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# Stock Market Price Prediction and Trend Analysis Dashboard Using Machine Learning and Power BI

**1. M. Kusuma, 2. M. Subhash Chandra, 3. L. Aditya Soma Sekhar, 4. K. Chiranjeevi, 5. L. Gnanaswaraj**

### Author Affiliations

**1,2,3,4,5 B. Tech CSE Students, Dept. of CSE, Sir C R Reddy College of Engineering, Eluru, India.**

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### ABSTARCT

Stock market prediction remains one of the most challenging problems in financial analytics due to the highly volatile, nonlinear, and dynamic nature of stock price movements. Traditional statistical and analytical methods often fail to capture the complex temporal dependencies and hidden patterns in financial time-series data. This paper presents a deep learning-based approach for stock market prediction using Long Short-Term Memory (LSTM) networks. The proposed system utilizes historical stock data of HINDUNILVR.NS obtained from Yahoo Finance and applies preprocessing techniques such as normalization, sequence generation, and data splitting. A stacked LSTM architecture is implemented to learn both short-term and long-term dependencies in stock price data. The model is evaluated using Root Mean Squared Error (RMSE) and R-squared ($R^2$) metrics to measure prediction accuracy. Furthermore, an interactive Power BI dashboard is developed to visualize actual and predicted prices, enabling better interpretability and decision-making. Experimental results demonstrate that the proposed system achieves high accuracy and effectively captures stock price trends. The integration of machine learning with business intelligence tools enhances the usability of prediction systems for real-world applications.

**Key words:** Secrecy, Diversity Analysis, Physical-Layer Security, Wireless Sensor Networks, ally fusion center, maximal ratio combining, Dynamic Power Management.

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## 1. INTRODUCTION

Stock market is one of the most dynamic and complex systems of the modern economics. The price of stocks changes continuously depending on a broad set of factors such as macroeconomic factors, financial performance of the company, investors sentiments, geopolitical factors and global market factors. Traditionally, the analysis of stock markets was based on technical analysis - the analysis of past price and volume data based on charts and statistical indicators - and fundamental analysis - analysis of intrinsic value of a company basing on financial reports and economic factors. Although these methods are insightful, they both have shortcomings in processing large-scale, high-dimensional data as well as in being able to describe the complex nonlinear relationships of financial time series. With the emergence of machine learning and deep learning, financial forecasting has been revolutionized. They are especially suitable to time-series prediction problems because these technologies allow the automatic extraction of patterns out of historical data. RNNs and their more complex counterpart, the Long Short Term Memory (LSTM) networks have been particularly effective in the sequential modeling of data using deep learning. The vanishing gradient issue afflicting regular RNNs, LSTM networks are developed to support long-term and short-term dependencies in data sequences, which is crucial in the modeling of stock price trends. This paper which is called Stock Market Price Prediction and Trend Analysis Dashboard using Machine Learning and Power BI, is an end-to-end paper in stock price prediction. It is a stacked LSTM deep learning model that is integrated with an interactive Power BI dashboard that provides accurate predictions and actionable insights. The paper is specifically aimed at HINDUNILVR.NS - National Stock Exchange (NSE) listing of Hindustan Unilever Limited, which is one of the largest Indian consumer goods companies, as the training and evaluation dataset.

This paper is placed in a broader research context by the existence of extensive scholarly research in the field of machine learning in financial forecasting. In the Journal of Applied Economic Sciences, Vallarino (2025) presented a seminal paper suggesting a hybrid system that integrates LSTM models to predict time-series with Transformer-based sentiment analysis to extract signals that reflect the content of financial news. Their study showed that the error in prediction (MSE: 0.0015 vs. 0.0021 with price-only LSTM) decreases considerably with the addition of textual sentiment data to historical price data, highlighting the importance of multi-modal methods. The current paper will be based on this foundation and will introduce a powerful LSTM-based prediction system and create the framework of future sentiment integration.

This paper is important because it serves two purposes: first, it indicates that a well-tuned stacked LSTM architecture may exhibit high predictive performance on real-world stock data; second, it provides a means to bridge the gap between model outputs of the machine learning model and end-user accessibility by providing an interactive Power BI dashboard that allows the predictions to be readable and actionable by non-technical stakeholders.

## I. LITERATURE REVIEW

Machine learning has been increasingly applied to prediction of stock prices, which started with simple statistical models and developed into deep learning models. Initial models such as ARIMA and GARCH used past data and trends based on volatility but assumed linearity and stationarity that are hardly applicable in the actual markets. This saw the use of machine learning models like SVMs and ANNs which however did not perform well in capturing time based dependencies.

