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AI-Driven Business Intelligence: A Case Study on Predicting Market Trends Using LSTM

Dr Melvin Victor[1*], K.S. Vigneswaran[2], Om Prakesh[3], Dr.K. Kumuthadevi[4], Begum Shameena[5], S. Rajeshwari[6]

[1*]Assistant Professor, School of Business and Management Christ University, Bengaluru, Karnataka, India.
E-mail: melvinvictor@gmail.com; melvin.victor@christuniversity.in, https://orcid.org/0000-0002-1499-075X

[2]Assistant Professor, Department of Mechanical Engineering, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India. E-mail: vigneshwaran13@gmail.com, https://orcid.org/0009-0000-3384-526X

[3]Institute of Business Management, Gla University, Mathura, Uttar Pradesh, India. E-mail: omprakash.agrawal@gla.ac.in, https://orcid.org/0000-0001-8861-8435

[4]Dean, School of Commerce, KPR College of Arts Science and Research, Coimbatore, Tamil Nadu, India.
E-mail: drkumuthadevi@gmail.com

[5]Department of CSE(CS), Ramachandra College of Engineering, Eluru, India. E-mail: shameenabegum@rcee.ac.in, https://orcid.org/0000-0002-2097-8693

[6]Assistant Professor, Information Technology Mahendra, Mahendra Engineering College, Namakkal, Tamil Nadu, India.
E-mail: rajeshwaris@ ahendra.info, https://orcid.org/0009-0007-3252-4422

*Corresponding author: Email: melvinvictor@gmail.com; melvin.victor@christuniversity.in

Abstract

The ability to predict market developments accurately helps in decision-making and planning more effectively. In the financial markets, however, classical methods such as ARIMA and exponential smoothing models are ineffective when the data has nonlinearities and seasonality's and is highly dependent in the long-term. The proposed paper provides an intelligent solution with the application of artificial intelligence techniques for forecasting market trends in the form of LSTM neural networks. Incorporating past price data, trading volume, and technical indicators such as SMA, EMA, RSI, MACD, the LSTM prediction algorithm uses these inputs to forecast market trends. The daily data of 14 years (2010–2023) have been used for training LSTM network. To generate the input windows, the missing values were imputed, feature variables were normalized, and outlier exclusion was performed during the pre-processing stage; 60 days' windows were formed. Various criteria were used to evaluate the performance of the proposed approach, and the obtained results were: RMSE – 0.97; MAE – 0.72; MAPE – 1.85% and R^2 – 0.91. The following conclusions can be drawn: The suggested algorithm is more accurate and has better features in terms of trend detection than the other prediction models. Apart from examining the predictive power of the chosen approach, other potential problems examined included data quality, complexity and interpretability. The fields where future research can be undertaken include combining various techniques of deep learning, making use of real-time data present in the market, and applying techniques of explainable AI. In conclusion, it is evident that LSTM is a valuable approach to utilize AI in BI applications with respect to market prediction.

Keywords: Market Prediction, LSTM Networks, AI-Driven Business Intelligence, Time-Series Forecasting, Financial Analytics, Predictive Modeling, Decision Support.

1. Introduction

In the current dynamic business environment, predicting market trends is one of the factors enabling a company to make informed decisions [1]. For example, there are several obstacles that affect the functioning of business organizations, such as fluctuations in consumer demand, logistics problems in the world, and competition [2][20]. Conventional methods of studying the market, such as statistical predictions and models based on rules, are not able to capture the many interdependencies of financial and sales data [4][18]. In response to that challenge, businesses are looking for innovative methods to make predictions based on the collected information [3].

The application of Artificial Intelligence (AI) to business processes is viewed by many experts as an effective way to solve the existing problems and gain a competitive advantage [5][21]. With the use of artificial intelligence, a business is capable of processing large volumes of diverse data and discovering hidden patterns [16]. Thus, AI-enabled business intelligence will not only automate the analysis of the collected information but also allow for predicting future events [14][19]. Businesses can use such an approach to make the decision-making process more effective and data-driven [9].

