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Forecasting Financial Trends Using Time Series Based ML-DL Models for Enhanced Business Analytics

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Abstract
The role of time series analysis and forecasting cannot be overestimated because their application is not limited to a specific example in practice. Time series is the collection of values that a variable takes in a sequential manner with time. The stock market is comprised of stocks whose prices vary substantially over the period of a year making it one of the most complex financial systems in the world. The authors consider the applicability of the Long Short-Term Memory (LSTM) and Decision Tree (DT) models to predict financial trends to be performed using the NIFTY 50 index dataset that consists of more than 27 years of data starting January 1997 through December 2019 in total (more than 6,000 trading days). The data that had the properties of opening, high, low, and closing were cleansed, normalized, and feature-selected. Then, the data were divided into training data and testing data 70% and 30% respectively. Used the Coefficient of Determination (R^2) and the Mean Absolute Percentage Error (MAPE) to test the suggested models. The results of the experiment showed that both models were very predictive with LSTM model having R^2 of 99.08 and MAPE of 0.92 and the DT model having R^2 of 98.65 and MAPE of 1.35. As it has been demonstrated in the comparison study, the proposed models are more effective than other methods, including SCG and ANN. In general, the findings indicate that LSTM is highly effective in identifying complex temporal relationships in time-series data, whereas DT is straightforward to understand and operates efficiently, therefore, both algorithms are robust and reliable tools for predicting financial trends.

Keywords: *Time Series Forecasting, NIFTY 50, Stock Market Prediction, Financial Trend Analysis, Business Analysis.*

I. Introduction

The Indian economy's finance industry has a troubled past. Three distinct periods can be used to describe the history of the Indian financial industry after independence, specifically after 1947. The first period, which lasted from the 1950s to the 1960s, had some instability linked to laissez-faire but underdeveloped banking, the second period, which lasted from the 1970s to the 1980s, started the process of financial development nationwide under government sponsorship, though there was some financial repression during this time, and the third phase, which has been marked by gradual and calibrated financial liberalization and deepening since the 1990s [1]. Financial development is the process by which financial assets are accumulated more quickly than non-financial assets. Academics and politicians alike have begun to pay more attention to the role that the financial sector plays in driving economic growth. In many emerging economies, financial development has been crucial to economic growth. A common belief among policymakers is that financial development boosts productivity, which in turn spurs growth [2][3]. Because financial time series data exhibit erratic movements, cyclical changes, seasonal fluctuations, and long-term trends, they are more complex than other statistical data. Forecasting data that is so erratic and variable is typically fraught with significant mistakes. There is also considerable interest in financial data mining research to develop more accurate financial time series data forecasting models, thereby more efficiently and precisely extracting relevant information from it [4][5]. Financial forecasting using traditional statistical methods was straightforward, but due to the nonlinearity of the data, it had several drawbacks.

The phrase "business analytics" is relatively new, but it is becoming more and more well-known in academic and corporate circles than it has ever been. In order to obtain insights that support better and quicker/more efficient decision-making, business analytics combines a variety of data sources and expert knowledge with sophisticated mathematical, statistical, machine learning (ML), and network science techniques [6]. As a result, business analytics may be seen as a tool that facilitates problem-solving and decision-making [7]. AI has a significant impact on computer systems that handle numerous intelligent tasks previously performed by humans. Even in the absence of explicit instructions, they could potentially address creative challenges. Computers can learn without explicit programming thanks to ML [8]. To make predictions more straightforward and genuine, ML itself uses a variety of models. The newest and most popular method in research is deep learning (DL), which has been effectively used in several domains. DL models learn the data's features layer by layer using a multilayer network topology, and they may independently abstract high-level feature representations from the data's low-level features.

A. Motivation and Contribution

The financial sector has undergone a significant transformation, moving from instability and underdeveloped systems in the early decades to financial deepening and liberalization in recent years. With the rapid growth of financial markets and their increasing impact on economic development, there is a pressing need for more robust and accurate predictive models. The motivation for this study stems from the limitations of conventional forecasting techniques in handling nonlinear and volatile financial data, as well as the growing role of business analytics and artificial intelligence in enhancing decision-making. Such models not only improve predictive accuracy but also support policymakers, enabling financial institutions and stakeholders to swiftly and intelligently respond to a dynamic economic landscape. This research offers several key contributions as listed below:

- Utilization of the NIFTY 50 dataset sourced from Kaggle, ensuring access to reliable and relevant financial market data.
- Implementation of systematic preprocessing steps, including data cleaning, min–max normalization, and feature selection, to enhance data quality and model performance.
- Application of two different models LSTM to learn sequentially, and DT to classify using interpretable rules.
- Rigorous evaluation of R^2 and MAPE are statistical parameters that are employed by the models to ensure complete evaluation.

