2.0 Literature Review

2.1 Overview of Stock Price and Market Prediction.

Everyone who puts money into the Stock market invariably entrusts their money to companies by buying stock listed on the stock exchange expects that such stocks become high-yield defensive income stocks which provide long-term, consistent patterns of dividends, stable earnings, and low risk in comparison to other stocks being traded. As a result, there are huge requests for Stock price and market trend predictions by financial and investment banks, scientists, asset managers, and academia, to achieve that consistency in such a market filled with volatility. Below are some of the related works and their perspective on Stock prediction using different statistical, machine learning and Deep learning models.

Over the years, the interest of academia in attempting and proposal for models and techniques due to the high unpredictability nature of the stock market has been on the increase (Mohanty et Al., 2021). Classification models focus on stock price movement which depends on the time variable, but regression models focus on the level estimation of stock prices (Rana et al., 2021). One major benefit of stock price movement tends towards the prospects of the company's stock. This review is done to forecast the prices of stock.

Predictive analytics methods include Logistic regression, time series analysis and decision trees, each with strengths and disadvantages. Linear Regression performs well with a large dataset, whereas Long-Short-Term Model, a deep learning model outperformed with more accurate results, especially with large datasets ((Wang et al., 2021).

One critical consideration for stock trend forecasting has been time series analysis, a descriptive modelling method which takes in the essential variable 'time' in the stock data, and has recorded success in predicting future data, using historical data. Autoregressive Integrated Moving Average (ARIMA) is one of these time series analysis models which is quite effective in non-linear problems (Ma, 2020).

In the year 2020, (Ma, 2020), made a similar comparison work analysing the strength of ARIMA model accuracy with respect to predicting short-term stock prices, and long-term stock prediction focusing on Long Short-Term Memory (LSTM) with the capacity to learn current and previous datasets in future prediction using only close price feature for both ARIMA and LSTM, applying Apple Incorporated dataset for four years.

A downside to the use of historical data analysis however is that it cannot be relied upon to understand the trend and trusted pattern to embark on stock investment (Bhavani et al., 2022).

Some prior research work had approaches that combine social and financial information which are an aggregation of political decisions, federal reserve position on monetary policies, financial distress news, global economy, and natural disaster. Technical analysis often outperforms fundamental analysis in the use of statistics and historical prices to determine patterns and trends but is irrational (Shen & Shafiq, 2020) and (Lu et al., 2020). A tabular illustration of previous work on stock prediction was made in table 1, with the table bringing to light the many conventional techniques to which academia had considered the prediction of stock prices.

Table 1

S/N	Technique used	Positives	Issues	Metrics	Project detail
1	Linear Regression and Decision Trees	Linear regression performed better	Amazon dataset size is just for one year. Short-sighted because it is just for just one single stock	R Squared	Karim et al., (2021)
2	ARIMA and LSTM	Walmart stock for 5days future values had higher values for LSTM.	ARIMA could only predict short term future stock price thus only suitable for very short term.	RMSE	Liu, (2022)
3	LSTM	Google, Nifty50, Tata Consulting services (TCS), InfoSys, Reliance Stock were all predicted to give at least 93% accuracy	Train-test percentage is 75%-25% (could be improved to 80%). Adjusted close was not considered.	RMSE and MSE	Dinesh, S. *et al.* (2021)
4	LSTM	300 days Open price for National Stock Exchange (NSE) India as an Entity was predicted and error rate was low.	Optimizer used was Stochastic gradient descent (SGD). Adam should give a higher accuracy than SGD.	MSE	

5	LSTM	Chinese Stock price was predicted using dataset for just two years stocks. Model accuracy was which was quite good at 93%	Close price was just predicted for 10days, and duration was a short-term thus with long-term accuracy might be better or worse depending.	MSE and RMSE	Shen & Shafiq, (2020)
6	SARIMA	The dataset was of long term (10years Apple Inc.). Considering one year Closing Price Prediction, and Close price feature was used. 3 SARIMA models were developed, and the best gave a low MAPE of 36.5% and least RMSE.	Although LSTM was used, and had a good MAPE and RMSE, Apple Inc. Stock is quite a highly Volatile and fundamental analysis only might not reflect real prices for an informed decision. An improvement on this work will be a better RMSE and MAPE could be arrived at, whereby with lesser values for all the three SARIMA models.	RMSE and MAPE	Daryl et al., (2021)
7	ARIMA and LSTM	S&P 500 stock from NYSE was predicted for 81days and Both Metric yielded good error loss however LSTM was better with all metrics than ARIMA for dataset between 2010 to 2019 being a	Data cleaning was not mentioned as data was directly collected from NYSE, and datasets prior to 2010 were carefully avoided however irrespective of dates, there is tendency that the 10years dataset has missing values, because it was	MAE, RMSE, MSE	Xiao & Su, (2022)