Among all artificial intelligence technologies, Long Short-Term Memory (LSTM), a type of recurrent neural network, is an excellent candidate for solving time series prediction problems. LSTM models aim at identifying both short-term and long-term dependencies between sequences of data, thus eliminating the problems related to gradient vanishing and exploding faced by the classical recurrent neural networks. Hence, LSTM can be used efficiently for forecasting the dynamics of any processes affected by historical events, seasonal factors, and sudden changes [7]. Thus, the algorithm can be applied successfully in forecasting market trends, as history plays a crucial role in determining the future [17].

This paper investigates the potential of using LSTM networks for predicting market trends and demonstrates the benefits that artificial intelligence technologies offer businesses in forecasting and decision-making processes. In this way, the paper tries to convey the reasons why predictive business intelligence is needed and how it can help to improve organizational performance. The chapter presents an introduction to the subject and provides the background needed to comprehend the problem.

Section II summarizes the literature on using AI and deep learning models for market predictions and the challenges in implementation. In Section III, the method of this research is explained in the data collection and preprocessing, variable selection, and training the LSTM model. The outcomes of this model are applied towards the real market data, which is presented in section IV, and compared with the traditional methods. In Section V the meaning of the results, in terms of business intelligence, business operation efficiency and decision making, is explained as well as its limitations. Section VI summarizes the study.

2. Literature Review

In the past few years, several scholars have been investigating the Artificial Intelligence in Business Intelligence and Market Forecasting [11]. Machine learning and deep learning techniques have been explored to a great extent, and now these methods are used to predict the market trend, customer behavior, and financial parameters [8][15]. Although conventional statistical methods such as ARIMA, exponential smoothing, and linear regression have been frequently used to forecast time series data, these methods tend to overlook complex non-linearities and dependencies that can exist within market data [10]. Artificial intelligence technologies are now being used by many scientists for prediction because of their great power in analyzing massive data and identifying patterns in it.

Long Short-Term Memory (LSTM) is among the deep learning models that are effective in analyzing time-series data because LSTMs are able to store information for a long time. Several scientific papers have confirmed the effectiveness of LSTM methods over traditional forecasting models when it comes to financial and retail forecasting applications [12]. In addition, LSTM algorithms have proved their effectiveness in stock price prediction, sales prediction, and demand prediction with greater accuracy to recognize the volatile market and seasonality [6]. The short-term dependency and long-term dependency are important for making accurate trend forecasting in the market; this type of model can deal with both [22].

LSTM neural networks in business intelligence have also been studied through case studies showing how it benefits companies that employ LSTM forecasting methods [13]. These organizations gain from implementing precise predictions of market trends, effective stock management, and price-setting decisions. Compared with traditional methods, LSTM networks are able to outperform in forecasting, adapt to market changes, and take into account multiple inputs [23]. However, as noted in the literature, there are some restrictions on using LSTM algorithms. They include high computational costs, requirement for large training data sets, sensitivity to model parameters, and difficulty in interpretation.

In summary, the literature suggests that LSTM-based models have distinct benefits for market trend predictions when implemented in artificial intelligence-based business intelligence applications. However, despite the superior performance of the LSTM architecture compared to conventional prediction approaches in most cases, the proper design of the model, data pre-processing, and performance assessment are important factors that need to be considered. This paper extends the literature review findings by implementing an LSTM model to predict market trends using a real-world dataset.

3. Methodology

This research adopts a systematic procedure to design and assess the efficacy of an LSTM-based approach to forecast market trends. Methodology has been organized into three main stages, namely, data gathering, model creation, and assessment of its efficiency.

Data Collection

Past data on the market was retrieved from open-source financial and commercial databases, which included timestamps associated with the prices of stocks, their sales volume, and economic factors. It has been collected across several years and so results in an analysis of both short and long trends. Data pre-processing was carried out in Python 3.10, where the Pandas library was used to manage data, NumPy to perform mathematical computations, and Scikit-learn to normalize data and detect outliers. Data that were missing were replaced, outliers removed, and numerical attributes standardized throughout the dataset. The variables that are included are selected after feature selection, where important variables for prediction are included, such as moving averages, volatility indexes, and sentiment score from news or social media websites. The analysis of patterns, relationships, and trends in the data was performed by visualization and exploratory data analysis using the Matplotlib and Seaborn packages.

