The Role of Machine Learning Algorithms in Stock Market Prediction: A Performance Evaluation

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***Abstract*— The stock market is where people buy and sell shares of publicly listed companies. These stock prices fluctuate up and down based on demand and supply. The other factors include weather, company news reports, changes in management, etc. People can earn a great fortune if they can find a way to predict the future prices of the stock market and accordingly make their investments. Our research aims to find the best model to predict the stock prices effectively. The models we tested include simple regression models and a stacked LSTM (Long-Short-Term Memory) model designed for accurate prediction of stock prices. The reason behind choosing a stacked LSTM model is that it enables us to process time-series data, hence enabling our model to understand the trends better. The metrics used include Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RME). The final scores enable us to determine the best model that does not overfit our data, hence enabling us to maximize our profit. Furthermore, the model is tested by recording prices at an interval of 24 hours, 1 hour, and 5 minutes to find a model that gives us the best accuracy.**

Keywords — Random Forests, Long Short-Term Memory, Polynomial Regression, Linear Regression, Support Vector Machines, Stock Prediction Model.

I. Introduction

A person who invests in the stock market wants to maximize his profit by buying a stock for a low price and selling it at a comparatively higher price [1]. Business Spectator is a tool that indicates the nation's economy [2] and reveals corporations' general business climate and performance [3]. Traders buy stocks to make some profit. Hence with time, traders tend to find patterns in stock prices [4] and know the right time to invest and sell stocks of a particular company [5]. The factors affecting the stock price of a specific company include the company's performance [6], economy [7], politics, global events, exchange rates, etc. With time traders gain knowledge [8] on which factor influences a stock price more than the other hence making them profits [9]. However, several \extra operations are needed to improve the method's ability [10].

Our main aim of this research is to compare the existing research models and make a model that not only accurately helps us predict whether a stock price will increase or decrease but also ensures that the data does not overfit. The model made by us is a stacked LSTM model [11]. A stacked LSTM model is a model that has multiple hidden LSTM layers where each layer contains memory cells. The features of the LSTM model like the learning rate, the type of loss function, the number of epochs [12], the type of scheduler, batch size, and even the activation function have been tuned in a manner that the LSTM model would perform at its best and forecast more accurately [13].

The primary contributions of this research are:

- LSTM model optimized to achieve better prediction accuracy determined by metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RME), and Mean Squared Error (MSE) [14].
- Compare the accuracies by taking different datasets and applying our model to the same i.e. 24 hours, 1 hour, and 5 minutes of data.

II. Literature Review

The researchers [15] researched to make a design from a history dataset and get current values and future predictions based on input values provided [16]. They used Support Vector Classifiers (SVC) which are useful for solving machine learning challenges [17] and can be applied in various domains, such as predicting travel routes [18] or identifying normal tissues in medical imaging [19]. They also discussed various regression algorithms commonly used in computer vision [20], including Linear Regression and Logistic Regression [21]. These algorithms are utilized to model the correlation between independent values and

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dependent binary attributes [22]. However, they did not explore LSTM models which provide better results in time series data [23].

A Support Vector Machine (SVM) is used. The SVM model gives a hyperplane that correctly separates training data and maximizes the geometric margin [24]. In cases where data is not linearly separable, SVM employs kernel functions, such as the Radial Basis Function (RBF) kernel, to predict nonlinear mapping of the data [25]. However, their model assumes linear separability of data which may not hold for all cases and hence cannot be generalized [26].

Some explored algorithms such as backtracking, decision tree regression [27], Monte Carlo simulation, and moving averages [28]. They found out that the Monte Carlo simulation is the most accurate method. However, they did not try modern methods such as LSTM models [29].

Some combined the news sentiment data with the stock market data to train two machine learning systems—Cat Booster and Random Forest [30]. These models were used to detect stock prices based on both the financial data and the news sentiment. However, they assumed that stock prices reflect all available information and follow a random walk pattern, and the models used are susceptible to overfitting, especially when trained on limited datasets or complex architectures.

Some used Lasso and Ridge models in which their goal was to reduce the sum of residuals while at the same moment incorporating shrinkage penalty to get a better fit. However, these models assume linear relationships, hence missing out on complex patterns as well as lacking the ability to capture temporary dependencies.