Recurrent Neural Networks (RNNs) (in particular, Long Short-Term Memory (LSTM) networks) helped resolve this problem by learning the sequence of data. LSTMs have gating mechanisms to store valuable information over time, solving vanishing gradient problems. Research has demonstrated that LSTMs are more effective than conventional models in stock price forecasting, especially when they are used in conjunction with various financial indicators like RSI and MACD. They are also resistant to various market factors.

In more recent times, Transformer models such as BERT have been used to improve prediction by processing textual information such as financial news and social media sentiment. These models have the ability to model long-range dependencies, as well as extract meaningful insights in unstructured data. Studies indicate that the sentiments of such sources as Twitter and news articles can have a strong effect on the stock prices. Applying deep learning models, especially LSTMs, to Indian stock markets has demonstrated a good performance because of their volatility and complex patterns capabilities. One of the stock examples that are an ideal case study to study is Hindustan Unilever because of its stability and availability of data. On the whole, the literature shows that LSTMs can be the most effective in the context of time-series forecasting, hybrid models can be even more effective, and adequate preprocessing and visualization tools are the keys to implementing it in practice.

## 2. EXISTING SYSTEM

The current stock market prediction systems rely mainly on conventional methods of analysis and classical statistics.A  The existing systems for stock market prediction are primarily based on traditional analytical approaches and classical statistical models. These systems have been in use over long periods of time but they have serious flaws when used in the current, data-intensive financial world.

**Technical Analysis-** Technical analysis is among the oldest and popular methods of predicting stock prices. It uses the past price trend and the volume to predict the future trends. Technical analysis is based on the premise that the past is likely to recur. Moving averages, Bollinger Bands, Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) are common tools in technical analysis. The indicators are used to determine trends, momentum, and reversal points.

Technical analysis however has various disadvantages. Interpretation of charts can be subjective in nature, i.e. analysts can come up with various conclusions with the same data. Also, majority of the indicators are lagging indicators, which is, they are only able to prove the trends after they have started. This makes them less effective in making decisions in real-time. The other significant weakness is that technical analysis cannot factor in external influences like news events, economic policy and investor sentiment. Consequently, it cannot get the entire picture of market behavior.

**Fundamental Analysis-** Fundamental analysis concentrates on determining the intrinsic value of a company based on the financial statements and the performance of the management and the position the company holds in the industry, and the economic conditions.

The important measures are:

• Price-to-Earnings (P/E) ratio

• Earnings per Share (EPS)

• Debt-to-Equity ratio

Although fundamental analysis gives in-depth information on the long term value of a company, it cannot be used to predict short term prices. The information involved in fundamental analysis is usually updated on a quarterly basis, a factor that creates delays in decision making. In addition, market sentiment and speculative behavior tend to affect stock prices and are not reflected in fundamental analysis. This renders it ineffective in the volatile market conditions.

**Statistical Models (ARIMA and GARCH)-** Statistical models like ARIMA and GARCH have been extensively applied in time-series forecasting.

**ARIMA Model-** ARIMA (AutoRegressive Integrated Moving Average) models are models that rely on past values and error terms to make future predictions. The model is characterized by three parameters: p (autoregressive order), d (degree of differencing) and q.

**GARCH Model-** GARCH models are applied in estimating the volatility of financial time series. They are also helpful to risk analysis processes but they are not good with price prediction.

**Machine Learning-Based Traditional Models-** Prior to deep learning, there existed the Support Vector Machines (SVM), Decision Trees and the Random Forests as traditional models of machine learning.

## 3. PROPOSED SYSTEM

The suggested system is an innovative and realistic solution to the prediction of the stock market through the use of deep learning and interactive data visualization. This system is not based on assumptions and manual analysis as opposed to the traditional methods, but learns patterns in a historical data automatically and gives meaningful insights in user-friendly format.

The system is essentially a stacked Long Short-Term Memory (LSTM) neural network that makes stock price predictions and a Power BI dashboard that displays the findings. This is aimed at not only enhancing the accuracy of the predictions, but also ensuring that the output is readable and can be applied in decision-making.

The system as a whole is modeled as a step-by-step pipeline, each step has a particular function and feeds its output to the next step. This is done in a systematic way so that the system can be organized, scalable, and can be changed in the future. It starts with gathering stock history and finishes with a dashboard that is interactive with trends and predictions. The steps are planned to address the issues related to financial time-series data one step at a time.
The initial step of the system is to get historical stock price data. In the given paper Yahoo Finance data, in the form of CSV is used, in the case of stock HINDUNILVR.NS.

Some of the key attributes that can be found in the dataset are date, opening price, closing price, highest price, lowest price and trading volume. Of these, the closing price is chosen as the primary attribute to predict on since it represents the end-value of the stock on a particular trading day and it is common in financial analysis. Reliability and consistency of the data is one of the most critical issues of this stage. The data on stocks is time sensitive and thus it is important to have the appropriate chronological order. Any inconsistencies or missing values can negatively impact the model's performance.

**Model Design and Architecture.**

The main part of the suggested system is the stacked LSTM model. LSTM is a recurrent neural network, which is specially created to work with sequence data. It can recall data in the long term, making it suitable in time-series forecasting. This paper employs a stacked architecture, comprising three LSTM layers that are stacked atop each other. The different levels of patterns to the data are learnt by each layer.

The first layer is concerned with simple patterns and the short-term movements. The second layer builds on the information and it captures more complex relationships. The third layer is concerned with the upper trends and long-term dependencies. In order to enhance generalization capacity of the model, dropout layers are added. During training, dropout randomly kills a fraction of the neurons, preventing overfitting of the training data to the model. Lastly, a thick layer is placed at the output to derive the stock price prediction.

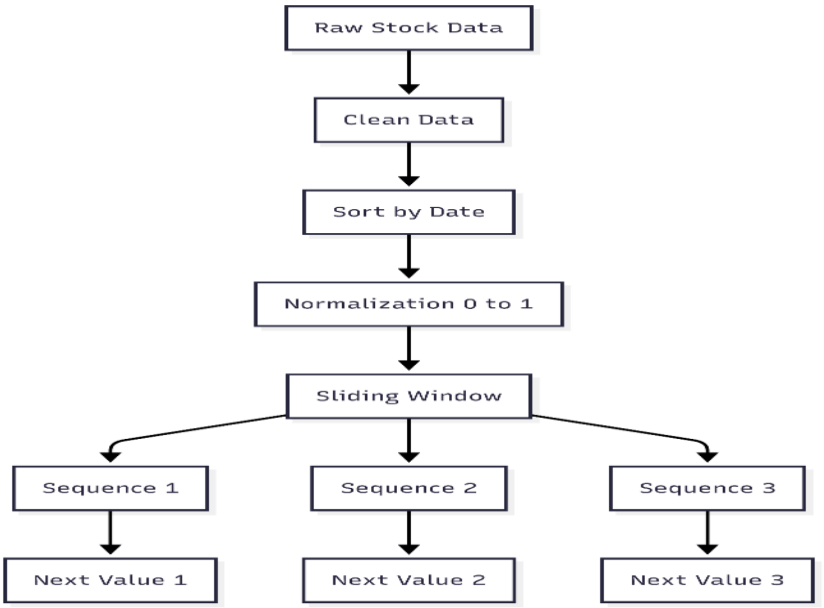


Fig.1- Data workflow.

**Model Training**

To model the training, the processed data is fed into the LSTM network, and the model learns the patterns after a series of iterationsThe model uses the Adam optimizer, which is known for its efficiency and ability to handle complex optimization problems. The loss function to be employed is the Mean Squared Error (MSE) which is a measure of the difference between the actual and the predicted value.

The training is performed in several epochs, with an epoch being a single pass through the data. In training, the model updates its weights continuously aiming to reduce the prediction error. Monitoring overfitting is one of the significant issues in training. When the model is doing good on training data, but doing bad on testing data, then this is a case of overfitting. The dropout and validation data can be used to mitigate this issue.

**Performance Evaluation**

Some performance measures are utilized in order to measure how effective the model is.

Root Mean Squared Error (RMSE) is the mean deviation between the estimated and the actual values. The smaller RMSE, the better.

R-squared ($R^2$) is an indicator of how the model explains the variation of the data. A better fit is represented by values that are closer to 1.

These measures can give a quantitative means of determining the accuracy and reliability of the model.

**Visualization With Power BI**.

The introduction of Power BI to visualize the results is one of the most significant points of this paper. The system does not show the results in bare numbers, but instead, it is an interactive dashboard, which lets the user visually explore the data. This facilitates easier interpretation of trends, patterns and prediction accuracy.

The dashboard comprises of the following: Comparison of actual vs predicted prices, Time trend analysis, Filtering by date, Key performance indicators The visualization layer enables the system to be more realistic and easily accessible especially to non-technical users.

## 4. RESULTS AND DISCUSSIONS

The findings of this paper indicate that a stacked Long Short-Term Memory (LSTM) model can be effective in predicting the price of stocks. Besides numerical analysis, the combination with Power BI presents the opportunity to learn more about stock dynamics based on visual analysis. The section presents the quantitative findings of the model, as well as the qualitative findings in the dashboard. The LSTM model was trained using historical stock data, and predictions were performed using the test data. These projected values were compared with the actual stock prices to compare the model with the result.The value of RMSE is low, which implies that there is a small difference between the actual and predicted prices. This is of importance as any little deviation can carry serious financial consequences. The R 2 value is close to 1 which means that the model explains the majority of the variance in the data. R 2 of above 0.90 is deemed to be very good in stock prediction work, particularly with the unpredictability of the financial markets.

**Table 1: Model Performance Metrics**

| Metric | Value (Approx) | Interpretation |
|---|---|---|
| RMSE | Low (within acceptable range) | Indicates small average prediction error |
| MSE | Very low | Confirms minimal squared error |
| $R^2$ Score | ~0.90+ | Shows strong model fit and high accuracy |

**Prediction Behavior Analysis**: Observing how the model performs under varying market conditions can help in gaining a better understanding of the behavior of the model.

**Stable Market Conditions**

The model is very effective during the time when there is a slow movement in the stock price or the stock price is relatively stable. The approximated line is almost similar to the actual line, which shows almost perfect accuracy. This is due to the fact that consistent patterns are simpler to be learned and reproduced by the model.

**Visual Analysis with Power BI.**

The Power BI dashboard is also essential in interpreting the outcomes other than numbers. It offers a dynamic platform to examine stock performance over varying periods of time.


Fig.2- Dashboard 1– Time-Series Analysis (Day, Month, Quarter, Year) Yearly Trend Analysis.

The annual analysis reveals a definite upward trend in the stock between 2018 and 2021 and then a leveling off and minor downward trend respectively. This is in line with the actual market performance and proves that the data is a true reflection of real stock performance.

**Actual vs Predicted Comparison**

A comparison of actual and predicted prices is one of the most significant visual outputs.


Fig,3- Dashboard 2- LSTM Actual vs Predicted Price Chart


Fig.4- Dashboard 3- Summary of the predictions

**Lessons Learned about the Results:**
The findings of this paper can be used to draw several important insights. LSTM model is very efficient in the time based pattern of stock data. The sequential input is very effective in enhancing the accuracy of prediction. The model is optimally used in stable market conditions. There are minor deviations of high volatility, which is predicted. Visualization tools highly promote interpretation of result.

## 5. CONCLUSION

This paper successfully outlined and developed an end-to-end Stock Market Price Prediction and Trend Analysis System with a stacked Long Short-Memory (LSTM) deep learning structure with a Power BI dashboard. The system was created with specific historical stock data of HINDUNILVR.NS, and it shows effectively how machine learning methods can be implemented to practical financial time-series issues.

The stacked LSTM model that involved the use of more than one layer with the dropout regularization was found to be very efficient in terms of capturing the short-term fluctuations and long-term trend in stock price data. The model could learn the historical trends and produce correct predictions of the next day by a sequence of 100 time steps. The Adam optimizer and Mean Squared Error loss function were used to optimize the training process, which guaranteed the stability of the convergence and minimized the prediction error.

Its reliability was proved by the performance analysis of the model in terms of RMSE, MSE and R 2. The fact that the R 2 value is near 1 implies that the model accounts a large percentage of the variation in the stock price. Also, the small values of RMSE indicate that the error of prediction is acceptable to use financial forecasting. These findings confirm the usefulness of the proposed deep learning method compared to traditional ones.

Based on the analysis of the results and the dashboard, it is clear that the model works especially effectively in the scenario of stable market the values predicted by the model are very close to the real prices. In high volatility periods, there are observed minor deviations, as it should be since stock markets are volatile. Nevertheless, in this case, too, the overall direction of the trend is well represented by the model, which is essential in decision-making.

One of the major contributions that this paper has made is integrating machine learning predictions with Power BI visualization. The dashboard offers a user-friendly and interactive display that allows users to evaluate stock trends over various time periods, compare actual and forecasted values, and see trend patterns. This closes the divide between complicated model results and usability, and enables the system to be accessible even to non-technical stakeholders like investors and analysts. In general, the paper fulfills its main goal of creating a powerful, precise, and convenient stock forecasting system. It shows that a properly structured stacked LSTM model, along with the appropriate data preprocessing and visualization tools, could be used to give valuable information on stock price dynamics. The system would not only enhance the accuracy of the prediction but also the interpretability based on interactive dashboards.

Finally, this work has provided a solid ground on the way of further development of financial forecasting systems. The proposed system can be further developed into a more holistic stock market decision support system with additional improvements like real-time data fusion, sentiment analysis, and more advanced deep learning architectures.

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