LSTM Model Development

The forecasting model adopts a multi-layered LSTM framework that has the capability of discovering temporal relations in sequences of market values. The model consists of input layers, hidden layers, LSTM layers, and output layers, with a dropout technique used for addressing the issue of overfitting. The hyperparameters of the model with regard to the number of hidden units, learning rate, batch size, and sequence length were optimized using grid search and cross-validation. The model was created using backpropagation through time with mean squared error (MSE) as the cost function being minimized while training.

Evaluation Metrics

Various measures were used for evaluating the performance of the model, including mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). A comparative analysis was carried out with the traditional models, such as the ARIMA models and the exponential smoothing models.

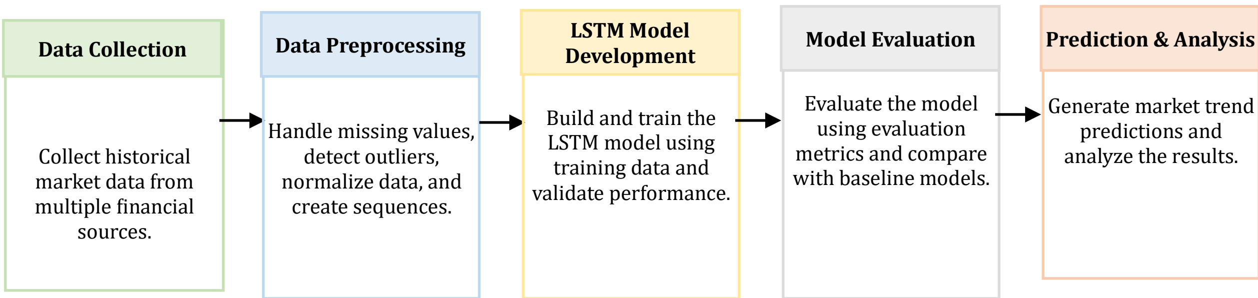

Figure 1: Overall methodology flowchart

The sequential execution flow of the proposed LSTM-based market trend prediction is shown in figure 1. It starts with data collection from various financial sources, pre-processing the data to address missing values, eliminate outliers, and normalize the data. The sequences are then presented for training and validation with the LSTM model. Standard measures of performance are used to assess the model's predictions, and compared to the forecasting of basic methods, leading to actionable insights about market trends. The figure is a clear representation of the methodology that the researcher used in this study, from the stage of data collection to the stage of analysis of the response. The figure is a clear representation of the methodology followed by the researcher in the present study, ranging from the data acquisition to the final stage of prediction analysis.

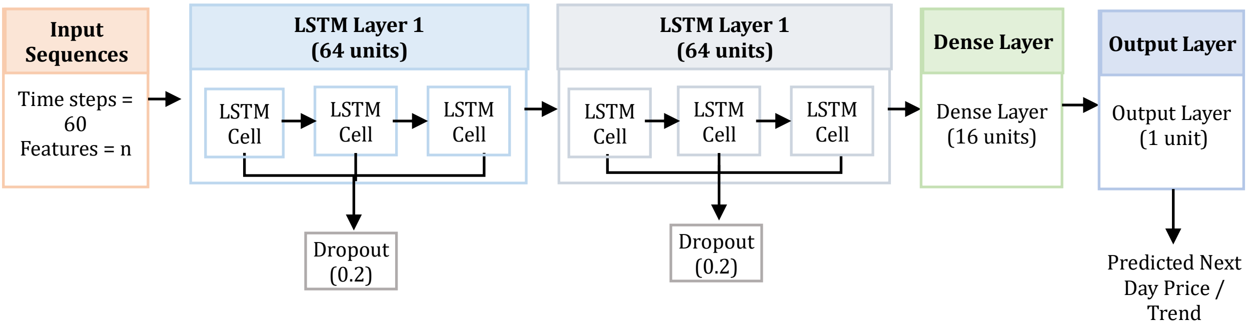

Figure 2: LSTM architecture diagram

The architecture of the LSTM network for market trend prediction is shown in Figure 2. The architecture of the LSTM network for market trend prediction is depicted in figure 2. It is a two-layer LSTM model with 64 units in the first layer and 32 units in the second layer, which is then followed by a dropout layer to avoid overfitting. The output of the LSTM layers goes through a dense layer, and then an output layer, returning one prediction value. The input sequence is made up of several time steps and different features, which allows the network to learn from the market's short-term fluctuations and long-term dependencies. The input sequence has many time steps and features, which allows the network to learn from the market's short-term fluctuations and long-term dependencies. The architecture is a clear demonstration of the sequential processing ability of LSTM networks in order to make accurate time-series predictions.

