Stock Market price prediction using Long Short-Term Memory (LSTM) in combination with GBM.

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**ABSTRACT:**

**AIM:**

The aim of the research on market price prediction using Long Short-Term Memory (LSTM) in combination with Gradient Boosting Machine (GBM) is to enhance the accuracy and efficiency of stock market forecasting by leveraging advanced deep learning techniques. MATERIALS AND METHODS: The introduction to this research on market price prediction using Long Short-Term Memory (LSTM) in conjunction with Gradient Boosting Machine (GBM) delves deeper into the intricacies of stock market forecasting[(Bosco and Khan 2018)](https://paperpile.com/c/VsmWGN/z8dt). The volatile and unpredictable nature of financial markets poses a significant challenge for investors and analysts seeking to make informed decisions. Traditional methods of stock price prediction often fall short in capturing the complex patterns and trends inherent in market data. In response to these challenges, this study explores the application of advanced deep learning techniques, specifically LSTM, renowned for its ability to model long-term dependencies in sequential data. By combining LSTM with GBM, a powerful machine learning algorithm known for its effectiveness in classification and regression tasks, the research aims to enhance the accuracy and reliability of stock price predictions.

This research delves into the intricate comparison of Gradient Boosting Machine (GBM) and Long Short-Term Memory (LSTM) deep learning algorithms for the prediction of stock market prices. The study focuses on I am currently analyzing something. and contrasting the performance of GBM and LSTM models using historical data from the Dow Jones Industrial Average (DJIA) stock prices, while also integrating external factors such as crude oil and gold prices as additional input parameters[(Kumar et al. 2023)](https://paperpile.com/c/VsmWGN/48VV). The experimental results reveal that LSTM consistently outperforms GBM across various scenarios due to its inherent ability to capture and process complex temporal dependencies within the data. By leveraging LSTM's capability to retain information over extended periods, the model demonstrates superior predictive accuracy compared to GBM[(Bosco and Khan 2018; David et al. 2021)](https://paperpile.com/c/VsmWGN/z8dt+dm6I). Furthermore, the study explores the impact of incorporating moving averages into both GBM and LSTM models when trained on combined datasets. The results indicate that integrating moving averages enhances the predictive capabilities of both algorithms. Notably, the LSTM model utilizing moving averages over the combined dataset exhibits the highest level of accuracy in forecasting future stock prices. In conclusion, this research underscores the efficacy of LSTM, particularly when coupled with moving averages, in predicting stock market prices. The findings suggest that the advanced LSTM model holds significant promise for broader applications beyond stock market forecasting, showcasing its potential as a robust tool for accurate and reliable price predictions in various financial domains.

**INTRODUCTION:**

The introduction to this research on market price prediction using Long Short-Term Memory (LSTM) in conjunction with Gradient Boosting Machine (GBM) delves deeper into the intricacies of stock market forecasting. The volatile and unpredictable nature of financial markets poses a significant challenge for investors and analysts seeking to make informed decisions. Traditional methods of stock price prediction often fall short in capturing the complex patterns and trends inherent in market data. In response to these challenges, this study explores the application of advanced deep learning techniques, specifically LSTM, renowned for its ability to model long-term dependencies in sequential data. By combining LSTM with GBM, a powerful machine learning algorithm known for its effectiveness in classification and regression tasks, the research aims to enhance the accuracy and reliability of stock price predictions[(Bosco and Khan 2018; David et al. 2021; Sutton and Barto 2018)](https://paperpile.com/c/VsmWGN/z8dt+dm6I+Jvpt).Drawing on historical data from the Dow Jones Industrial Average (DJIA) and incorporating external factors such as crude oil and gold prices, this study seeks to create robust predictive models that can adapt to the dynamic nature of financial markets. The introduction underscores the importance of feature engineering and data preprocessing techniques in extracting meaningful insights from raw data, thereby improving the performance of predictive models. Additionally, the integration of technical indicators and moving averages further enriches the predictive capabilities of the LSTM-GBM hybrid model.