B. Novelty and Justification of the Study

The innovation of this research is the combination of two types of models, namely DL and classic ML models, that is, LSTM and Decision Tree, to forecast NIFTY 50 stock-markets trends so that a balanced comparison can be drawn between the sequence-based modeling and rule-based classification methods. Unlike conventional studies that rely solely on one type of model, this research emphasizes the importance of combining the advanced temporal learning capabilities of LSTM with the interpretability and simplicity of DT to capture different market dynamics. The rationale behind this is based on the fact that they should not only offer the investors and analysts with performance robust models but also with interpretable information so that the models would be useful in decision making with regards to the real-life financial situations.

C. Organization of the Paper

The paper is organized in the following way: Section II reviews the prior studies regarding the application of time series to predict financial trends. Section III covers the dataset, pre-processing of the data, and implementation of a model. Section IV discusses experiment outcomes and a comparative analysis, whereas Section V presents certain guidelines on what to do in the future.

II. Literature Review

This research is based on a survey and critical analysis of past studies that have tried to forecast the financial trends through a time series analysis. This established the scope of the ongoing research and put it in perspective.

Chen et al. (2019) the relation networks (RNs) are a type of DL that is applied to forecast the cryptocurrency and fiat currency exchange rates. RNs can determine the relationships between several currencies by using the concept of visual question answering (VQA). There is also a novel design for the extraction feature stage that takes into account both temporal and spatial correlations at the same time. The experimental results demonstrate that the VQA concept based on RNs can achieve a high predictive performance for cryptocurrency, outperforming the forecast performance between cryptocurrencies and fiat currencies, with an estimated 65% accuracy rate [9].

Guo and Li (2019) proposed the TSS model, in which a novel baseline correlation approach is shown. Fast decision-making without previous data knowledge is possible, because it uses less computing power while still achieving good forecast accuracy. R is used for classification modelling, polynomial regression, and sentiment analysis, which is based on a lexicon. Predicting the stock market's future direction using 15-time samples (30 working hours) using the provided baseline criteria, the generated TSS achieves a 67.22% accuracy rate without referencing historical TSS or market data. In particular, TSS determines that a rising market is significantly more accurately predicted than a falling one. TSS uses LR and linear discriminant analysis to predict the future market's growing tendency with 97.87% accuracy [10].

Wen et al. (2019) presented a novel technique for using sequence reconstruction to minimize noisy financial temporal data by utilizing motifs (frequent patterns). The spatial organization of the time data is then ascertained using a convolutional neural network (CNN). By outperforming DL in stock trend prediction utilizing frequency trading pattern modelling and standard signal process techniques, The experimental findings demonstrate the effectiveness of the suggested feature learning approach, increasing accuracy by 4% to 7% [11].

Yang and Chen (2018) findings indicate that conventional forecasting has a 62.25% accuracy rate in anticipating the actual fluctuation pattern. The internal data serves as the basis for the technical and basic aspects of the study. Weighted forecasting yielded an accuracy of 73.55% for the actual individual stock swings after the chip facet analysis was incorporated, and the three aspects were examined. In general, the weighted forecasting may be used to determine the variations of particular stocks, improving the precision of forecasting stock fluctuations for the upcoming month and acting as a resource for investors and specialists [12].

Liu and Liu (2018) suggested preparing data based on movement trends, two phases of preprocessing the trend indicator and using the Gated Recurrent Unit (GRU) to simulate the stock index. Following their extraction from five different aspects, the trend indicators were discretized according to the dynamic connection in the two-stage preprocessing. In order to anticipate financial time series, three Recurrent Neural Networks (RNNs) were used. The model's prediction of in contrast to the random tri-prediction method boosted the stock index movement trend from 33% to 68% [13].

Gudelek, Boluk and Ozbayoglu (2017) present a unique CNN-based stock price prediction technique. Paper trading and final capital calculation are used to assess the approach. The strategy's effectiveness is also contrasted with those of well-known traditional trading tactics. When realistic transaction costs are taken into consideration, results show that it can forecast the prices for next day with a 72% success rate, and eventually earn back 5:1 of the initial investment [14].

Previous research on financial time series forecasting has employed diverse methods, including DL architectures, sentiment-driven models, weighted forecasting techniques, and recurrent or convolutional neural networks. Although these approaches have achieved encouraging outcomes, several shortcomings persist. Many existing models struggle to effectively capture the highly nonlinear, volatile, and dynamic behavior of financial markets, frequently resulting in unstable or inconsistent prediction accuracy. Some approaches concentrate primarily on a limited set of factors, such as technical indicators or sentiment analysis, without considering the broader interplay of financial, economic, and external variables. Furthermore, while certain models perform well in short-term predictions, they often lack the robustness and adaptability required for long-term trend forecasting across different market conditions.

The Table I below provides a consolidated summary of recent studies on forecasting financial trends using time series, outlining the models employed, datasets used, major findings, and the limitations encountered, along with suggested directions for future research.

Table 1: Recent Studies on Forecasting Financial Trends using Time Series.