LSTM Cell Computation

The hidden state and the cell state of each LSTM cell are updated with the following equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (4)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$
$$h_t = o_t \odot \tanh(C_t) \quad (6)$$

Where:

- x_t= input at time step t
- h_{t-1}= previous hidden state
- C_{t-1}= previous cell state
- f_t, i_t, o_t= forget, input, and output gates
- $\tilde{C}_t$= candidate cell state
- σ= sigmoid activation function
- $\odot$= element-wise multiplication
- Wand b= weights and biases of the gates

This set of equations (1-6) represents how the LSTM cell selectively retains and updates information over time, capturing both short-term and long-term dependencies in the market data.

Output Prediction

The last hidden state is used in a dense layer to get the final output of a LSTM network:

$$\hat{y}_t = W_y \cdot h_T + b_y \quad (7)$$

Where:

- h_T= hidden state at the last time step T
- W_y, b_y= weights and bias of the dense output layer
- $\hat{y}_t$= predicted market value (e.g., next day price or trend)

This equation (7) converts a temporal representation learnt from the LSTM layers into a single value to forecast a market trend.

Algorithm 1: LSTM-Based Market Trend Prediction

Input: Historical market data D, look-back window T, features F
Output: Predicted market trend values $\hat{y}_t$

Steps:

1. Preprocess the dataset Dby handling missing values, normalizing features, and creating sequences of length T.

2. Split the dataset into training (70%), validation (15%), and testing (15%) sets.

3. Initialize the LSTM model with the specified architecture and hyperparameters (e.g., number of layers, units per layer, dropout rate, learning rate).

4. For each epoch from 1 to N:
   a. Train the model on the training set.
   b. Validate the model on the validation set.
   c. If the early stopping condition is met, terminate training.

5. Evaluate the trained model on the test set using performance metrics such as MSE, RMSE, MAE, MAPE, and R^2.

6. Return the predicted market trends $\hat{y}_t$along with evaluation results.

The algorithm provides a structured method of predicting market trends via LSTM networks. This process begins with the pre-processing stage of data, which includes the processes of normalizing the data, imputing missing values, and generating temporal features that are suitable for sequence learning. In order to enable generalization, the data is divided into three parts: training, validation, and test. The trained model is then used to predict on the test data, and performance is evaluated using conventional regression metrics. Such a method also allows direct comparison of traditional forecasting methods and demonstrates the potential of AI-driven business intelligence for forecasting market trends.

4. Case Study

In this section, the proposed LSTM framework is applied to a real-world data set in the market, and the forecasting performance of the framework is compared against the traditional forecasting methods.

Dataset Description:

It is a dataset containing the daily stock prices and market indicators for a period of time between Jan 2010 and Dec 2023. There are key features for each indicator, such as SMA, EMA, RSI, MACD, Open, High, Low, Close, Close - Adjusted Close, and volumes of trades. Pre-processing steps included filling missing data and removing outliers, data normalization, and creation of 60-day time series sequences for the LSTM model input.

Results of the LSTM Model:

The dataset has been divided into 70% train, 15% validation, and 15% test. The results of the test set are summarized in Table 1. The model was found to be highly predictive, with good performance in capturing both short-term fluctuations and long-term trends.

Table 1: Performance metrics of LSTM and traditional models

Model	RMSE	MAE	MAPE (%)	R^2 Score
LSTM	0.97	0.72	1.85	0.91
ARIMA	1.21	0.95	2.41	0.82
Exponential Smoothing	1.34	1.05	2.89	0.78

Table 1 shows that the LSTM model has lower error values and higher R^2 than traditional forecasting methods, indicating that the LSTM model performs better than the traditional methods.