III. Methodology

A. *Dataset*

The dataset used for the research is of Apple Inc. This company has a specialization in electronics equipment, consultancy services, and software development. The data collected from Yahoo Finance includes which consists of various data related to economics, the stock market, financial transactions, government reports, news reports, etc. The dataset is divided into 2 sectors 80% for the training dataset and 20% for the test dataset. LSTM is split into three sectors, 80% training dataset, 10% validation dataset, and 10% test dataset.

B. *Linear Regression*

Linear regression is a mathematical tool that people use to get information about how dependent variables are changed because of one or more independent values. Its practicality and elucidation have made it one of the key statistical techniques in predictive modelling and data analysis. In fact, among the main advantages, linear regression can produce reliable regression analysis, which is of utmost importance in the precise identification of the extent to which variation in independent values affects the dependent values. Moreover, financial, economic, and marketing arenas are reaping the benefits of its contribution to planning being the case. When speaking of linear regression, several conditions must be fulfilled for the method to be valid. Between the resulting unwanted and the change of the independent variable, the situation of an identical change brings about the same change in the dependent variable. It is crucial that the observations are not dependent and the score of dependant value for iterations would not be hampered or be dependent on other observations. Also, the variations need to be homoscedasticity between all independent values, and the residual errors must be normally distributed. Finally, the independence of multicollinearity should be provided, which means the variables-intervals should not be highly correlated with each other. The use of these prerequisites is linear regression which represents the strongest framework for analyzing and forecasting the relationships of variables.

Types of Linear Regression:

Simple Linear Regression: Consists of an independent value as shown in equation 1.

$$\hat{y} = \beta_0 + \beta_1 x \qquad (1)$$

Multiple Linear Regression: Consists of two or more independent values as shown in equation 2.

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \qquad (2)$$

C. *Polynomial Regression*

The assumptions for polynomial regression are parallel to those of linear regression; linearity of the relationship (in time transformed the polynomial to a space), independence of observations, homoscedasticity (constant variance of the errors), and normality of residuals are among them. Polynomial regression, however, needs special care to be given to the degree of the polynomial to balance the model complexity and prediction accuracy. On the one hand, too little a degree may cause us to underfit, i.e., the true relationship between the variables is not captured by the model, whereas too much a degree may lead us to overfit, i.e., the model captures noise in the data as shown in equation 3.

$$\hat{y} = \beta_0 + \beta_1 x^1 + \beta_2 x^2 + \cdots + \beta_d x^d \qquad (3)$$

D. *Random Forests*

Random forests are a complex machine learning algorithm seeking to calculate the value of a given dependent variable by training in building multiple representations of decision trees and outputting the average of the calculations of the separate nodes. That kind of learning, based on the sum of many variously designed systems, intelligent by their independence, succinctness, lack of further decisions, and, of course, variability of linear and nonlinear links between given items, is so. Random forest regression overfitting can be eliminated because the model tells the major truth through the way of averaging the results of many similar trees. Thus, it facilitates the distribution of analysis to new kinds of data found in these. The models are mostly used in finance, health care, and environmental areas where accurate predictions and complex data structures are requisite as shown in equation 4.

$$\hat{y} = \frac{1}{B} \sum_{b=1}^{B} T_b(X) \qquad (4)$$

E. *Support Vector Regressor*

One of Vapnik's most powerful machine-learning systems, the support vector machine (SVM), has a variation called the support vector regressor (SVR). The idea behind SVR is that it finds a function that sets the value by approximating the target variable within a given margin of tolerance (epsilon), without considering the entire data set. This boosts efficiency. SVR Model seeks a line best fitted as per given values in a continuous environment by managing the hyperplane in the provided equation, SVR resolves the issue. The visualization is shown in Figure 1.

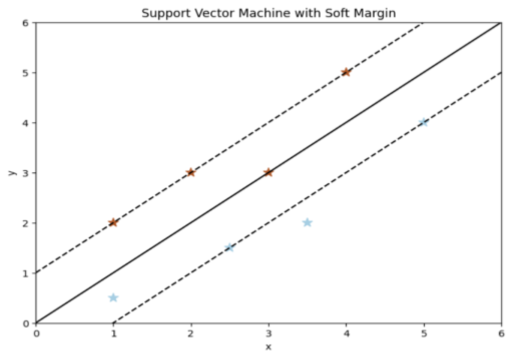

Fig. 1. Soft Margin Support Vector Machine (SVM) Visualization.

The slack variables are represented by ξ_i and * I, and the kernel function is represented by the function f (x, w). The parameters that regulate the maximum margin hyperplane are w and b, and the I^{th} input is x_i The SVR Model can handle non-linear correlations between the input and target variables because it utilizes a kernel formula to translate the dataset to a higher-dimensional environment.