		considerable long term dataset. An Hybrid Model of ARIMA-LSTM rather gave a more lower error results that just LSTM.	not cleaned, next work can improve upon this.		

For the scope of this work an improvement to 80%:20% for train and test split will be applied, and 60 days prediction will be done as well, short- and long-term datasets (more than 10years dataset) will be analysed as an improvement upon baseline research work, to give a perspective to provide for stock prediction using statistical, and deep learning models.

LSTM requires feature extraction, and the efficacy of deep learning is highly dependent on the input data used in training and testing (Shah, 2020); thus, an in-depth analysis of the input feature is needed. For the prediction of future stock price, research focuses on the low price, closing price, open price, and high price of a stock (Chaudhari et al., 2021), (Zhou, 2021) and (Tang et al., 2021).

While the prediction of the stock price using deep learning models is based on time series, financial time series, news sentiment, textual data, and numerical and textual features (Wang et al., 2021), from the perspective of advancement into the application of recurrent neural networks (RNN) for stock price prediction (Moghar and Hamishe, 2020) diverse types of Long short-term memory (LSTM) are good for time series forecasting depending on the number of variables to be analysed, for example, the LSTM network, Gated Recurrent Unit (GRU) which is a simpler variant of LSTM, RNN, and State Frequency Memory Network (SFMN), traditional RNN can suggest fair output but has limitations (Sandhya et al., 2022). These are vanishing gradients, and the inability for long-term dependency storage limiting their prediction capacity (Kumar et al., 2022).

The LSTM network can address the vanishing gradient drawback (Saurabh, 2021), another issue with RNN is that for time series the hidden layer parameters might be adjustable into two (Fu & Xiao, 2022).

Major differences between GRU and LSTM include the design in which a single hidden state is for both long dependencies and short-term memory, as such LSTM does well with long-term information (Chaudhari et al., 2021) and (Gao et al., 2021).

An analysis into the combination of LSTM with GRU but with distinct parameters by Gao et al., (2021) where a variety of technical indicators which include financial data on Shanghai Composite Index data and investor sentiment indicators were amalgamated such that Principal Component Analysis (PCA) and least absolute shrinkage and selection operator (LASO), an estimation method which is capable of simplifying the indicator set were introduced for dimension reduction (Obrubov & Kirillova, 2021) concerning multiple influencing factors of the extracted stock price, resulting into both LSTM and GRU yielding high accuracy as well as for dimension reduction prediction results (Albahli et al., 2022), were over and above those with PCA data.

The focus of this related theoretical review is on Vanilla LSTM, following related work by which the researcher proposes that overfitting is avoided when parameters are tuned and LSTM combined with wavelet (Wu et al., 2021) transform, and because it can yield low error rate using MSE (mean squared error) (Tang et al., 2021), MAE (mean absolute error) and RMSE (root mean squared error) evaluation metrics with diverse data nature, sequential or numerical, irrespective of data shape and most importantly real-life scenarios (Zargar, 2021). To ascertain this, the reproducibility of the research will be considered using real-world data from five industries having different qualities. Moreover, the error rate of each evaluation metric will be considered with a focus on RMSE because it is a measure of the difference between predicted and actual values and finds the efficiency of LSTM (Pattanayak et al., 2022).