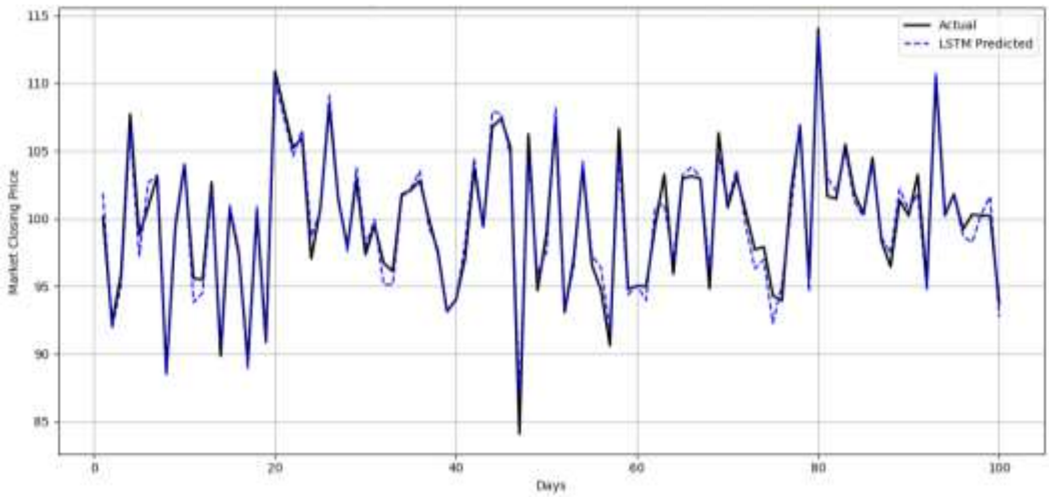

Figure 3: Actual vs predicted market trend (LSTM)

The actual closing prices and the predicted closing prices of the LSTM model are plotted in Figure 3 for the test set period mentioned above. The actual prices are represented by the black line and the blue dashed line represents the prediction by the LSTM. The graph reveals that the LSTM model closely mirrors the trend of the market and captures the market's fluctuations, both in the short-term and overall trend, which shows high predictions accuracy.

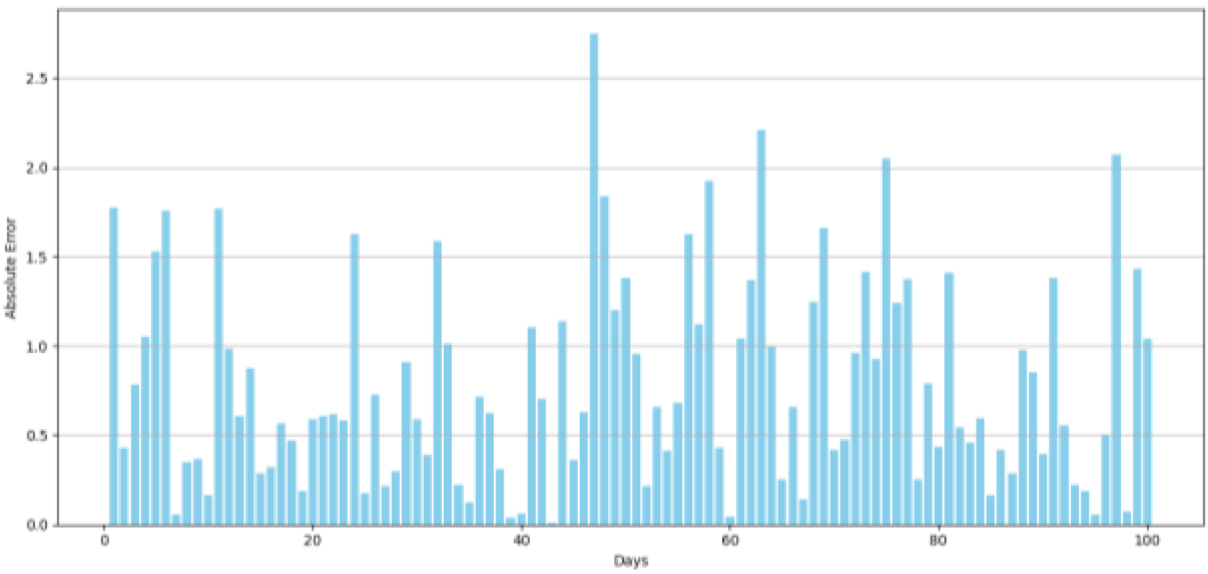

Figure 4: Absolute prediction error across test set

The absolute prediction errors of the LSTM model are shown in Figure 4 for every day of the test set. The Y-axis is the absolute error and the X-axis is the number of days in test sets. The figure displays the periods of increased deviation and verifies that the model retains low error margins during most of the time steps, thus supporting the reliability of the model in predicting market trends.