Author	Proposed Work	Results	Key Findings	Limitations & Future Work
Chen et al. (2019)	Relation Networks (RNs) with Visual Question Answering (VQA) for forecasting the value of several cryptocurrency and fiat currencies.	Achieved ~65% accuracy for cryptocurrencies.	VQA helps capture relationships among currencies; proposed architecture considers both spatial and temporal features.	Accuracy is moderate; future work can explore hybrid deep learning models or advanced architectures for higher performance.
Guo and Li (2019)	Trend Sensitive Score (TSS) model with baseline correlation approach using polynomial regression, classification modeling, and sentiment analysis in R.	Overall accuracy 67.22%; upward market prediction accuracy 97.87%.	Reduces computation burden; predicts stock market trends 30 hours in advance without historical data.	Performance weaker for downward trends; future work could integrate hybrid methods to balance predictions.
Wen et al. (2019)	Sequence reconstruction with motifs (frequent patterns) + CNN for noisy financial temporal series.	4%–7% accuracy improvement over traditional methods.	Motifs help simplify noisy data; CNN captures spatial structure effectively.	Needs more validation on large-scale datasets; extension to multi-modal data suggested.
Yang and Chen (2018)	Weighted forecasting combining fundamental, technical, and chip facet analysis.	Accuracy improved from 62.25% to 73.55%.	Weighted approach improves prediction of individual stock fluctuations.	Limited to monthly prediction; future work can extend to high-frequency forecasting.
Liu and Liu (2018)	Movement trend-based preprocessing with Gated Recurrent Unit (GRU) for stock index modeling.	Accuracy improved from 33% to 68%.	Two-stage preprocessing (trend indicator extraction + discretization) improves GRU performance.	Model complexity high; scalability and robustness to different markets should be studied.
Gudelek, Boluk & Ozbayoglu (2017)	CNN-based stock movement prediction with paper trading evaluation.	72% accuracy; achieved 5:1 return on initial capital.	CNN outperforms traditional trading strategies; realistic transaction costs considered.	Limited to next-day prediction; future work could explore multi-day forecasting and LSTM/CNN hybrids.

III. Research Methodology

The proposed methodology begins with collecting the NIFTY 50 dataset sourced from Kaggle, which undergoes a systematic preprocessing phase. Feature selection is used to save the most important properties for training the model, data cleaning is used to fix missing or inconsistent values, and using min-max normalization, the features are scaled into a consistent range. The processed data is further divided into a training set (70%) and a testing set (30%) to produce a fair assessment. Predictive modeling is done using two ML models, LSTM and DT. Strict evaluation criteria, such as R^2 and MAPE, with the help of the above models, were evaluated. Lastly, the results rely regarding the effectiveness of the suggested models in comparison to one another, which implies their capability to forecast the NIFTY 50 stocks' movements. In Figure 1, the entire procedure of the proposed technique is presented.

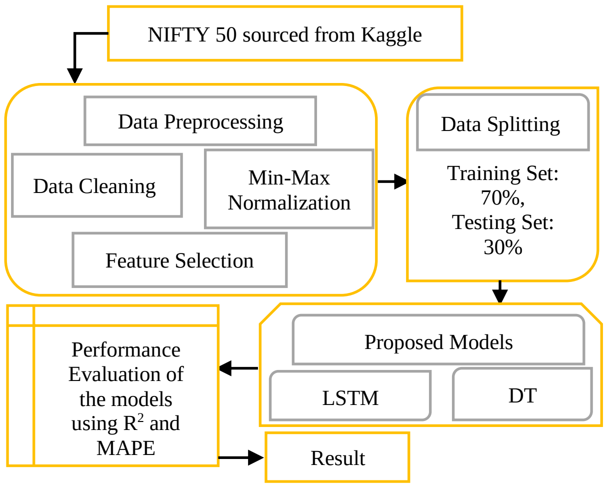

Fig. 1. Proposed flowchart for Forecasting Financial Trends using Time Series

The next section gives a comprehensive explanation of each step as seen in the suggested Forecasting Financial Trends using Time Series flowchart.

A. Data Gathering and Analysis

The dataset used in this research is the NIFTY 50 index dataset provided by Kaggle, which spans a 27-year period (from January 1, 1997, to December 31, 2019). This dataset has the fluctuations of the NIFTY 50, and the data covers a period of over 6,000 days. The dataset contains data parameters such as the opening, high, low and closing value. The data have some data visualizations provided below:

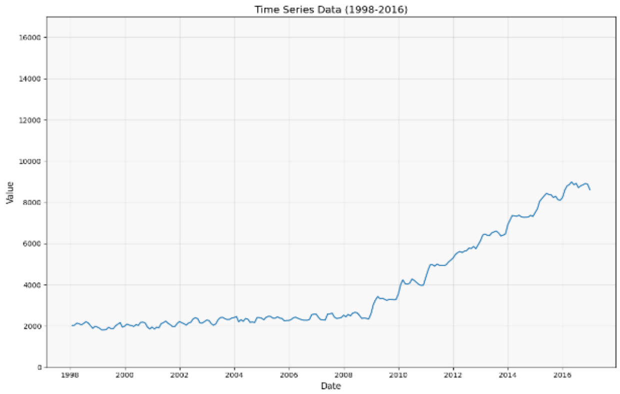

Fig. 2. NIFTY 50 movement from 1998 to 2016

Figure 2 represents the time series data of 1998-2016. The values stand at relatively constant levels towards the year 2000 till 2008 when an upward trend takes off rapidly to almost 9000 by 2016. This means that stability has changed to high growth.