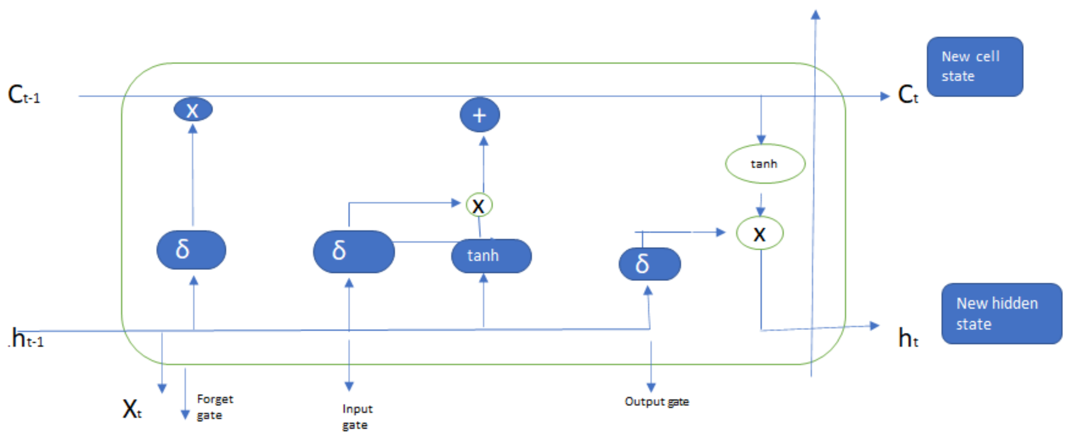
2.2 Deep Learning Models

With the trending of big data and many breakthroughs of artificial intelligence especially with respect to machine learning had attracted analyst to apply machine learning technique to forecast time series. Deep learning models are capable to e effectively predict stock prices yielding minimum error rate and delivering higher accuracy of forecasted time series analysis. Some of the deep learning models are CNN (Convoluted Neural Network), LSTM, Autoencoder, Recurrent Neural Network (RNN), and Gated Recurrent Unit (GRU). One common ground in several literatures that were reviewed suggested the use of hybrid models more than a single deep learning model, and the use of LSTM in combination with other models is a common practise. As a result, LSTM will be discussed as the only deep learning model applied in this research work.

2.2.1 LSTM

Designed explicitly to address the vanishing gradient drawback of RNN thereby remembering information over a long period becomes easy as an improvement upon RNN, the latter irrespective of the challenge of vanishing gradient is perfect for temporal predictions (Zhou, 2021), however, faces the difficulty of training deep neural networks, (Van Houdt et al., 2020) thus LSTM evade the exploding gradient problem of RNN by gradient clipping. The gradient exploding challenge in RNN is because of the gradient passing via a continuous matrix multiplication during backpropagation, a routine which makes the gradient vanish or explode therefore the model crashes, the consequence will be that since information is not reliably retained for a long time, it will be impossible to accurately use the information at earlier time steps in making reliable predictions (Zargar, 2021) therefore the first identified importance of LSTM is in its prediction capacity, enabled by using both long-term and short-term memory cells on data (Firouzjaee & Khaliliyan, 2022). Moreover, LSTM is effective for data on time series, processing, making decisions, and classification, based on the architecture consisting of three gates (input, keep, and output) and a cell (Chaudhari et al., 2021). Cell states provide mechanism regulation information that the cell state needs for the update, forget or upload, and the new cell state thus provides information for output update in the updated hidden state (Van Houdt et al., 2020). Receipt and exit of information into and from the memory cell are dependent on the opening and closing of each of the input and output gates respectively, while information to forgot is determined by the forget gate (Huang et al., 2022).

Figure 1: Architecture of LSTM



Where:

δ = sigmoid activation function
x =vector pointwise multiplication
+ =vector pointwise addition
.tanh =activation function
ht = hidden state at present timestep t
Ct = Cell state at present timestep t
Xt =input vector at present timestep t
ht-1 = hidden state at former timestep t -short term memory

C_{t-1} = Cell state at former timestep t -long term memory
Input gate adds value required to the cell state
Forget gate removes data to be forgotten from cell state
Output gate creates vector, makes filtering and multiply value of the filter thus sending it as output.

Data preparation is an essential aspect of univariate series. A single hidden layer LSTM is Vanilla LSTM, while the one with peepholes effective in learning towards stable streams of precise time spikes as well as richly nonlinear periodic pattern is Peephole LSTM (Joshi et al., 2022). Vanilla LSTM is the original variant with only one hidden layer having the forget gate and peephole connections. Applications about time series forecasting, computer vision, text recognition, natural language processing, and video captioning among others (Rekha & Sabu, 2022).