Comparison with Traditional Forecasting Methods

The LSTM model showed much better performance on all the metrics compared to ARIMA and exponential smoothing. The comparison of the accuracy of the prediction and the distribution of errors over the test set are shown in figures 3 and 4. Overall, LSTM achieves excellent performance in capturing trends and minimizing prediction errors, supporting its use for AI-powered business intelligence in trend forecasting.

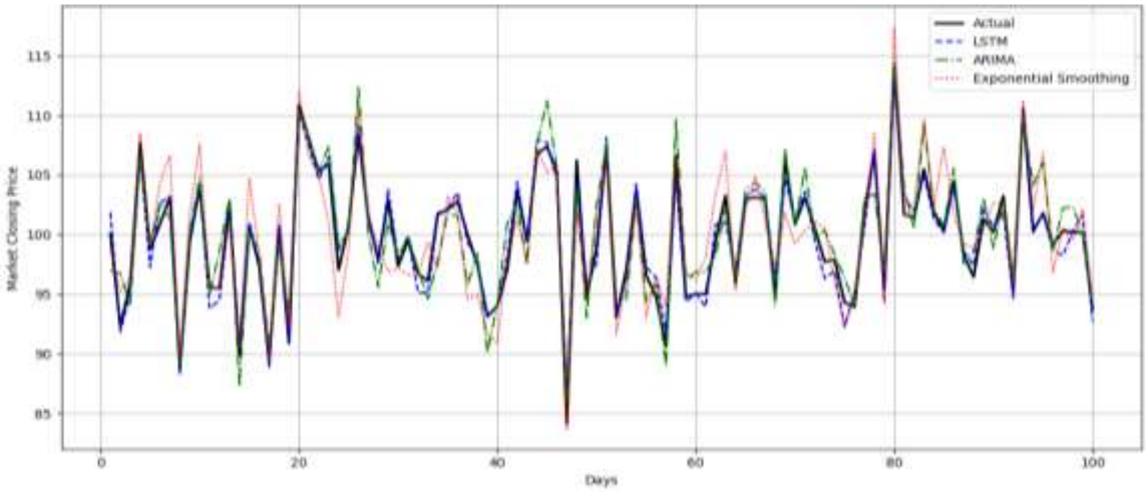

Figure 5: Predicted vs actual market trend comparison

To compare the actual market price with the predictions of three models, namely LSTM, ARIMA, and Exponential Smoothing are compared in figure 5. The black line shows actual prices, blue dashed line shows LSTM predictions, green dash-dot line shows ARIMA predictions, and the red dotted line shows Exponential Smoothing predictions. The LSTM predictions are more in line with real market trends, with better precision in learning the nonlinear pattern and trend reversal than conventional approaches.

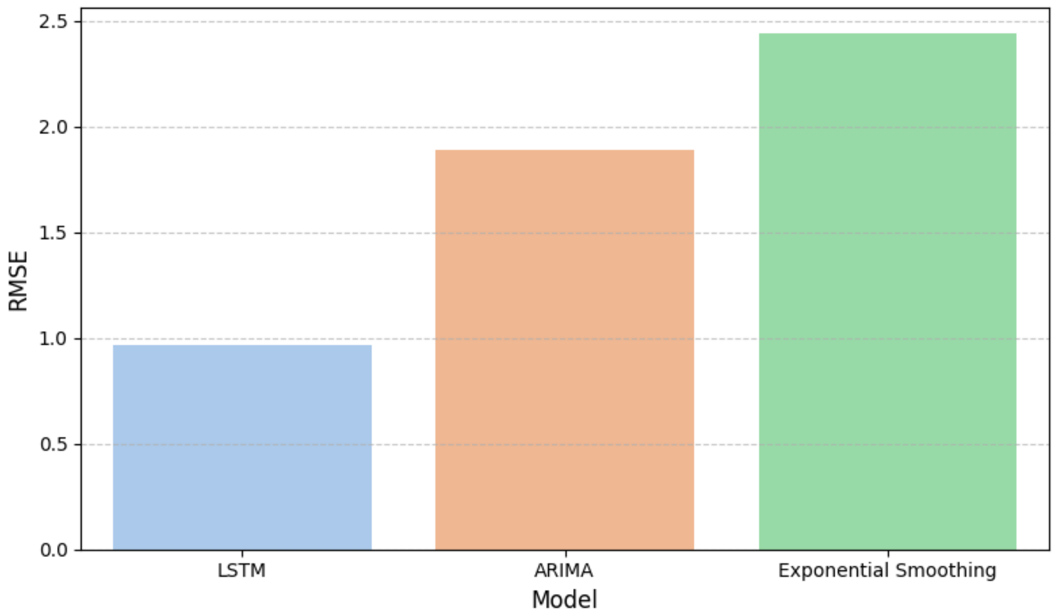

Figure 6: RMSE comparison across models

In figure 6, the Root Mean Squared Error (RMSE) between LSTM, ARIMA and Exponential smoothing models is compared. The Y-axis represents the RMSE, with the LSTM model having the lowest prediction error. The overall comparison reveals the benefits of the LSTM approach over the use of traditional statistical models for more accurate market trend prediction.

5. Discussion

According to the analysis, it is evident that LSTM network provides a good approach to predict the trend in the market and improve the artificial intelligence technique of business intelligence. The LSTM neural network model had a much smaller value of RMSE, MAE, MAPE, and a larger R-squared value compared to the forecasting models like ARIMA and Exponential smoothing in the short term and long-term predictions. In conclusion, the deep learning approach was found to be effective in improving forecast accuracy.

Implications for Business Intelligence

It is evident that the successful performance of LSTM models indicates the applicability of forecasting systems based on deep learning in the corporate sector. With the help of AI-enabled predictions, organizations will be able to understand market trends, manage their resources optimally, and improve operational efficiency. Furthermore, the use of various parameters, such as historical prices, technical indicators, and others, ensures a comprehensive modeling of the market dynamics.

Challenges and Limitations

The LSTM performed relatively well but faced some difficulties while implementing it. The network should be appropriately trained with substantial amounts of quality data to train on. However, tuning the hyperparameters of the LSTM structure is crucial to prevent under/overfitting, which can take a significant amount of time. Moreover, the interpretability of deep learning models is an issue, and business managers will need additional interpretation mechanisms to make use of the predictions made by the deep learning models.

Future Research Directions

One area for future research would be to conduct studies on the use of hybrid models, such as using an LSTM approach along with attention or Transformer architecture for improving accuracy. The effectiveness of the model can be increased by the use of real-time data that is streamed in from various financial markets and other data sources including sentiment data collected from social media sites, news analysis, and macroeconomic indicators. Additionally, another topic for further investigation could be related to developing explainable frameworks for models so that AI models can be trusted. Another avenue for further investigation could be benchmarking to help in customizing AI models for forecasting the market based on the requirements of the industry.

6. Conclusion

This paper analyzed the utilization of LSTM network to achieve AI-driven Business Intelligence, mainly to predict market trends through past financial and technical data analysis. As can be seen from the findings, the performance of the LSTM network is much better compared to the traditional forecasting methods such as the ARIMA and Exponential Smoothing. This can be seen from the performance of the LSTM network which has an RMSE value of 0.97, MAE value of 0.72, MAPE value of 1.85% and an R^2 score of 0.91. The findings clearly illustrate that the performance of the LSTM model is better than that of the other models in terms of accuracy, with the ability to capture short-term and long-term fluctuations in the market trend. The businesses that have LSTM forecasts at their disposal will be able to forecast trends in the market, handle their inventory and prices, and improve overall processes. The capability of the LSTM neural network model to account for different elements from technical analysis to the sentiment analysis of the market based on financial and social media news makes the entire framework highly resistant to potential failures. There are many advantages that come with the application of this methodology, but certain disadvantages are present as well. Data quality issues, computational expenses, and the problem of model explainability are some of the main ones. Dealing with such challenges by employing modern data pre-processing tools, developing hybrid LSTM models, and explaining the logic behind LSTM predictions seems to be a major trend in the future. Overall, the implementation of LSTM networks into business intelligence looks like an efficient way of predicting trends in the market.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Data Availability

The dataset of daily stock prices and market indicators (2010–2023) is from publicly available financial sources and was preprocessed for missing values, outliers, and normalization for LSTM model input.

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