B. Data Pre-Processing

It is necessary to pre-process the data prior to analysis once it has been gathered. The step entails data cleaning, min-max normalization and feature selection as explained below:

- **Data Cleaning:** Data undergo cleaning in the preparation phase of the time series analysis to solve a diverse range of data quality issues such as noise, outliers, and missing values.
- **Min-Max Normalization:** Normalization process is conducted with the help of Min-Max Scaler that limits the input to the same scale as in the case of the input presented in Equation (1):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where, the x is original value, x_{min} is minimum value in the feature, x_{max} is maximum value in the feature and x_{norm} is a normalized value.

Feature Selection: Selection of features is a crucial procedure that allows the model to be more accurate and efficient. Various financial indicators or factors that significantly influence market trends are recognized and selected in this process. This process enhances model performance and reduces computational complexity by eliminating redundant or irrelevant characteristics that could negatively impact the predictions.

C. Data Splitting

The grounded experiment should be conducted by creating two training and testing subgroups from the raw data, using a 70:30 ratio.

D. Proposed Models

This section presents the proposed framework for the effective and efficient implementation of Time-series data is used to forecast financial trends using LSTM and DT models. The details of each model are described below:

LSTM: In addition to image data, DL technology is used to a variety of other data types, with time-series data being particularly common in financial data. Initially, sequential patterns in time series data were discovered using RNNs. Nevertheless, for RNNs, There is still a problem with the disappearing gradient that appears as the network goes deeper [15]. This issue was resolved by the LSTM network. In the context of the RNN, the vanishing gradient issues were resolved using the gate process and memory blocks. For each gate and cell state, the computations are presented in Equations (2) through (7):

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \quad (2)$$

$$i_t = \sigma(W_{ix}x_t + W_{hi}h_{t-1} + b_i) \quad (3)$$

$$\widetilde{c_t} = \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (4)$$

$$c_t = f_t * c_{t-1} + i_t * \widetilde{c_t} \quad (5)$$

$$o_t = \sigma(W_{xo} + W_{ho}h_{t-1} + b_o) \quad (6)$$

$$h_t = o_t * \tanh(c_t) \quad (7)$$

Where W represents weight matrices, b is a bias term, tanh(·) is a hyperbolic tangent function, and σ(·) is a sigmoid function.

DT: Decision tree is a categorisation technique that produces a tree structure that resembles a flowchart. Although the D-Tree output is quite interpretable, it has to be shown as categorical data [16]. The "J48" DTree method is used in this study to categorise the future direction of the stock market.

E. Evaluation metrics

To measure, to see how well the model works, utilize statistical indicators, including its accuracy and efficacy, such as R^2 and MAPE:

1) Coefficient of Determination (R^2)

A statistical metric called the Coefficient of Determination (R^2) shows how effectively a predictive model accounts for the dependent variable's variance. Higher numbers indicate more explanatory power; it ranges from 0 to 1. It is shown in Equation (8):

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}} \quad (8)$$

Where the residual sum of squares is denoted by SS_{res} and the total sum of squares by SS_{tot} and R^2 is the variability in the data of the model.

2) Mean Absolute Percentage Error (MAPE):

The accuracy of predictions in statistics is gauged by MAPE, the accuracy of the model has been calculated per the given Equation (9):

$$MAPE = \left[\left(1 - \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right| * 100\right) * 100\right] \quad (9)$$

Where, n is the number of observations, y_i is the actual value of the $i-th$ observations, e_i is the error of the $i-th$ observations.

IV. Results and Discussion

The experimental environment is configured with 2 * NVIDIA GTX 1080 Ti GPUs for the hardware; the software is configured with PyTorch version 1.0.1 (GPU), Python version 3.6.0. Table II illustrates the predictions made by the suggested models, LSTM and DT, which forecast the movement of the stock market using time series data. The results reveal that both models can make decent predictions; however, the DT model is marginally outperformed by the LSTM model. Specifically, LSTM achieved an R^2 value of 99.08%, reflecting its high accuracy in capturing the variance within the data, while DT attained a closely comparable R^2 of 98.65%. The Mean Absolute Percentage Error (MAPE) for LSTM was 0.92%, which is less than the 1.35% for DT. This means that LSTM makes more accurate predictions with less inaccuracy from the real values. Overall, the results show that both models are good at forecasting financial trends, although LSTM is a bit more accurate and reliable.