Consequentially just like other variants, the LSTM network shares basic similarities with RNN concerning hyperparameters, their momentum values, weight initialization, gradient normalization, the rate at which each model learns, their gradient clipping, and activation functioning (Firouzjaee & Khaliliyan, 2022). One of the great advantages of this model as with other LSTM variants is the ability for risk reduction (Atharva et al., 2022). Some previous works on vanilla LSTM accounted for the complexity of the financial market, however dynamic trends during the covid era, and post covid pattern of the stock market price, have not been explored extensively yet research had covered the strength of vanilla LSTM (Saurabh, 2021) and (Joshi et al., 2022). The combination of vanilla LSTM with other networks as hybrid models has also been a great application and effectiveness of LSTM (Sen & Mehtab, 2022), and (Sun et al., 2021).

There is an impact of extracting features from data using multi-layered architecture, especially for annual, quarterly, and monthly data (Sen et al., 2021), as it further enables LSTM to have better results when dealing with large data that has well-defined behaviours (Atharva et al., 2022). An application of LSTM for accuracy and stability of prediction by Tang et al., (2021) involved building a prediction model which focuses on data denoising. The said model reconstructed sequence and was introduced into LSTM to forecast the stock price of four distinct stocks listed on the India Stock Exchange using error metrics RMSE, mean absolute error (MAE), mean absolute percentage error (MAPE), to conclude that the effectiveness and generalized ability of LSTM are best improved by data denoising in short-term, middle-term, and long-term. Another work by Gao et al., (2021) uses LSTM and GRU in making stock price predictions both models are effective in higher accuracy of prediction.

2.2.2 Vanilla LSTM

The word vanilla LSTM simply denotes the original LSTM variant. Vanilla LSTM is relatively simple in terms of configuration, appropriate and yields high accuracy for classification and future value prediction and of wide application. For a regression problem, since LSTM involves one model, an extension was introduced which assists to overcome overfocus only on past information of input in learning for prediction concerning unidirectional output (Aslam et al., 2021), thus the introduction of a bidirectional network whereby the second model learns a reverse and the first learns the sequence of input provided (Zargar, S.A. (2021).

Joshi et al., (2022) upon comparing Peepholes and Vanilla, peephole gives a slightly significantly higher margin in the prediction value than vanilla. However, because not much research work had been explored in the comparative analysis among various LSTM models and the fact that models are significantly dependent on how large datasets are, peephole LSTM significantly recorded higher values subject to the ability to deal with highly nonlinear and periodic patterns in time series better due to hidden state added to three gates in classic LSTM with higher accuracy from RMSE and MAE metric than Vanilla LSTM, both variants are said to have recorded good result with time series

2.2.3 Time Series using LSTM.

Time series prediction entails univariate and multivariate. While the former applies past values to predict future prices, the later employs external variables in addition to series of values for its prediction. Since best fitting model is often preferred in time series forecasting to predict future, overfitting and underfitting of the neural networks in applying LSTM.

Prediction accuracy is largely dependent on input representation, feature selection, and prediction algorithm (Wang et al., 2021) since LSTM is capable to learn and predict prices especially when the technical indicator is used, as input features, because non-linearity and volatility are better managed (Van Houdt et al., 2020) thus enhances the prediction performance. LSTM can store information for a long term and thus can be easily calibrated to predict future values from previous sequential data. LSTM models used to analyse time series stock datasets are univariate time series modelling, multi-variate modelling, multi-step, and multi-variate multi-step modelling (Usmani & Shamsi, 2021).

In Sen, 2021, an LSTM-based model was used to predict the future price of seventy stocks from various sectors listed on the national stock exchange of India and they all predicted highly accurate stock prices. LSTM applies to learn and prediction especially when the technical indicator is used

CNN is extremely effective in modelling challenging computer vision and image problems using multivariate time series (Sen, 2021) therefore a combination with LSTM fosters a higher accuracy. While in univariate one single variable changing with time is required for prediction and processing of sequential data.

LSTM outperforms random forests, standard logistic regression, standard neural networks, and support vector machines in complex features. For example, input features with diverse lengths (Shen & Shafiq, 2020), and demand data with diverse seasonality. LSTM had evolved as relevant even in the application of LSTM in the prediction of oil market prices due to its ability to identify the cells which invigorated and compressed based on prior state, memory, and current input (Firouzjaee & Khaliliyan, 2022). The efficacy of the memory block lies in the ability to maintain the status whilst regulating data flow through the non-linear gating units. Another research work by Saeed et al. (2020) evidenced that LSTM applies to statistical analysis for the process required in creating a flexible fault diagnosis model in the nuclear energy domain. Just as the stock price is quite volatile, the oil price prediction is grossly affected by the stock market, the value of gold, and the dollar, making the oil price also volatile (Ishwarappa & Anuradha, 2021), however, the capacity of vanilla LSTM in terms of memory modification via metric MSE, MAPE, MAE, and RMSE, verifies LSTM having interpretability for the investigation of all surprising correlation features applicable to them all (Taghizadeh Firouzjaee & Khaliliyan, 2022). In a broad context, since the political event, political decisions, wars, and political status change in time, LSTM is efficient in the prediction of these just as it can predict time series in the prices of stock whose data shares features of political changes and many diversities (Aslam et al., 2021).

2.2.4 Sentiment on LSTM

As much as LSTM applied to stock price movement concerning the capacity in arriving at lower error with time series data, the LSTM approach is also relevant to investors' sentiment concerning stock movement (Srinivas et al., 2021), (Gandhi et al., 2021), and (Suriah et al., 2022). A research work by Wang et al., (2020) considered the importance of sentiment in assisting in investment decisions on which stock to invest in and the effect of this on major money flow in the market. Moreso LSTM in investors' sentiment is about the LSTM network used in terms of sentiment classifier in the training of data available on social media platforms as comments such as comments from people's Twitter pages, and Facebook gross happiness index which are vital for making an informed investment decision (Bhandari et al., 2022). In Valle-Cruz et al., (2021), the use of Twitter sentiments considered perhaps if there exists any correlation between Twitter sentiments and stock market behaviour concerning price and market trends and the conclusion was that during the pandemic twitter sentiments maintained a high correlation with stock market behaviour. Kaur et al., (2021) find out that there exists a relationship between Twitter sentiments and share price concerning stock price prediction from time series. A Bidirectional LSTM with Attention layered on top also resulted in a time lag elimination such that the model focus is on relevant input whereas model attention is later considered. Other models of LSTM are effective with varied kinds of data hence data type has a major influence on model performance (Chaudhari et al., 2021) and (Nabipour et al., 2020). As a result of the above applications, technical features have been deemed to be influential on data behaviours. When LSTM was applied with continuous data to predict stock price, the result was a significant increase in model performance (Vikas et al., 2022), (Behera et al., 2021), and (Son & Jang, 2020).

2.3 Other Combinations of LSTM and their applications

Deep autoencoder is also a powerful model for stock prediction, even with noised data, suppressing noise (Nguyen *et al.,* 2021). Examining the power of deep learning model from the perspective of noise removal, consideration for market sentiments in addition to a mere prediction accuracy, Rekha & Sabu, (2022) work presented an architecture based on deep autoencoder, lexicon-based software and GRU/LSTM for price prediction using top twenty-five news in a day, and the evaluation metric for precision. The work of applying the deep autoencoder in denoising historical stock data along with sentiments (Albahli et al., 2022), and the combination of GRU and LSTM model for the prediction provided a perspective of model performance about news sensitivity of stock price prediction (Bhavani et al., 2022), an improvement upon mere price forecasting. Another combination of the LTSM model with empirical and modal decomposition with sentimental index produces higher accuracy than a vanilla LSTM for stock price forecasting (Cheng et al., 2022), concluded that for prediction performance, LSTM records lower error compared to GRU but a longer time frame. Wu et al., (2022), also with his work verified that LSTM is more tolerant to price volatility however, both predictions are close to real-life test values, and both were consistent with time series data, with a sample of nine stocks evaluated on both models.

The capacity of LSTM improves when combined with the CNN model and it works efficiently more than GRU with non-linear data however for Bidirectional, and Stacked LSTM models need to be trained and their hyper-parameters tuned (Istiake Sunny et al., 2020). Specifically, upon application (Aslam *et al.* 2021) for a normalized dataset using the closing price for analyses, Bilateral LSTM among other models’ performance yielded a higher precision, and a lower RMSE signifying an improved accuracy (Sen 2021), and excellent convergence in the short and long-term and Proposition also suggests that short-term price prediction is more reliable than the long-term predicted result (Chatziloizos et al., 2021). The stacked LSTM is a different variant of LSTM in that it has more than one hidden layer and each of the layers is on top of another thus the name stacked due to the hierarchical pattern of the model, results in the model capable of performing temporal tasks and eventual performance in data sequences (Van Houdt et al., 2020).

LSTM is good for application when developing a robust automated trading system model towards a price movement prediction capturing stock market index futures as well as in areas of risk management, stop loss and profit applied to enhance the avoidance of falsified entries (Silva et al., 2020).

With a multi-layered LSTM network, profit generation in the real market was evaluated with the Volume-Weighted Average Price indicator (VWAP) as analysis criteria (Aslam et al., 2021), whereby using trading signals buy, hold, or sell, taking into consideration macro-economic factors, and the application of risk management as a major difference between profit and loss, considering that previous knowledge of the market is not sufficient to decide on risk and only technical knowledge is also limited (Silva et al., 2020).

Following the need to fully extract features that identify with the necessary qualities of input training data, the event binary feature noise-prone values often promise and are influential in arriving at a better prediction performance than mere simple price values (Song & Lee, 2020).

The GRU in comparison with LSTM is simple (Zargar, 2021) because just the input gate provides the amount required for the next cell while the reset gate determines information to be treated as forgotten by which only critical and relevant details are passed as a result faster than LSTM however, for accuracy and large datasets, LSTM had a better prediction performance (Rekha & Sabu, 2022).

More previous work on GRU, the model also provides information acquisition, holds internal variables, and integrates long-term and short-term memory as well as solving the gradient disappearance of RNN but a drawback is an absence of emotional indicators, and the capacity to yield a better performance above LSTM could not be ascertained (Gao et al., 2021).

In comparing GRU with the LSTM model, using an evaluation metric of percentage loss of RMSE and MAPE, the result constructed by three layers each, a total of nine company stocks listed on the New York Stock Exchange (NYSE), for a period of one year, the result revealed GRU has a higher accuracy of about 5% over LSTM value (Lawi et al., 2022), however, accuracy has proven not to be the most important metric to evaluate the performance of a model. While some also had done a good job developing hybrid models that combined LSTM with other models such as GRU and CNN (Zhou, 2021), (Bhavani et al., 2022) and (Gao et al., 2021). A two-stream network was used in a research work where a major increase occurred in the accuracy of the model even with the addition of sentient analyses on trained financial news and the overall performance of LSTM, deemed to have the same as CNN (Sen et al., 2020). In most research, a combination of models following their perspective on the hybrid model returns more accurate predictions. One research proposed that GRU has less gateway control than LSTM, based on the architectural design of the Movement (Gao et al., 2021).

One critical opinion is that although GRU often promises high performance in terms of accuracy, simpler and faster due to reduced gate in comparison with LSTM, both are effective for time series except that GRU cannot manage large datasets which in real life are available for most stock (Bhavani et al., 2022). A new model was considered called L-RSR having four layers whereby the LSTM layer addresses the stock prediction sequence pattern, the relation layer learns dependency among stocks, the graph layer, Light GCN checks the interaction of user and item, and the prediction layer, the performance of the model on ensuring investors make a high rate of return is considered using regression MSE (Yang et al., 2022).

The MLP is another model in which the training is with a backpropagation learning algorithm and has been for stock price prediction, pattern classification, and recognition (Usmani & Shamsi, 2021).

In applying a DNN model, the backpropagation method having trained and with the input layer, predicted the closing price. Backpropagation involves the modification of parameters to ensure that there is little to no difference between any predicted value and the actual value (Goswami et al., 2022). The MSE is used for variance calculation between the correct result and the predicted result, and the MAE gets the training error of each model and the model's actual performance guaranteed using their measured error values (Song & Lee, 2020).

2.4 **Other Models**

2.4.1 LINEAR REGRESSION

Linear Regression explicitly indicate relationship which exists between two variables (independent and dependent) and in respect to stock prediction is time and stock prices (stop loss price of stock, exit price, and corresponding entry price.

Karim et al., (2021) in their research work carried out a comparison of linear regression model and decision trees model to predict stock prices for both small and large datasets with close price as the label data, resulting into linear regression giving the most preferred prediction accuracy higher than decision tree for both small and large datasets although decision trees gave a slightly low prediction for only small dataset.