F. *Artificial Neural Networks*

One of the most effective machine learning algorithms is the artificial neural network (ANN), whose construction and functioning are inspired by biological neural systems. Neurons consist of an aggregation function that computes the sum of its inputs and neurons produce outputs via an activation function. ANNs contain levels of connected hosts or neurons which are arranged into input invisible and output levels. In Stock prediction, the raw data of stock prices, and trading volume is received by input layer. Through hidden layers data is processed, and complex transformation and feature extraction occurs. An artificial neural network (ANN) learns using two processes: backpropagation, which propagates errors back through the network to modify weights and biases, and forward propagation, which moves data from the input level to the output level.

ANN standard models are divided into three major types:

- Feedforward Neural Networks (FFNNs): They are the easiest form of ANNs where no form of cycles is formed between the connection of nodes.
- Convolutional Neural Networks (CNNs): Used for image processing, The convolutional layer is the first level of a convolutional model. While additional convolutional levels or pooling levels can precede convolutional levels, the last level is completely connected. As the number of levels enhances the complexity of the CNN model enhances which helps to recognize the larger part of the image. Group of neurons operates on different regions of the image which reduces parameters compared to the densely connected FFNNs.
- Recurrent Neural Networks (RNNs): Unlike FFNNs, RNNs are artificial neural networks with connections between nodes that allow cycles to form along temporal sequences, which enables the network to handle sequential data and exhibit temporal dynamics. However, RNNs suffer from the vanishing gradient problem, where gradients either shrink or get enlarged over time if the network is unfolded too many times. Long short-term memory (LSTM) networks, a specialized form of RNN resolve the issue.

G. *Long Short-Term Memory*

The major quality of the stacked LSTM organized in a show is that it captures and learns from consecutive information through several steps. To begin with, there will be a required preprocessing and shape information fittingly for the LSTM layers, ordinarily requiring groupings to either be cushioned or truncated to a uniform length. Freely, the building of this algorithm will include stacking different LSTM layers on the beat of each other. Each consequent LSTM layer treats this successive input, and its yield is nourished which provides input to the below LSTM level. This permits the model to learn progressive designs and conditions. When characterizing a show, parameters such as the number of LSTM units or neurons in each level, the number of layers, and dropout rates in arrange to dodge overfitting, are a few of the critical parameters that require to be specified. The final layer is ordinarily a thick layer, which yields the last result for the assignment at hand, either relapse or classification. After the model has been made, an optimizer will be characterized, and the model prepared on the consecutive information utilizing backpropagation through time. While preparing, the model will learn how to alter the weights of the LSTM layers to diminish the loss, consequently learning transient conditions. The stacked LSTM model can be utilized for forecasts on modern successive information after preparing; it will get both brief- and long-term conditions. This will come in especially great utilize in applications such as time arrangement determining, where it seems to anticipate future values based on past groupings, or indeed in normal dialect preparing errands where understanding the setting inside an arrangement of words is vital.

IV. Results and Discussion

After applying five machine learning algorithms—Linear Regression, Polynomial Regression, SVM, Random Forest, and ANN—to the historical closing price data of Apple Inc., with an 80-20 training testing data split. The outputs of the test set are shown below. Figure 2 shows the prediction of various regression models.

