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# Forecasting Equity using LSTM Value-at-Risk Estimation

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**Abstract** — A deep learning hybrid approach (LSTM-VaR) is proposed for risk-based stock value prediction by comparing the relationship and temporal sequence of stock value data. By utilizing time in its predictions, the model can improve accuracy and reduce volatility in stock price projections. It can anticipate changes in stock market indices and develop a reliable strategy for projecting future costs while calculating normal fluctuations of indices.

**Keywords** - Stock market, LSTM VaR, hybrid approach, Moving Average, risk analysis, prediction.

## I. INTRODUCTION

The process of trying to anticipate an organization's stock price on the stock market is called equity forecasting or share value prediction. An accurate prediction of an equity's prospective value could lead to an immense financial gain. The efficiency of the market conjecture and the stochastic speculation govern the fluctuations in equity valuation. Today's stock brokers rely on Intelligent Trading Systems to help them make quick investment decisions and to foresee costs based on a variety of factors [1]. Since stock market prices are based on a combination of established factors such as open, close, and profit to earnings ratio, they are recognised as being remarkably active and having an ability of making quick changes. due to the basic nature of the financial universe. Trained traders can anticipate changes in stock value and act accordingly, buying shares before their price rises and selling shares before their value falls. An exact forecast algorithm can easily come into high benefits when used by individual experts, which demonstrates a straight correspondence between precision and benefit produced when utilising a particular method [2].

A substantial amount of literature has been written about various technical analyses of stock price changes. Moreover, trend lines, exponential moving averages, comparative toughness indices, random upheaval indices, and other relevant indicators are suggested for extracting equities trends. In addition, traders employ famous structures such as the rising and falling wedge, candle, pennant, inverted pyramid, and pyramid to make smart stock market trades [3][4]. Regular investors may use these strategies to get graphic representations of the indications that show which way stock prices are most likely to go in the upcoming months. Analysts may combine past market data with information collected from social media networks to predict shifts in the economic and commercial sectors. Performance in forecast systems is very sensitive to the quality of the features used [5].

## II. LITERATURE REVIEW

The authors of [6] investigated several Machine Learning (ML) evaluation techniques. Their research focused on daily stock trades made under two scenarios: transaction costs and no transaction costs. They contrasted conventional ML algorithms with cutting-edge NN approaches using 500 Dow Jones Index stocks over a period of seven years, from 2010 to 2017. NB, SVR, Decision Tree and Linear Regression were used as conventional techniques, while Auto Encoders, Multilayer Perceptrons, RNN, LSTM, and GRU were utilised as DNN models. Their findings demonstrate that DNN models perform better when including business figures, but standard ML algorithms have a tendency to provide more accurate predictions by excluding business figures.

The financial transaction data of Shenzhen Stock Exchange for 2008-19 are modelled and predicted by the authors of [7] using a sequentially accurate forecast system utilising DNN with long short term memory. The model took into account variables for equity, fundamental, technical, economical index patterns, and their combinations. The authors also contrasted the LSTM DNN, conventional RNN, and BP neural network. The outcomes shown that the LSTM DNN can accurately forecast stock market time series and has a greater prediction accuracy. A more accurate forecast is often provided by conventional ML algorithms.

The work in [8] offered stock price prediction models based on GRU, RNN and LSTM improved with focus parameter, which can pick out and concentrate important information. These models were based on traditional recurrent neural network. According to results, the GRU and LSTM performed much better than the RNN in the most basic comparison test, and the GRU marginally outperformed the LSTM. The accuracy and stability of the stock fluctuation prediction model were helped by the addition of the attention mechanism layer.

The authors undertook look back period analysis for Nepal Investment Bank (NIB) and Nabil Bank Limited (NABIL), listed on the Nepal Stock Exchange with RNN and juxtaposed its performance with VRNN, long short-term memory, and gated recurrent unit [9]. In terms of stock price prediction, our research has demonstrated that GRU and LSTM can perform better than VRNN. Given the little amount of data required to train the prediction model, the examination of average mean absolute percentage errors (MAPEs) revealed that GRU outperforms LSTM marginally. The fact that GRU has less parameters than LSTM means that it can be trained and predicted outcomes more quickly. This is another advantage of GRU over LSTM. For improved performance with LSTM and GRU, the authors recommended appropriate look-back period settings. For LSTM networks, the look-back time should be less than 5, while for GRU networks, it should be between 5 and 10. The rendition of share forecasting may suffer when the look-back period is used at higher levels.

The research of [10] concentrated on the environmental, social, and governmental (ESG) news events to investigate their ability to predict stock volatility. To anticipate future stock price volatility, they specifically constructed a method of obtaining environmental, social and governmental news using DL in a framework dubbed ESG2Risk. Superior forecasting performance and the relationship between adverse risk- return ratioed equities and ever changing forecasts were both shown by experimental assessment on real data from various marketplaces. They also revealed that, in addition to raising the ESG profile of an equity choice, integrating ESG news flow can help to develop lucrative investing strategies.

The investigation in [11] suggested a fully tailor-made DL approach for anticipating index movements. This study is divided into three sections: data normalization, parameter representation and equity forecast method for the Shanghai Composite Index. The authors gathered, purified, and organised data from the index for 730 days. They combined principal component analysis with the feature expansion and recursive feature removal methodologies to create an excellent representation method. The system was adjusted and improved to achieve high prediction accuracy that exceeded the leading models in the majority of pertinent studies by integrating the feature engineering method with a prediction model.

The authors of [12] suggested a FACNN focus specific factorization method for the aim of forecasting stock price movement utilising financial time series data. The authors extracted the intra-day parameter occurrences of equity using the Deep FM module. To extract multiday temporal information, they employed an ATT-CNN module, or attention-based convolutional neural network. The outcomes demonstrated that the excessive features of (a) intra-day occurrences between input characteristics and (b) sub-industry index data significantly increased forecast precision. The suggested FA-CNN system’s prediction accuracy peaked at 65%. It was 8% and 4% greater than the performance of a conventional LSTM and a system not having the addition of a sub-industry index as an extra set of input characteristics. Comparison tests revealed that the FA-CNN approach was better than CNN and LSTM.

A CNN-LSTM approach was created by the authors of [13] to forecast tomorrow’s share price. The approach made full advantage of the sequential properties of the stock data by using the low, high, open, close, volume, rise and fall of equity as input. LSTM was used to learn characteristics and estimate tomorrow’s share value. CNN extracted characteristics from the input. The Shanghai Composite Index's diurnal equity from 1991-2020, were used by the authors to conduct their studies. Comparing CNN-LSTM, MLP, CNN, RNN, LSTM, and CNN-RNN, the experimental findings demonstrate that LSTM with an intermediate CNN layer is greatly precise and offers best results. The lowest of all techniques, including the MAE and RMSE, and an R2 that was very near to 1. For the purpose of predicting stock prices, this study developed a thorough methodology.

To anticipate the daily stock values of a certain firm, the author of [14] presented a DL recurrent NN approach. RNNs are capable of accepting and taking into account the sequential information, which aids in durability and makes them an excellent option for time series stock data. Epochs, multiple layers of LSTM and optimizers were combined to assess the model in order to choose the hyper-parameters that would finally produce a system that performed better. Using Keras, TensorFlow, and Python libraries, the model was assessed using a collection of data on Google stock prices. According to the experimental findings, the model performed better when using 4 LSTM layers, 100 epochs, and the Adam optimizer, with a mean squared error of 0.0014.

## III. METHODOLOGY OF PROPOSED APPROACH

The two methods of stock market analysis are known as fundamental and technical. Fundamental analysis takes into account both historical and current data like a company's assets, financial statements, managerial efficiency, strategic initiatives,

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and customer behaviour to determine revenue, assets, costs, liabilities, and other essential financial measures for long-term investments [15]. Technical or quantitative analysis of the stock market involves looking at things like stock prices, historical returns, and trading volume to draw conclusions about the market. It is more commonly utilised for day trading because of its ability to anticipate future index movements utilising historical performance. The fleeting nature of news has a significant impact on the results of technical analysis. Uptrend, downtrend, price charts, simple and exponential moving average are usual technical analysis tools [16].

Our proposed approach consists of the following steps.

*A. Data sets collected together*

The suggested procedure's first and arguably most important stage is collecting datasets. This is the most important step because it determines whether or not the final results will be reliable. First, we need to settle on a system for categorising the data we acquire.

Primary data collection begins with a choice about what kind of information will be gathered. Several methods can be utilised to gather information that can be put to good use, including surveys, online tracking, transaction tracking, online market analytics, social media monitoring, and data gathered via subscriptions and registrations [17]. Most of these techniques aren't suitable for gathering the information we need.

*B. Calculating and Organizing Variables using preprocessing of data*

The practise of arranging data in a way that makes sense and is easier to understand, analyse, or show is known as data sorting and includes the steps of collecting raw data on learning issues and then arranging them in a meaningful order. Data visualisation techniques like sorting are widely employed in the research business to make the data's story more transparent. Raw (across all records) or aggregated (grouped) data can be sorted in many ways (in a table, chart, images, or some other aggregated or summarised output).

To feed a machine learning algorithm, once the data has been cleaned and organised, it is divided into instructing and examining sets. After all, selecting the appropriate training and testing procedures prior to applying them to amassed datasets is an integral part of the prediction pre-processing step [18].

Weights and bias must be trained to learn (choose) appropriate values for the training samples. Constructing a supervised learning model requires a machine learning algorithm to examine numerous samples and pick the one where the loss is lowest.

*C. Feature data set extraction*

After all, picking the right training and testing methods before applying them to the collected datasets is part of the prediction process's pre-processing stage. Because using a variety of prediction algorithms on disparate data might degrade accuracy and performance, it is crucial to carefully pick the appropriate datasets.

Feature extraction is the process of selecting and analysing key aspects of a picture or signal with the purpose of gaining insight into the larger datasets [19]. In this article, "disability feature" represents a unique property of the signals contained inside a data collection. Therefore, accuracy prediction techniques can be used to evaluate categorization machine learning models. One of these techniques is called the Holdout procedure, and it entails separating the data into an instructing and examining set (often with a 70:30 ratio designation) and then comparing the trained model's performance on the test set .

D. *Verification of data with the proposed strategy*

In risk analysis, a model's performance can be measured against a "test set" of data points that are meant to represent an ideal level of performance. The trained, validated and tested datasets cannot coincide in any way. Testing an algorithm's ability to generalise from the training set to new datasets with different values is complicated if the test set incorporates examples from the training set [20].

Using the most recent information, adapted software should reliably complete a task. As a result, training has emerged as the central component of our method for foreseeing TB. However, unlike software that merely makes educated guesses, software that learns from its failures by memorizing an extremely complex model has a better chance of success when predicting response variables for the training set.

*E. Display of outcome and its record*

Then, when losses and errors have been minimized, essential measures have been taken, and the predictions' accuracy has been bolstered through risk analysis, parameters like stock market projections can be obtained. This prediction can help improve our portfolio's risk management and increase investment results. After displaying the forecasts, the data should be carefully archived for use in later analysis and education [21].

## IV. IMPLEMENTATION

A. *Regression forecasting of equity prices*

The first section's focus is on forecasting equity prices using regression. An ML module (Fig. 1) was used to do this.

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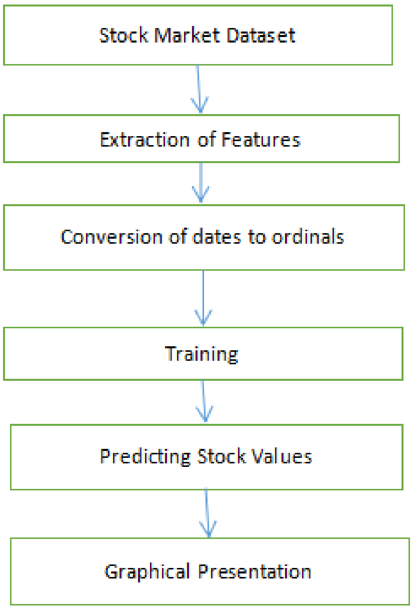


Figure 1. Flowchart for section 1 (Equity price forecasting)

The share values at the beginning of the market day for 4 firms from the dates 2021-01-01 to 2023-1-1 were used and they were found on Yahoo Finance in the format YYYY-MM-DD as shown in Fig. 2. Before we can apply LSTM to the stock price, we need to pre-process the data. We can use the fit transform command to adjust the numbers we've collected. In order to normalise all of the monetary figures, a min-max scaler is applied to the figures. The data is divided into two sets namely instructing and examining one, each consisting of 20% of the total.

| Date | Open | High | Low | Close | Adj Close | Volum |
|---|---|---|---|---|---|---|
| 2022-11-30 | 92.470001 | 96.540001 | 91.529999 | 96.540001 | 96.540001 | 1026 |
| 2022-12-01 | 96.989998 | 97.230003 | 94.919998 | 95.500000 | 95.500000 | 6848 |
| 2022-12-02 | 94.480003 | 95.360001 | 93.779999 | 94.129997 | 94.129997 | 7242 |
| 2022-12-05 | 93.050003 | 94.059998 | 90.820000 | 91.010002 | 91.010002 | 7153 |
| 2022-12-06 | 90.500000 | 91.040001 | 87.900002 | 88.250000 | 88.250000 | 7550 |
| 2022-12-07 | 88.339996 | 89.889999 | 87.480003 | 88.459999 | 88.459999 | 6808 |
| 2022-12-08 | 89.239998 | 90.860001 | 87.879997 | 90.349998 | 90.349998 | 7330 |
| 2022-12-09 | 88.900002 | 90.300003 | 88.629997 | 89.089996 | 89.089996 | 6731 |
| 2022-12-12 | 89.209999 | 90.580002 | 87.870003 | 90.550003 | 90.550003 | 6199 |
| 2022-12-13 | 95.230003 | 96.250000 | 90.519997 | 92.489998 | 92.489998 | 1001 |

Figure 2. Sample datasets of Amazon for analysis purpose

## B. *Risk Calculation*

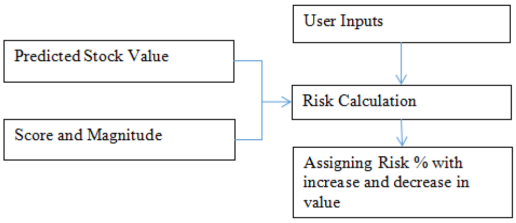


Figure 3. Block diagram for module 2 (Risk calculation)

There is a lot of uncertainty and risk involved in predicting stock values. The risk level of each of the four companies is calculated, and the findings are displayed in Fig. 3. After converting the date to an ordinal number, the instructed regression system anticipated the value of the stock on each day starting on this date and continuing until the end of the investment term [22]. The current stock price was compared to these predicted values, and the number of days in which the share value was more or less than predicted was recorded. This operation was performed on each of the 4 companies and and Fig. 4 and Fig. 5 were created for closing price by combining them together.

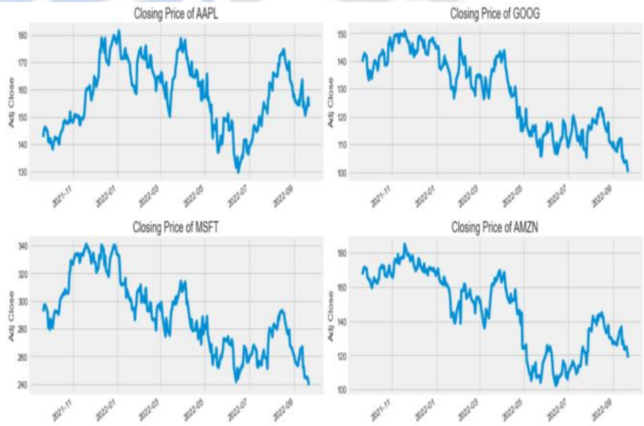


Figure 4. Historical view of the closing price

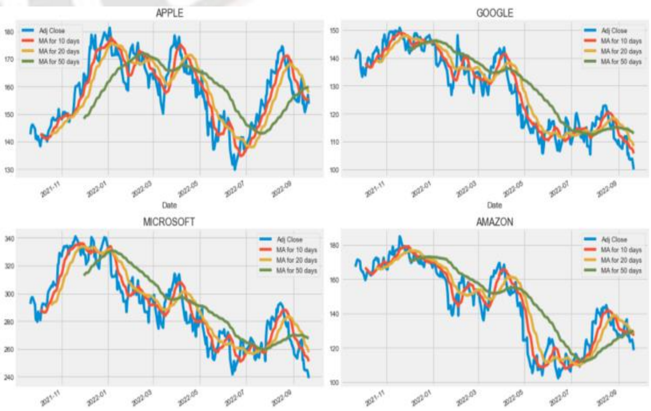


Figure 5. Moving average of stocks

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The resulting graph is plotted using the matplotlib package in Python. Each stock's dollar increase or decrease was calculated by taking the average of the predicted values and subtracting it from the value as of the day of the investor's investment. These charts make it easy to see whether a company's stock price has been going up or down over time [23].

## V. EXPERIMENTAL ANALYSIS

Predictions for the stock markets of Amazon, Google, Apple, and Microsoft are compiled in this exploratory study. The suggested algorithm's efficiency is measured against data mining-based approaches to stock market forecasting.

SVR: Predicting categorical variables is a common use of Support Vector Regression, a supervised learning algorithm. Similar to SVMs is the technique of Support Vector Regression. The primary goal of SVR is to identify the line of best fit. The hyperplane with the most data points is the optimal fit in SVR (Fig. 6).

SGD Regressor: Stochastic gradient descent (SGD) is a method for updating a model with a decreasing strength schedule based on estimates of the loss gradient at each sample (Fig. 7) [24].

Linear SVR carries out regression using linear SVM. It is obtained when the kernel='linear' option is specified. It is relatively similar to SVR because it is built on top of liblinear rather than libsvm. It is better suited to large sample sizes and gives you more flexibility over your penalty and loss functions. Data in this category might be high-dimensional or low-dimensional (Fig. 8).

Random Forest Regressor: A meta estimator known as a random forest uses averaging to reduce overfitting and boost projected accuracy by fitting multiple classification decision trees to different subsamples of the datasets [25]. The max samples option governss sub-sample size if introI/P=1, otherwise, each tree uses the complete datasets. (Fig. 9).

LSTM Hybrid Approach: The Long Short-Term Memory prediction system is subsequently employed to anticipate the standard deviation of stock returns. Value at Risk (VaR) is calculated by creating a probability distribution of the expected rate of recovery under the conditional distribution. As a warning line, the LSTM-VaR model incorporates the sample data. The results indicate that the RMSE value for the hybrid approach is 0.014 when the Leaky ReLu activation function is used and gives a MAPE of 0.0984 (Fig. 10).

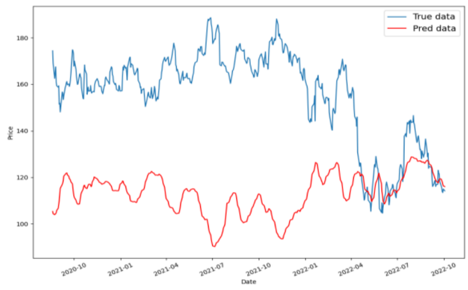


Figure 6. SVR Closing Price Prediction

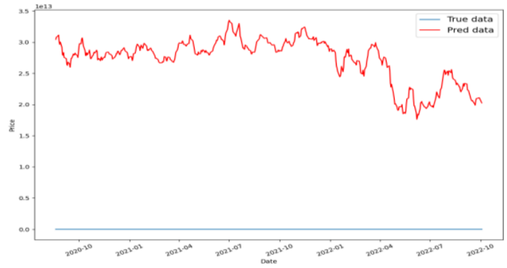


Figure 7. SGD Closing Price Prediction

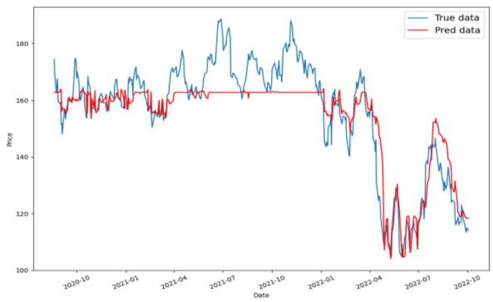


Figure 8. Linear SVR Closing Price Prediction

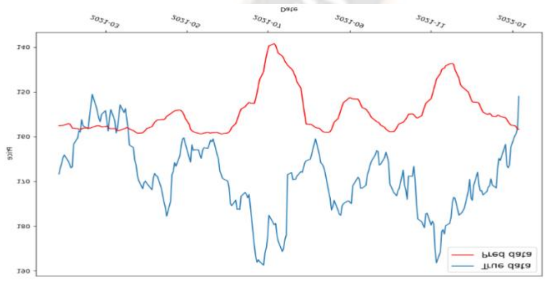

Figure 9. Random Forest Closing Price Prediction

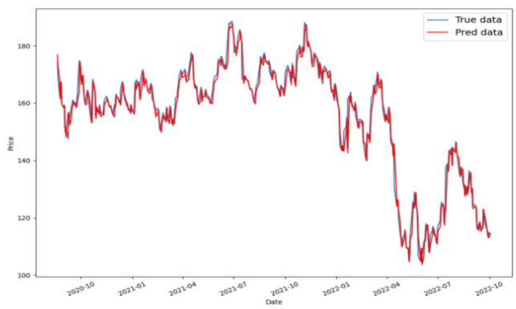


Figure 10. LSTM Hybrid Closing Price Prediction

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The next graph in Fig. 11 gives a summary of all methods giving a comparison of the error involved in the predicted value. The proposed LSTM hybrid approach demonstrates that it improves prediction accuracy while reducing uncertainty in stock market forecasting.

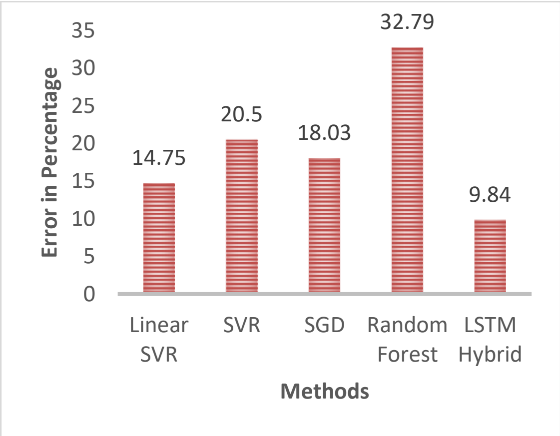


Figure 11. Comparison of Prediction Methods

## VI. CONCLUSION AND FUTURE SCOPE

Stock market prediction was evaluated and contrasted in this study based on the data types utilised as input, the pre-processing techniques used, and the machine learning procedures used to produce predictions. It also analysed how various studies used various metrics for measuring performance. Additionally, a thorough comparison was performed, and LSTM was shown to be the most popular method for SMP. However, SVR and SGD are commonly utilised due to their ability to quickly and accurately forecast outcomes. The hybrid method enhances prediction precision by including both market data and textual data collected from the web. Studies of performance have revealed that the hybrid is more accurate than earlier techniques. The analysis of the results provides a summary of all methods using the proposed LSTM-VaR, revealing that the suggested method provides the superior predication accuracy when compared to existing methods. This demonstrates that the suggested hybrid approach allows for more accurate stock market value predictions with reduced uncertainty.

The suggested model can be used on a big scale in the future if the information comprises additional firms and their corresponding stock values with other characteristic parameters. Group of stocks from a particular sector such as automotive, biotech, banking, etc may be evaluated together on an ETF basis giving outlooks for specific sectors.

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