closing prices. The fact that the data is presented in a time series format matters since it allows us to perform a comprehensive

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analysis of the stock's performance over time. Closing prices ranged from 40.79999 to 75.596001, while opening prices ranged from low to high, 39.966 to 47.34. 36.576 is the lowest recorded stock price during this period, while 77.38999 is the highest. With a maximum daily volume of 989,570,000, the data indicates fluctuating trading volume. The dataset has a picture of long-term performance in stock, which spans all the data dating from the inception to the present day. Data for making intelligent investment decisions is critical for analysing trends, volatility, and trading volumes. Additionally, this dataset can be useful in risk assessment, predictive modelling, and analysis of long-term stock performance. Wrapping up, the dataset gives a thorough and in-depth history of Tesla's stock performance, delivering insightful information to researchers, analysts, and investors who wish to know more about the workings of the stock market and make informed financial decisions.

V. SYSTEM ARCHITECTURE

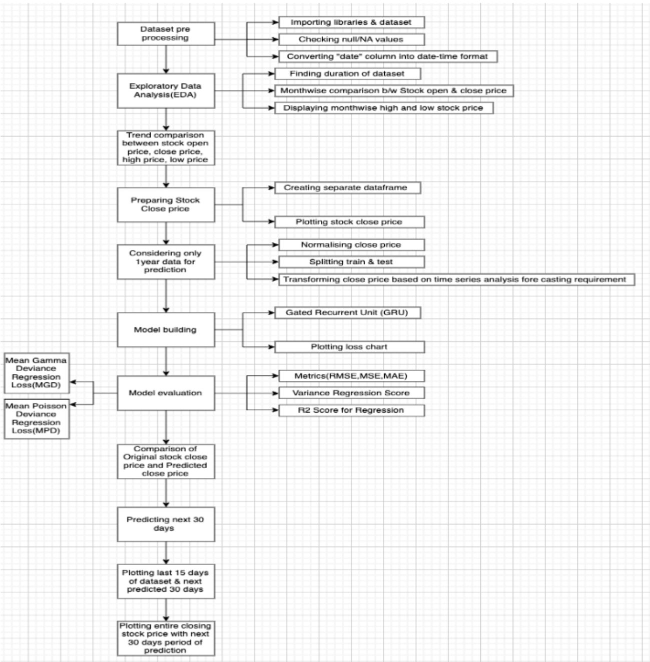

Fig 2. Proposed Architecture

1. The above flowchart outlines the process for predicting Tesla stock prices, beginning with data preprocessing and exploratory analysis, including month-wise comparisons and trend analysis.
2. The stock's close price is prepared and normalized, with a focus on one year's data for prediction.
3. Model building using GRU is followed by evaluation using various metrics.
4. The original and predicted prices are compared, and future prices are forecasted for the next 30 days. Finally, the predicted trends are visualized alongside historical data for the last 15 days and the next 30 days.

VI. METHODOLOGY

A. Exploratory Data Analysis (EDA)

Machine Learning methods like EDA are developed to explore patterns, summaries and visualizations.

B. Sequential Model Building

This is integrated to extract the time series data, thereby enhancing the accuracy and comprehensiveness of the predictive models. Usually, this process starts with a simple linear model, but it is improved by adding new features or strengthening its functionality as it grows. At every stage of development, the model will be able to foretell future stock prices with great perfection. The only algorithm available for stock price prediction, when it comes to sequential model building, is a neural network and the decision tree.

This dual approach ensures a thorough analysis of structured data, leading to more robust and reliable stock price predictions.

C. Gated Recurrent Unit (GRU)

Various GRU models are built for sequence prediction. GRU layers captures long-term dependencies and effectively handles vanishing gradients that can be a problem in other RNN architectures. GRU layers are added to stock price prediction model by feeding in past stock prices as input and outputting the predicted future stock prices. A combination of GRU layers with other models like LSTM (Long Short-Term Memory) is also used for better performance.