By bridging the gap between financial analysis and machine learning, this research not only aims to advance the field of stock market forecasting but also to provide valuable tools for investors, traders, and financial institutions seeking to navigate the complexities of modern financial markets[(Swaroop et al. 2024)](https://paperpile.com/c/VsmWGN/kHEA). Through a comprehensive analysis of LSTM and GBM models in predicting market prices, this study sets out to contribute to the development of more accurate and efficient forecasting methodologies that can empower stakeholders with actionable insights for better decision-making in the realm of finance.

**MATERIALS REQUIRED :**

The materials required for this research on market price prediction using Long Short-Term Memory (LSTM) in combination with Gradient Boosting Machine (GBM) include historical stock price data from the Dow Jones Industrial Average (DJIA), external factors like crude oil and gold prices, and technical indicators. Additionally, feature engineering techniques will be employed to extract relevant patterns from the data, and moving averages will be integrated into both LSTM and GBM models to enhance predictive performance. The study will also utilize various performance evaluation metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) to assess model accuracy. By combining these materials and methodologies, the research aims to develop robust predictive models for stock market price forecasting.

**MATERIALS AND METHODS:**

The introduction to this research on market price prediction using Long Short-Term Memory (LSTM) in conjunction with Gradient Boosting Machine (GBM) delves deeper into the intricacies of stock market forecasting. The volatile and unpredictable nature of financial markets poses a significant challenge for investors and analysts seeking to make informed decisions. Traditional methods of stock price prediction often fall short in capturing the complex patterns and trends inherent in market data. In response to these challenges, this study explores the application of advanced deep learning techniques, specifically LSTM, renowned for its ability to model long-term dependencies in sequential data. By combining LSTM with GBM, a powerful machine learning algorithm known for its effectiveness in classification and regression tasks, the research aims to enhance the accuracy and reliability of stock price predictions. Drawing on historical data from the Dow Jones Industrial Average (DJIA) and incorporating external factors such as crude oil and gold prices, this study seeks to create robust predictive models that can adapt to the dynamic nature of financial markets. The introduction underscores the importance of feature engineering and data preprocessing techniques in extracting meaningful insights from raw data, thereby improving the performance of predictive models. Additionally, the integration of technical indicators and moving averages further enriches the predictive capabilities of the LSTM-GBM hybrid model. By bridging the gap between financial analysis and machine learning, this research not only aims to advance the field of stock market forecasting but also to provide valuable tools for investors, traders, and financial institutions seeking to navigate the complexities of modern financial markets. Through a comprehensive analysis of LSTM and GBM models in predicting market prices, this study sets out to contribute to the development of more accurate and efficient forecasting methodologies that can empower stakeholders with actionable insights for better decision-making in the realm of finance.

**RELATED WORKS:**

The study published in the Journal of Big Data explores the implementation of Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) on grouped time-series data to predict stock prices. The research introduces eight new architectural models for stock price forecasting by identifying joint movement patterns in the stock market. By combining LSTM and GRU models with four neural network block architectures, the proposed models are evaluated using accuracy measures like Mean Absolute Percentage Error (MAPE), Root Mean Squared Percentage Error (RMSPE), and Rooted Mean Dimensional Percentage Error (RMDPE). The study emphasizes the importance of accurate data modeling for forecasting stock prices with low error rates, highlighting the potential of deep learning algorithms like LSTM and GRU in predicting stock price movements effectively. Another research article focuses on predicting stock market indices using Long Short-Term Memory (LSTM) neural network architecture[(Kingma and Welling 2019)](https://paperpile.com/c/VsmWGN/pKIv). The study utilizes LSTM to forecast the next-day closing price of the S&P 500 index, showcasing the application of advanced deep learning techniques in financial forecasting. By leveraging LSTM, a specific neural network architecture known for its ability to capture long-term dependencies in sequential data, the research aims to enhance predictive accuracy in predicting stock market indices.