As an update, this research work will apply linear regression model to predict stock price to determine if there are relationships between time and stock price**.**

The Simple Linear Regression equation is below:

$$\boldsymbol{y = \beta_0 + \beta_1 x_1 + \cdots \cdot \beta_m x_m + \epsilon_t}$$

where: $\beta_m x_m = Coefficient\ of\ previous\ independeny\ variable$
$\beta_1 x_1 = The\ first\ variable's regression\ coefficient$
$\epsilon \quad = regression\ error$
$\beta_0 \quad = This\ is\ the\ absolute\ value\ of\ y\ at\ parameter\ 0\ (zero)$

2.4.2 ARIMA/SARIMA

One of the most applicable statistical and econometrics model is ARIMA, a combination of AR (Autoregressive) and MA (Moving Average) with the inclusion of "Integrated" is ARIMA model (Fathin et al., 2021). A twist to the ARIMA model is an addition of linear blend of previous seasonal values and forecasted errors resulting into SARIMA (Seasonal Autoregressive Integrated Moving Average) therefore for univariate analysis without seasonality, ARIMA is applied, and the opposite is SARIMA (the third is SARIMAX -with the "X" denoting external variables however resulting into multivariate analysis.

The linear increasing model equation of ARIMA is given below, where (p,I,q) is:

p=Order of AR,
q= Order of MA
I =The differencing order of integration
d= Seasonal differencing

$$x_t = C + \varepsilon_t + \sum_{i=1}^{p} \varphi\, x_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \delta t$$

θ_i = *Coefficient of moving average*
x_t = *Variable value at t time*
x_{t-i} = *Previous value*

The SARIMA model equation is given below:

$$(1-\theta_1 B)(1-\theta_1 B^4)(1-B)(1-B^4)y_t = (1+\theta_1 B)(1+\theta_1 B^4)e_t$$

Where

$$B \quad = y_{t-1}$$

$\theta\varphi\Theta\phi$ = *model parameters*
$(1-B^4)$ =*denotes seasonal differencing*
e_t =*model random error at time t*
$(1-B)$ =*non seasonal differencing*

2.5 Evaluation Method

Basically, five metrics will be discussed in evaluating the various models for prediction stock price and these are:

2.5.1 MSE (Mean Squared Error)

This is a prediction evaluation metric in which lower prediction error is preferred when comparing other models using the same dataset however, since it is not an accuracy metric due to the metric lacking a fixed scale, there tends to be interpretation difficulty using this metric (Korstanje, 2021). As a result, this metric serves comparison purpose better because it acts as an average.

MSE= $\frac{1}{n}\Sigma(y_i\hat{y}_i)^2$

2.5.2 RMSE (Root Mean Squared Error)

The formula for the equation

$$\sqrt{\frac{1}{n}}\Sigma(y_i\hat{y}_i)^2$$

This is a twist to MSE model because it is a squared root of the result. Unlike MSE, it yields a relevant error in that the values of RMSE are usually quite relevant to real life stock values and just like the MSE metric, the lower is preferred (Fathin et al., 2021). Other qualities of this metric are same as MSE in terms of inability to compare metric result using different dataset.

2.5.3 MAPE (Mean Average Percentage Error)

This metric has the formula: $\frac{1}{n}\Sigma\left|\frac{y_i-\hat{y}_i}{y_i}\right|$

This evaluation metric is the only percentage error metric which takes in the actual values to arrive at a relative error, such that each prediction error is divided by the actual value. This metric is prone to complication in case actual value is zero, giving rise to deceptive result which does not align what should be or what is obtainable.

2.5.4 MAE (Mean Absolute Error)

The word absolute denotes complete thus this error calculates error taking in the complete discrepancy between actual values and those prediction per row with same dataset (Korstanje, 2021).

This metric has the formula: $\frac{1}{n}\Sigma|y_i - \hat{y}_i|$

2.5.5 R- squared

This metric has the formula below.

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

This metric is a performance metric rather than an error metric and as a result enables analysts to determine how well the model fits the actual dataset. Invariably, the metric yields values between 0 and 1 (0≤ 1), with the closer to 0 the poorer, and values close or equating 1 being the best.

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