D. Gated Recurrent Uni t(GRU) Layers

2 layers of GRU are added named Dense layer and Dropout layer. Dense layers are fully connected layers that take in a flattened input tensor and output a scalar or vector. In the context of stock price prediction, a dense layer could be used as a final output layer, taking in the hidden state of the GRU network and producing a predicted stock price.

E. Dropout Layer

Dropout is a regularization technique used to reduce overfitting in neural networks. It works by randomly dropping out nodes (i.e., setting their values to zero) during training. This forces the network to learn more robust representations of the data and can improve generalization performance.

Methodology 6.1: Implementation of Machine Learning Techniques & Model Building

6.1.1 Data Collection and EDA

This step includes importing the dataset, and checking for missing values. EDA includes looking for null/NA data, converting columns related to dates to datetime format, and exploring the statistical summaries and visualizations to understand the overall structure and distribution within the dataset.

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6.1.2 Data Visualization

Using visualizing techniques to understand the dataset better and understanding the relation and dependence of one relation with another. Also understanding the relation of the feature columns with the target column. Graphs such as line plots and histograms are employed to visually inspect the stock price trends over time and any seasonal or cyclical patterns.

6.1.3 Data Pre - processing and Train Test Split

Pre -processing involves dropping of missing values, dropping of columns which do not significantly impact the accuracy. Train-test split is a method used in machine learning to divide a dataset into two subsets: one for training the model and the other for evaluating its performance. This is done to assess how well the model generalizes to unseen data and to prevent overfitting by validating its performance on independent test data. This also involves an extensive data pre-processing step in preparing the data for modelling, which includes creating separate data frames for the target variable, normalization to ensure uniform scales, and splitting the dataset into training and testing sets. Similarly, Normalization is a pre - processing technique in machine learning that scales data to a standard range, preventing features with larger magnitudes from dominating the model training process. Dimensionality reduction is a technique used in machine learning to reduce the number of features or variables in a dataset, aiming to simplify model complexity, improve computational efficiency, and avoid the curse of dimensionality.

6.1.4 Model Building

A Gated Recurrent Unit (GRU) is a type of recurrent neural network that can be used in the modelling of sequential data, namely time-series stock price data. The GRU is chosen because it can effectively capture long-term dependencies in time-series data and avoid the vanishing gradient problem that plagues traditional RNNs. It is chosen for its simple architecture that speeds up the training and reduces the amount of computational work needed while maintaining strong predictive performance.

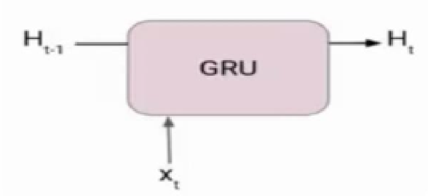

Fig 2. Basic GRU network

At each timestamp t, it takes an input Xt and the hidden state $Ht{-}1$ from the previous timestamp (t-1). Later it outputs a new hidden state Ht which is again passed to the next timestamp.

GRU has 2 primary gates as follows: -

6.1.4.1 The Reset Gate(Short Term Memory) –

This gate is responsible for the short-term memory of the network i.e. the Hidden State(Ht).

$$\boxed{r_t = \sigma(x_t * U_r * H_{t-1} * W_r)}$$

Where,

r_t is the reset gate vector at time step t which controls how much of the previous hidden state information to forget.

σ is the sigmoid activation function, which gives the output value between 0 and 1.

x_t is the input vector at time step t.

U_r is the weight matrix for the input vector Xt in reset gate.

H_{t-1} is the previous hidden state vector at time step t-1

W_r is the weight matric for the previous hidden state vector $Ht{-}1$ in reset gate.

6.1.4.2 The Update Gate (Long Term Memory) –

This gate controls how much of the previous hidden state information to retain and how much of the new candidate state information to incorporate.

$$\boxed{r_t = \sigma(x_t * U_u * H_{t-1} * W_u)}$$

Where,

r_t is the update gate vector at time step t which controls how much of the previous hidden state information to retain.

σ is the sigmoid activation function, which gives the output value between 0 and 1.

x_t is the input vector at time step t.

U_u is the weight matrix for the input vector Xt in update gate.

H_{t-1} is the previous hidden state vector at time step t-1

W_u is the weight matrix for the previous hidden state vector $Ht{-}1$ in update gate.

6.1.5 Adding 2 GRU Layers

The GRU layers are made up of interconnected units that process sequential data, like past stock prices. Update and reset gates are a part of every GRU unit, which regulates information flow and helps to solve the vanishing gradient issue that traditional RNNs frequently have.

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The 2 layers added in the GRU model are described as follows:

6.1.5.1 Dense Layer –

Dense layer is typically added after the GRU layers to perform feature extraction and transformation. It consists of fully connected neurons that apply a linear transformation to the input data, followed by an activation function to introduce non-linearity.

$$\boxed{y = f(W_x + b)}$$

Where,
y is the output vector.
f is the activation function.
W is the weight matrix.
x is the input vector.
b is the bias vector.

6.1.5.2 Dropout Layer –

Dropout layer is often included after the Dense layer to prevent overfitting by randomly dropping a fraction of the neurons during training. This regularization technique helps improve the generalization performance of the model.

$$\boxed{y = \frac{1}{1-p} * x}$$

Where,
y is the output vector.
x is the input vector.
p is the dropout rate i.e. the probability of dropping a neuron.

Methodology 6.2: Various Model Evaluation Techniques Used Before Prediction

6.2.1 Root Mean Squared Error (RMSE) –

RMSE measures the square root of the average of squared differences between the actual and predicted values. It provides an indication of the average magnitude of error between the predicted and actual values.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where:

- y_i is the actual value
- $\hat{y}_i$ is the predicted value
- n is the number of observations

6.2.2 Mean Squared Error (MSE) –

MSE measures the average of squared differences between the actual and predicted values. It provides a quantitative measure of the model's accuracy, with lower values indicating better performance.

$$\mathbf{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

$\mathbf{MSE}$ = mean squared error
n = number of data points
Y_i = observed values
$\hat{Y}_i$ = predicted values

6.2.3 Mean Absolute Error (MAE) –

MAE measures the average of absolute differences between the actual and predicted values. It provides a measure of the average magnitude of error, regardless of direction.

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

where,

n: *number of observation*

y_i: *the actual value of the* i^{th} *observation*

$\widehat{y}_i$: *the predicted value of the* i^{th} *observation*

6.2.4 Explained Variance Regression Score (EVS) –

R-squared measures the proportion of variance in the dependent variable that is explained by the independent variables in the model. It ranges from 0 to 1, with higher values indicating better model fit.

$$explained\ variance(y, \hat{y}) = 1 - \frac{Var(y - \hat{y})}{Var(y)}$$

Where,
Var : Variance
y : Actual values
$\hat{y}$: Predicted values

6.2.5 R-squared Score for Regression –

R-squared measures the proportion of variance in the dependent variable that is explained by the independent variables in the model. It ranges from 0 to 1, with higher values indicating better model fit.

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$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

Where,

R^2 : R-squared score

y_i : Actual value

$\hat{y}_i$: Predicted value

$\bar{y}$: Mean of actual values

n : Number of data points

6.2.5 Mean Gamma Deviance (MGD) –

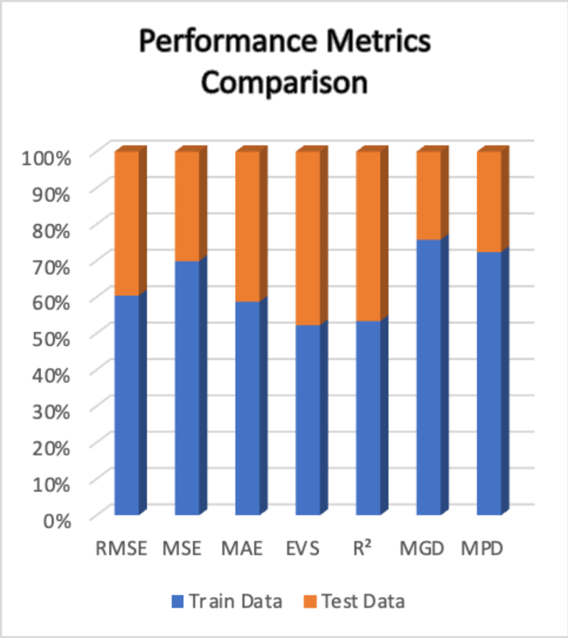
MGD measures the mean deviance of predicted values from actual values for gamma distribution regression tasks. It quantifies the discrepancy between the actual and predicted values, considering the logarithm of the ratio of actual to predicted values.

6.2.5 Mean Poisson Deviance (MPD) –

MPD measures the mean deviance of predicted values from actual values for Poisson distribution regression tasks. It evaluates the discrepancy between the actual and predicted values, considering the difference between the actual and predicted values and their logarithmic ratio.

VII. RESULT

In this research, we have used 7 different model evaluation methods which gave results on train and test data as follows:



The expanded forms of the above evaluation metrics shown in the bar chart are given below:

A. RMSE: Root Mean Squared Error

B. MSE: Mean Squared Error

C. MAE: Mean Absolute Error

D. EVS: Explained Variance Score

Here, Scores close to 1.0 are highly desired, indicating better squares of standard deviations of errors.

E. R^2: R-Squared Score (Coefficient of Determination)

Here, 1 = Best & 0 or < 0 = worse

F. MGD: Mean Gradient Deviation

G. MPD: Mean Percentage Deviation

Overall, The results indicate that our predictive models demonstrate strong performance across multiple metrics. The Root Mean Squared Error (RMSE) on the test data is 18.44, indicating a relatively low average magnitude of error in our predictions. Similarly, the Mean Squared Error (MSE) and Mean Absolute Error (MAE) on the test data are 339.90 and 14.73, respectively, further demonstrating the accuracy of our models. The Explained Variance Regression Score (EVS) on the test data is 0.89, suggesting that our models explain approximately 89% of the variance in the dependent variable. Additionally, the R-squared score for regression on the test data is 0.85, indicating a strong correlation between the predicted and actual values. Moreover, the Mean Gamma Deviance (MGD) and Mean Poisson Deviance (MPD) on the test data are 0.00078 and 0.515, respectively, showcasing the goodness-of-fit of our models to the underlying distribution of the data.

In conclusion, these results highlight the effectiveness and robustness of our predictive models in forecasting Tesla stock prices, providing valuable insights for investors and stakeholders in the financial domain.

Fig 3. Plot of entire Closing Stock Price with next 30 days period of prediction

VIII. CONCLUSION

In conclusion, the analysis brings out the effectiveness of advanced machine learning techniques, especially GRU-based models, in accurately predicting stock prices. Our results show that these state-of-the-art prediction approaches can effectively model complicated patterns underlying financial times series as shown by their superior performance across several evaluation measures such as RMSE, MSE, MAE and R^2 scores. There are numerous possible applications for these models that can contribute valuable information to traders, investors and financial analysts concerned with trading on the stock exchange. The prospects for future development include additional features incorporating technical indicators and sentiment analyses into a combination of ensemble learning techniques for model improvement, adaptive refinement algorithms and deep architectures for more accurate predictions. Additionally, real-time prediction systems integrated with trading platforms would improve decision-making process and risk control mechanisms. In addition, there is need to consider interpretability challenges and how they can be used to enhance this approach so as to make it easily understandable by key stakeholders in the industry including practitioners and policy makers. This paper paves way for future improvements and applications made in finance predictive modeling.

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