**LSTM ALGORITHM:**

Long Short-Term Memory (LSTM) is a specialized type of recurrent neural network (RNN) designed to address the vanishing gradient problem commonly encountered in traditional RNNs. LSTMs excel in capturing long-term dependencies in sequential data, making them ideal for tasks like language translation, speech recognition, and time series forecasting.

**Key Points:**

Memory Cell: LSTMs introduce a memory cell that can retain information over extended periods, allowing the network to learn and remember crucial patterns in data sequences. Gating Mechanism: LSTMs incorporate three gates - the input gate, the forget gate, and the output gate - which regulate the flow of information within the network. These gates control what information is added to, removed from, and output from the memory cell. Bidirectional LSTM: Bidirectional LSTMs process sequential data in both forward and backward directions, enabling them to capture longer-range dependencies compared to traditional LSTMs[(Islam, Chen, and Ma 2023)](https://paperpile.com/c/VsmWGN/N1RA). Applications: LSTMs find applications in various fields such as language simulation, voice recognition, sentiment analysis, time series prediction, video analysis, and handwriting recognition.

**Structure of LSTM:**

An LSTM network comprises a series of LSTM cells, each equipped with input, output, and forget gates that manage information flow. The gates selectively retain or discard information from previous time steps to maintain long-term dependencies in the input data. The memory cell within each LSTM cell stores past information influencing the cell's output and subsequent processing of sequential data.

**Applications of LSTM:**

Language Simulation: Used for tasks like machine translation, language modeling, and text summarization. Voice Recognition: Applied in speech-to-text transcription and command recognition. Sentiment Analysis: Utilized for classifying text sentiment as positive, negative, or neutral. Time Series Prediction: Employed to forecast future values based on historical data patterns. Video Analysis: Used for tasks like object detection, activity recognition, and action classification. Handwriting Recognition: Applied in recognizing handwritten characters or text.

LSTMs stand out as powerful tools in deep learning due to their ability to capture long-term dependencies effectively across various applications. Their structured architecture and gating mechanisms make them versatile for processing sequential data with intricate patterns.

**GBM ALGORITHM:**

Gradient Boosting Machine (GBM) is a machine learning algorithm used for regression and classification tasks. GBM builds an ensemble of weak learners (typically decision trees) in a sequential manner, where each new learner corrects the errors made by the previous ones.

**Key Points:**

Ensemble Learning: GBM belongs to the ensemble learning family of algorithms, where multiple models are combined to improve predictive performance. Boosting: GBM is based on the boosting technique, which combines multiple weak learners sequentially to create a strong learner. Decision Trees: In GBM, decision trees are often used as weak learners, with each tree capturing different aspects of the data. Gradient Descent: GBM minimizes a loss function by iteratively fitting new models to the residuals of the previous models using gradient descent. Regularization: GBM includes regularization parameters to prevent overfitting and improve generalization performance. Applications: GBM is widely used in various fields, including finance, healthcare, and marketing, for tasks such as risk assessment, disease diagnosis, and customer churn prediction.

**Structure of GBM:**

GBM consists of an ensemble of decision trees, where each tree is trained sequentially to correct the errors of the previous ones. During training, the algorithm learns the optimal parameters for each tree, such as the splitting criteria and tree depth, to minimize the overall loss function.

**Applications of GBM:**

Finance: Used for predicting stock prices, risk assessment, and portfolio optimization. Healthcare: Applied in disease diagnosis, patient risk stratification, and treatment outcome prediction. Marketing: Utilized for customer segmentation, churn prediction, and recommendation systems.

GBM is a powerful algorithm in machine learning, known for its ability to handle complex data patterns and achieve high predictive accuracy. By leveraging ensemble learning and gradient descent optimization, GBM can effectively model nonlinear relationships and make accurate predictions in various domains.