Table 2: Prediction Results of the Proposed ML and DL Models for Forecasting Financial Trends using Time Series

Performance Matrix	LSTM	DT
R^2	99.08	98.65
MAPE	0.92	1.35

Figure 3 shows the time series plot of movement (red line) and actual movement (green line) of a predicted value of one of the Closing values of 2014 to 2019. The two lines are virtually indistinguishable, demonstrating The model's predictions closely resemble the data from the real world and are fairly accurate. The error between the actual and anticipated numbers is shown by the yellow line at the bottom, which is labelled Difference. It consistently stays at or near zero, providing strong visual proof of the model's superior performance across the whole time period and low error rate.

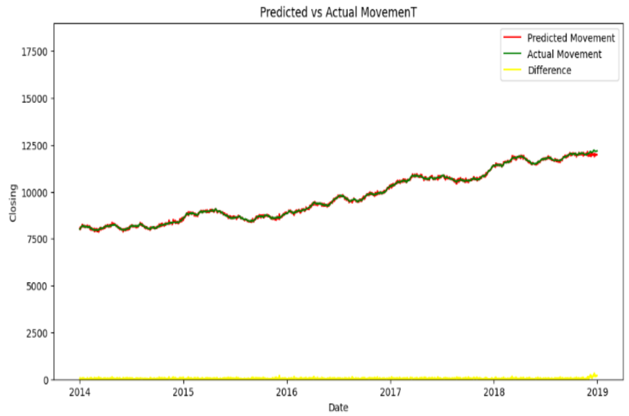

Fig. 3. Prediction vs. Actual vs. Difference Testing matrix of the LSTM Model

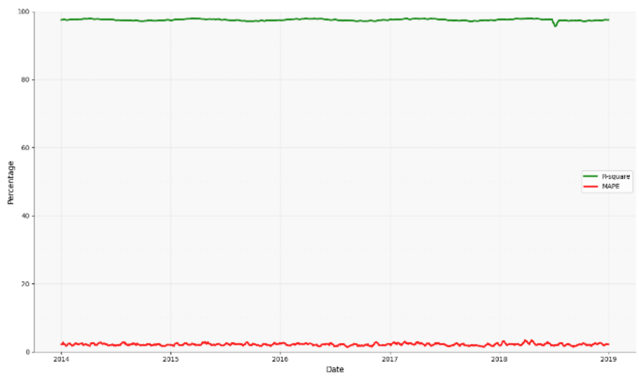

Fig. 4. Prediction R2 vs. MAPE of the LSTM Model

Figure 4 illustrates the model's performance from 2014 to 2019. The R-squared (green line) remains near 100%, indicating the model explains almost all variability in the dependent variable. Simultaneously, the RMSE (red line) stays close to 0%, showing minimal prediction error. Overall, the chart demonstrates consistently high accuracy and predictive reliability over time.

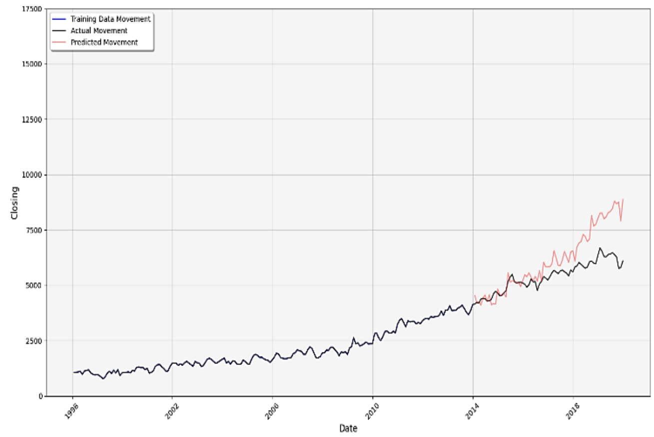

Fig. 5. LSTM model implementation data

Figure 5 presents a time series of "Closing" values from 1998 to early 2018 with a forecast. The training data is displayed by the blue line, the actual values are displayed by the black line, and the projected values are displayed by the red line. From 1998 to 2014, the series rises gradually, after which the model forecasts a continued upward trend. Notably, predicted values exceed actual observations, indicating an optimistic bias in the forecast.

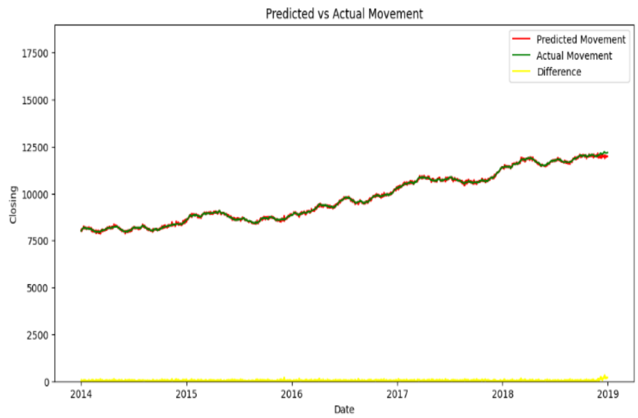

Fig. 6. Prediction vs. Actual vs. Difference Testing matrix of the DT Model

Figure 6 is a time series plot that compares the predicted movement of a value (red line) against its actual movement (green line) from early 2014 to the end of 2019. The two lines overlap almost perfectly, demonstrating that the model's predictions are highly accurate. The bottom of the graph shows a third line, labeled Difference (yellow), which represents the discrepancy between the actual and anticipated values. This line remains consistently close to zero, further confirming the excellent performance of the model and its low error rate across the entire period.

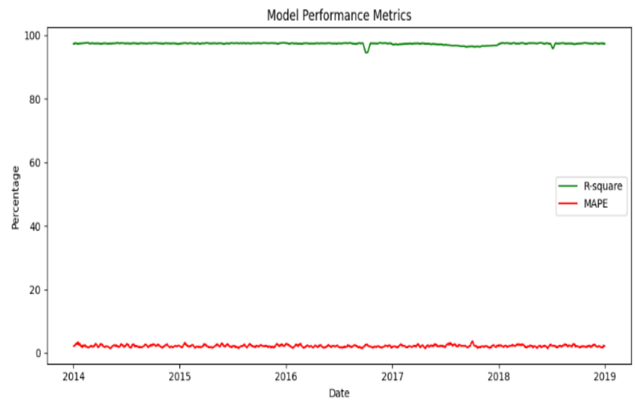

Fig. 7. Prediction R^2 vs. MAPE of the DT Model

Figure 7 presents a time-series evaluation of the model from 2014 to 2019, showing R^2 (green) and MAPE (red). R^2 remains near 100% and MAPE is very low throughout most of the period, indicating highly accurate predictions. A brief dip in R^2 and a corresponding spike in MAPE around mid-2017 highlight a temporary increase in prediction error, likely due to unusual market volatility.

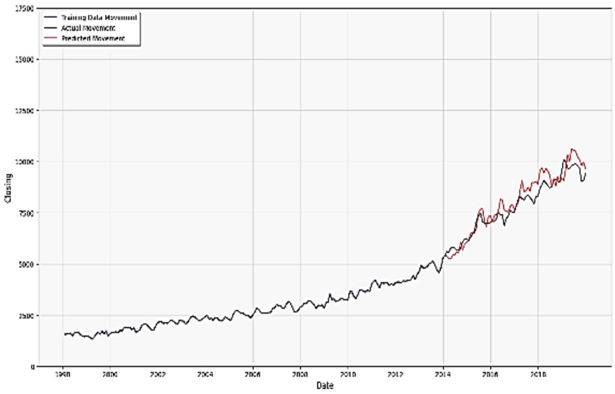

Fig. 8. DT model implementation data

Figure 8 shows a time series of "Closing" values from 1998 to 2019, including historical and forecasted data. The blue line represents training data, the black line shows actual values, and the red line depicts predictions. The actual series trends upward, especially after 2014, while the forecast closely follows this pattern with minor deviations, indicating the model effectively captures the underlying trend.

F. Comparative Analysis

Table III presents a comparative analysis of different models used for forecasting financial trends based on time series data.

It is demonstrated that the suggested models are LSTM and Decision Tree (DT) are better than the previously reported practices, which are Artificial Neural Network (ANN) and Scaled Conjugate Gradient (SCG). The optimum model is LSTM with an R2of 99.08 and the second optimum is DT with a 98.65 R2. This implies that the two models are very effective in identifying complex market trends. Conversely, the SCG and ANN values of R^2 are 95.5 and 84.81, which are less than the two other model values. This analogy shows with much clarity the effectiveness and usefulness of the proposed method in coming up with very accurate predictions regarding the movement of finances.

Table 3: Performance Comparison of Different Models for Forecasting Financial Trends using Time Series

Models	R^2
SCG [17]	95.5
ANN [18]	84.81
LSTM	99.08
DT	98.65

The suggested LSTM and DT models have tremendous benefits towards the prediction of financial trends. LMST easily detects complex time-based relationships of time series. This enables it to show both the long-term and short-term trends in the correct way. It is also very good in predicting financial indexes since it can learn using the information it has been provided with. The influence of the past on the future is enormous. On the other hand, the DT model is less complicated to understand and apply; thus, it is simple to locate the most key areas in making forecasts. The two are robust and reliable and fit into a very broad market environment. The LSTM is more suitable in detecting certain patterns whereas the DT simplifies and speedy up the findings.

V. Conclusion and Future Study

Business predictive analytics allows companies to predict the operational and economic trends to maximize the performance. Forecasting, regression, and sophisticated ML models are used in the strategic decision-making process inside organizations. This paper compares the predictive accuracy of the Long Short-Term Memory (LSTM) and Decision Tree (DT) models at predicting the trends in the financial market using the NIFTE 50 dataset, which involves 27 years of historical stocks. Both models have good accuracy with an R^2 of 99.08 and DT of 98.65. These findings demonstrate that LSTM is better in its ability to model intricate time-dependent relationships in financial time-series data. Nonetheless, DT is very reliable, computationally fast and explainable, which is beneficial in the fast decision process and interpretation of model results. Collectively, the results indicate that the two models are both able to predict market behaviour well, particularly under volatile conditions. LTST is better adapted to the long-term market trend, whereas DT is easier and more stable in practice. Future research possibilities are to consider hybrid designs (such as CNN-LSTM or transformer-based networks) and external inputs (sentiment analysis and macroeconomic data) to increase the stability and performance of real-world high-stakes financial decision-making.

References

1. R. Mohan and P. Ray, "Indian Financial Sector: Structure, Trends and Turns," *IMF Work. Pap.*, vol. 17, no. 7, p. 1, 2017, doi: 10.5089/9781475570168.001.
2. J. T. Puatwoe and S. M. Piabuo, "Financial sector development and economic growth: evidence from Cameroon," *Financ. Innov.*, vol. 3, no. 1, p. 25, 2017, doi: 10.1186/s40854-017-0073-x.
3. S. S. S. Neeli, "Serverless Databases: A Cost-Effective and Scalable Solution," *Int. J. Innov. Res. Eng. Multidiscip. Phys. Sci.*, vol. 7, no. 6, p. 7, 2019.
4. A. K. Rout, P. K. Dash, R. Dash, and R. Bisoi, "Forecasting financial time series using a low complexity recurrent neural network and evolutionary learning approach," *J. King Saud Univ. - Comput. Inf. Sci.*, 2017, doi: 10.1016/j.jksuci.2015.06.002.
5. A. Thapliyal, P. S. Bhagavathi, T. Arunan, and D. D. Rao, "Realizing Zones Using UPnP," in *2009 6th IEEE Consumer Communications and Networking Conference*, IEEE, Jan. 2009, pp. 1–5. doi: 10.1109/CCNC.2009.4784867.
6. S. S. S. Neeli, "The Significance of NoSQL Databases: Strategic Business Approaches and Management Techniques," *J. Adv. Dev. Res.*, vol. 10, no. 1, 2019.
7. D. Delen and S. Ram, "Research Challenges and Opportunities in Business Analytics," *J. Bus. Anal.*, vol. 1, no. 1, pp. 2–12, Jan. 2018, doi: 10.1080/2573234X.2018.1507324.
8. A. Kushwaha, P. Pathak, and S. Gupta, "Review of optimize load balancing algorithms in cloud," *Int. J. Distrib. Cloud Comput.*, vol. 4, no. 2, pp. 1–9, 2016.
9. C. T. Chen, L. K. Chiang, Y. C. Huang, and S. H. Huang, "Forecasting Interaction of Exchange Rates between Fiat Currencies and Cryptocurrencies Based on Deep Relation Networks," in *Proceedings - 2019 IEEE International Conference on Agents, ICA 2019*, 2019. doi: 10.1109/AGENTS.2019.8929155.
10. X. Guo and J. Li, "A Novel Twitter Sentiment Analysis Model with Baseline Correlation for Financial Market Prediction with Improved Efficiency," in *2019 6th*

International Conference on Social Networks Analysis, Management and Security, SNAMS 2019, 2019. doi: 10.1109/SNAMS.2019.8931720.

11. M. Wen, P. Li, L. Zhang, and Y. Chen, "Stock Market Trend Prediction Using High-Order Information of Time Series," *IEEE Access*, vol. 7, pp. 28299–28308, 2019, doi: 10.1109/ACCESS.2019.2901842.
12. S. J. Yang and C. H. Chen, "Using Big Data Technology to Analyze the Fluctuation Trends in Stock Price-As a Practice of Taiwan Financial Stock Market," in *Proceedings - 17th IEEE/ACIS International Conference on Computer and Information Science, ICIS 2018*, 2018. doi: 10.1109/ICIS.2018.8466401.
13. Y. Liu and X. Liu, "A Trend-based Stock Index Forecasting Model with Gated Recurrent Neural Network," in *Proceedings of the 2018 IEEE International Conference on Progress in Informatics and Computing, PIC 2018*, 2018. doi: 10.1109/PIC.2018.8706267.
14. M. U. Gudelek, S. A. Boluk, and A. M. Ozbayoglu, "A deep learning based stock trading model with 2-D CNN trend detection," in *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*, IEEE, Nov. 2017, pp. 1–8. doi: 10.1109/SSCI.2017.8285188.
15. T. Kim and H. Y. Kim, "Forecasting stock prices with a feature fusion LSTM-CNN model using different representations of the same data," *PLoS One*, vol. 14, no. 2, p. e0212320, Feb. 2019, doi: 10.1371/journal.pone.0212320.
16. P. Paliyawan, "Stock Market Direction Prediction Using Data Mining Classification," *ARPN J. Eng. Appl. Sci.*, vol. 10, no. 3, 2014, doi: 10.13140/RG.2.2.26523.46882.
17. D. Selvamuthu, V. Kumar, and A. Mishra, "Indian stock market prediction using artificial neural networks on tick data," *Financ. Innov.*, vol. 5, no. 1, p. 16, Dec. 2019, doi: 10.1186/s40854-019-0131-7.
18. J. Patel, S. Shah, P. Thakkar, and K. Kotecha, "Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques," *Expert Syst. Appl.*, vol. 42, no. 1, pp. 259–268, 2015, doi: 10.1016/j.eswa.2014.07.040.
19. Polam, R. M., Kamarthapu, B., Kakani, A. B., Nandiraju, S. K. K., Chundru, S. K., & Vangala, S. R. (2021). Big Text Data Analysis for Sentiment Classification in Product Reviews Using Advanced Large Language Models. *International Journal of AI, BigData, Computational and Management Studies*, *2*(2), 55-65.
20. Gangineni, V. N., Tyagadurgam, M. S. V., Chalasani, R., Bhumireddy, J. R., & Penmetsa, M. (2021). Strengthening Cybersecurity Governance: The Impact of Firewalls on Risk Management. *International Journal of AI, BigData, Computational and Management Studies*, *2*, 10-63282.
21. Pabbineedi, S., Penmetsa, M., Bhumireddy, J. R., Chalasani, R., Tyagadurgam, M. S. V., & Gangineni, V. N. (2021). An Advanced Machine Learning Models Design for Fraud Identification in Healthcare Insurance. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *2*(1), 26-34.
22. Kamarthapu, B., Kakani, A. B., Nandiraju, S. K. K., Chundru, S. K., Vangala, S. R., & Polam, R. M. (2021). Advanced Machine Learning Models for Detecting and Classifying Financial Fraud in Big Data-Driven. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *2*(3), 39-46.
23. Tyagadurgam, M. S. V., Gangineni, V. N., Pabbineedi, S., Penmetsa, M., Bhumireddy, J. R., & Chalasani, R. (2021). Enhancing IoT (Internet of Things) Security Through Intelligent Intrusion Detection Using ML Models. *International Journal of Emerging Research in Engineering and Technology*, *2*(1), 27-36.
24. Vangala, S. R., Polam, R. M., Kamarthapu, B., Kakani, A. B., Nandiraju, S. K. K., & Chundru, S. K. (2021). Smart Healthcare: Machine Learning-Based Classification of Epileptic Seizure Disease Using EEG Signal Analysis. *International Journal of Emerging Research in Engineering and Technology*, *2*(3), 61-70.
25. Kakani, A. B., Nandiraju, S. K. K., Chundru, S. K., Vangala, S. R., Polam, R. M., & Kamarthapu, B. (2021). Big Data and Predictive Analytics for Customer Retention: Exploring the Role of Machine Learning in E-Commerce. *International Journal of Emerging Trends in Computer Science and Information Technology*, *2*(2), 26-34.
26. Penmetsa, M., Bhumireddy, J. R., Chalasani, R., Tyagadurgam, M. S. V., Gangineni, V. N., & Pabbineedi, S. (2021). Next-Generation Cybersecurity: The Role of AI and Quantum Computing in Threat Detection. *International Journal of Emerging Trends in Computer Science and Information Technology*, *2*(4), 54-61.
27. Polu, A. R., Vattikonda, N., Gupta, A., Patchipulusu, H., Buddula, D. V. K. R., & Narra, B. (2021). Enhancing Marketing Analytics in Online Retailing through Machine Learning Classification Techniques. *Available at SSRN 5297803*.
28. Polu, A. R., Buddula, D. V. K. R., Narra, B., Gupta, A., Vattikonda, N., & Patchipulusu, H. (2021). Evolution of AI in Software Development and Cybersecurity: Unifying Automation, Innovation, and Protection in the Digital Age. *Available at SSRN 5266517*.
29. Polu, A. R., Vattikonda, N., Buddula, D. V. K. R., Narra, B., Patchipulusu, H., & Gupta, A. (2021). Integrating AI-Based Sentiment Analysis With Social Media Data For Enhanced Marketing Insights. *Available at SSRN 5266555*.
30. Buddula, D. V. K. R., Patchipulusu, H. H. S., Polu, A. R., Vattikonda, N., & Gupta, A. K. (2021). INTEGRATING AI-BASED SENTIMENT ANALYSIS WITH SOCIAL MEDIA DATA FOR ENHANCED MARKETING INSIGHTS. *Journal Homepage: http://www. ijesm. co. in*, *10*(2).
31. Gupta, A. K., Buddula, D. V. K. R., Patchipulusu, H. H. S., Polu, A. R., Narra, B., & Vattikonda, N. (2021). An Analysis of Crime Prediction and Classification Using Data Mining Techniques.