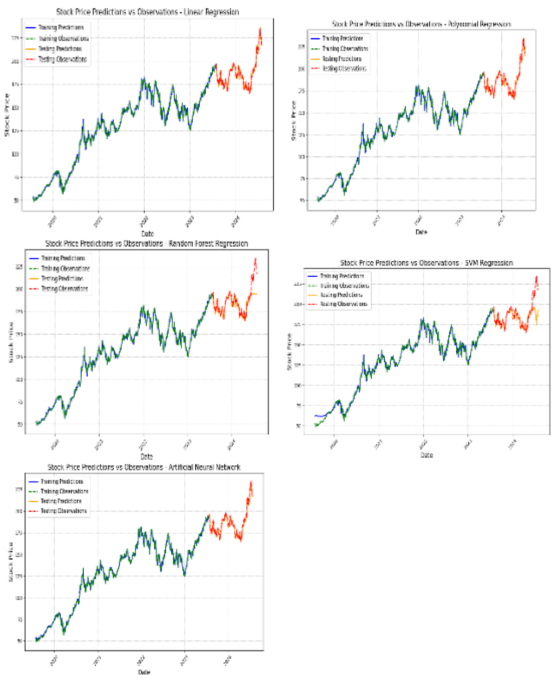

Fig. 2. Prediction of various regression models

TABLE I. MAE, MSE, RME, R2 SCORE COMPARATIVE ANALYSIS

Models	MAE	MSE	RME	R2 Score
Linear Regression	1.04	2.98	1.73	0.99
Polynomial Regression	1.21	3.90	1.98	0.98
Random Forest Regression	4.36	93.20	9.65	0.60
SVM Regression	4.95	146.45	12.11	0.38
ANN	2.07	7.74	2.78	0.97

Table I shows a comparative analysis of MAE, MSE, RME, R^2 scores. We found out that most of the models could not give us accurate predictions for future data as it heavily depended on their previous closing price. hence to improve the same and find better trends we have applied LSTM architecture.

LSTMs are a subfield in the Deep Learning category of Neural Networks designed to process data sequences that have a long-term dependency. They combat the gradient vanishing problem which is often seen in standard RNNs which do not allow the neural network to persist information over a significant length of time. The LSTM cell is shown in Figure 3.

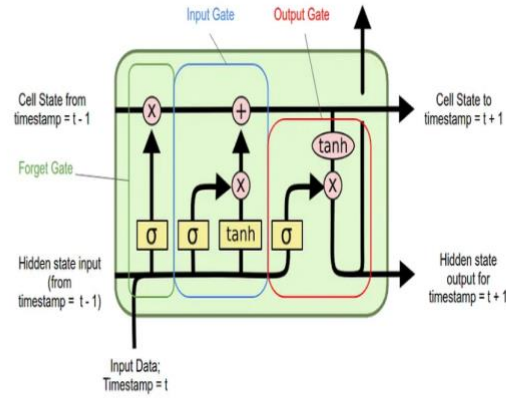

Fig. 3. A LSTM Cell

$$zt = \sigma(Wz \cdot [ht - 1, xt]) \quad (5)$$

$$rt = \sigma(Wr \cdot [ht - 1, xt]) \quad (6)$$

$$h{\sim}t = tanh(W \cdot [rt * ht - 1, xt]) \quad (7)$$

$$ht = (1 - zt) * ht - 1 + zt * h{\sim}t \quad (8)$$

The architecture used by us contains four layers the first one being a bidirectional LSTM layer with one hundred units, the next one being another LSTM level with two hundred samples another LSTM level containing one hundred samples, and a final output dense layer. The activation function of each LSTM layer is tanh. The formulas used are as shown in equations 5 to 8.

The Bidirectional LSTM layer is a highly sophisticated component of a neural network. It is tailored for processing sequential data while considering both the past and future context. This layer is particularly useful where it is important to know the full context of a sequence, like in Natural Language Processing (NLP). We have taken one hundred units of this since each unit includes its memory cell which can maintain information to contribute to the ultimate output. The second layer is an LSTM unidirectional which contains two hundred units. The presence of two hundred units signifies a thicker LSTM layer with increased units, enabling the system to understand more intricate patterns and connections within the dataset. This second pass over the input sequence serves to further refine the learned representations by emphasizing various aspects or features the first LSTM level did not capture. The third LSTM level in the model contains one hundred units – this is a few units compared to the previous layers. the purpose of this layer's data representation compression is to provide a neat way to make the final prediction. The last layer is a Dense layer to give us an output. A dense layer is a completely connected neural network level. The Dense level would accept the outcome of the rear LSTM level and transform it into our desired output space. The last layer is a Dense layer to give us an output. A dense layer is a completely connected neural network level. The Dense layer would accept the outcome of the rear LSTM level and transform it into our desired output space. The proposed system is shown in Figure 4.

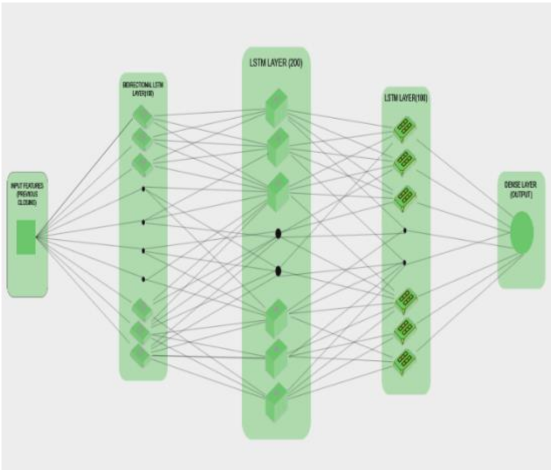

Fig. 4. Our proposed model

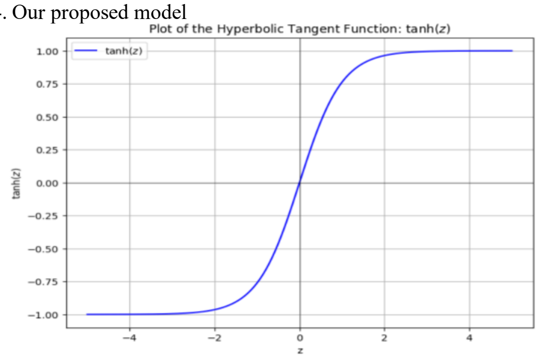

Fig. 5. Activation function – tanh(z)

$$tanh(z) \ = \ e^{z} - \ e^{-z} \, / \, e^{z} + \ e^{-z} \qquad (9)$$

The activation function is shown in Figure 5. A loss function of mean squared error is used to compile our model. The equation 9 shows the formula of tanh. Regression tasks use the loss='mean_squared_error' or mean squared error loss function whose objective is to minimize the average of the squared differences among the calculated and the standard values. We use an Adam optimizer. It merges two additional variations of the stochastic gradient descent (SGD) technique, Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMS Prop). Adam separates the learning rates for each parameter and updates them as learning proceeds. This helps enhance performance and quicker convergence. Figure 6 the model prediction with the proposed methodology based on a dataset taken for 24 hours.

Fig. 6. Model prediction with proposed methodology (24 hours data)

The Bidirectional LSTM at the start is important, as it allows the model to capture context from both directions. From there, the LSTM layers further process the sequence, continuing to refine the learned representations. At the end, the Dense layer maps the final LSTM output to a single scalar, making the model suitable for our required task.

The specific layers can capture temporal dependencies and patterns in sequential datasets. With multiple LSTM layers, the model will acquire increasingly complex concepts from the input dataset, enabling it to make accurate predictions. The Bidirectional layer bolsters this, by effectively looking at data from history and future period steps; this makes the model capable of understanding the entire context of the input sequence. By ending with the compilation step with MSE loss and the Adam optimizer, the model is set to be trained effectively. The table II shows the comparative analysis of the LSTM model MAE, MSE, RME, and R2 SCORE. Figure 7 shows the LSTM model with 1 hour data. Figure 8 shows the LSTM model with 5 minutes of data.

TABLE II. LSTM MODEL MAE, MSE, RME, R2 SCORE CCOMPARATIVE ANALYSIS

LSTM	MAE	MSE	RME	R2 Score
5 MIN DATA	0.03	0.00	0.05	0.96
1 HRS DATA	0.04	0.00	0.06	0.25
24 HRS DATA	0.03	0.00	0.04	0.94

Fig. 7. LSTM model with 1 hour data

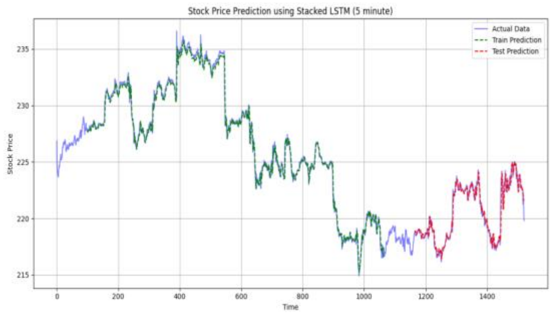

Fig. 8. LSTM MODEL WITH 5 MINUTES DATA

VI. Conclusion

The Linear Regression, Polynomial Regression, SVM Regression, Random Forest Regression, and Artificial Neural Networks models although provide great accuracy, they do not predict accurate values since those models overfit the dataset and apply mathematical formulas to predict value. On the other hand, due to our dataset being time-series data, the LSTM model provides better predictions. On further running tests we found out that 5 minute data is best to be used for predicting future stock prices with an R^2 score of 0.96 compared to the 24 hour and 1 hour data. The main drawback in the regression models is solved by our LSTM model since it can predict trends better independently since it depends less on previous data and remembers trends. Our model can be improved by adding attention mechanisms to highlight important points in time and combining CNN layers to capture local patterns alongside temporary dependencies.

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