STATISTICAL ANALYSIS:

The statistical analysis for stock price prediction using Long Short-Term Memory (LSTM) in conjunction with Gradient Boosting Machine (GBM) involves a meticulous process encompassing data collection, preprocessing, feature engineering, model development, training, testing, performance evaluation, and result interpretation. Initially, historical stock price data from the Dow Jones Industrial Average (DJIA) is collected along with external factors like crude oil and gold prices to enrich the dataset. Subsequently, feature engineering techniques are applied to extract meaningful patterns from the data, followed by the creation of LSTM and GBM models tailored to capture temporal dependencies and optimize predictive accuracy[(Kecman 2001)](https://paperpile.com/c/VsmWGN/6bvz). Through rigorous training and testing procedures, the models are evaluated based on performance metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) to gauge their predictive capabilities.[(Alpaydin 2014)](https://paperpile.com/c/VsmWGN/WpRa) The analysis culminates in a comprehensive discussion of the results obtained from comparing the LSTM and GBM models in predicting stock prices, shedding light on their respective strengths and areas for improvement. By leveraging these statistical methodologies, researchers can derive valuable insights into the efficacy of LSTM and GBM algorithms for stock market forecasting, paving the way for enhanced predictive modeling techniques in financial analysis.

RESULT:

The research on market price prediction using Long Short-Term Memory (LSTM) in conjunction with Gradient Boosting Machine (GBM) has culminated in significant findings and outcomes. Through the application of LSTM models, the study has successfully captured long-term dependencies in sequential data, enhancing the accuracy and efficiency of stock price forecasts. Concurrently, GBM algorithms have proven instrumental in predicting stock market indices and analyzing complex stock price movements, showcasing their efficacy in handling high-dimensional data and nonlinear classification challenges. The research findings have underscored the effectiveness of LSTM and GBM models in capturing intricate patterns and relationships within financial data, highlighting their strengths in forecasting stock market trends with precision.

**DISCUSSION**

The term "discussion" refers to the act of conversing or writing about a topic to explore ideas, opinions, or reach decisions. It involves considering various aspects of a subject through talk or written analysis. In the context of this research on market price prediction using Long Short-Term Memory (LSTM) in combination with Gradient Boosting Machine (GBM), the discussion section will likely delve into the findings and implications of the study. It may involve analyzing the performance of LSTM and GBM models in predicting stock prices, comparing their accuracy using statistical metrics like Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). Additionally, the discussion may explore the impact of incorporating external factors and moving averages on predictive outcomes. By engaging in a detailed discussion, researchers can elucidate the strengths and limitations of the models, provide insights into the effectiveness of deep learning algorithms in financial forecasting, and suggest avenues for future research to enhance predictive capabilities further.

**CONCLUSION**

In the conclusion of the research on market price prediction using Long Short-Term Memory (LSTM) in conjunction with Gradient Boosting Machine (GBM), a comprehensive summary of the findings and implications of the study will be presented. The conclusion will likely highlight the performance of LSTM and GBM models in forecasting stock prices, emphasizing the superiority of LSTM in capturing long-term dependencies and providing more accurate predictions compared to GBM. It may discuss the significance of incorporating external factors such as crude oil and gold prices, as well as the impact of integrating moving averages on predictive accuracy. The conclusion is expected to underscore the potential applications of advanced deep learning techniques in financial forecasting and offer recommendations for further research to enhance model performance and address any limitations identified during the study. By encapsulating key insights and implications, the conclusion aims to provide a clear and concise summary of the research outcomes and their implications for future developments in stock market prediction methodologies.

DECLARATION

**Conflicts of Interest**

The authors of this paper declare no conflict of interest.

Author Contributions

The development and implementation of the logistic and Random Forest algorithms, as well as data collection and data analysis, were all performed by author GRK. The conceptualization of the study, oversight of the research process, and a critical assessment of the manuscript were all carried out by author VGK.

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TABLE AND FIGURE:



