International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Revolutionizing Stock Price Prediction with CNN-BiLSTM-AM. A Deep Learning Hybrid Framework

Maram Yashwanth

B. Tech Student, Department of IT, GMR Institute of Technology, Rajam-532127, Andhra Pradesh, India
Email: 21341A1271@gmrit.edu.in

ABSTRACT

This analysis explores advanced deep-learning techniques for stock price prediction, assessing transfer learning-based DTRSI, CNNs, and collaborative networks with sentiment analysis. DTRSI effectively addresses overfitting, outperforming traditional models. CNNs excel in predicting stock trends across time frames, while collaborative networks combining sentiment analysis and candlestick data show promise, particularly for specific stocks over longer periods. The study investigates the relevance of sentiment analysis from platforms like Twitter and StockTwits in predicting market movements. It introduces an innovative active deep learning approach for stock price forecasting, considering data size and sector impact. Emphasizing LSTM-based models, it highlights their potential to enhance stock price forecasting, offering insights for traders and investors by consolidating diverse prediction methods. This research lays the groundwork for future studies optimizing trading systems via data integration and advanced neural network architectures.

Keywords: Stock price prediction, Deep learning techniques, DTRSI, Sentiment analysis, LSTM-based models.

INTRODUCTION

The Stock Price Prediction System (SPPS) stands as a cutting-edge tool designed to anticipate stock price movements within the rapidly evolving financial markets of today. Leveraging sophisticated machine learning and data analysis techniques, it harnesses historical stock price data alongside market trends and other pertinent variables to yield insightful predictions.

Its array of benefits serves as a testament to its efficacy. Firstly, SPPS prides itself on precision, offering remarkably accurate predictions that empower investors to make informed and strategic decisions. Furthermore, it establishes reliability by providing insightful assessments of individual stocks, indices, and overarching market trends. Equally crucial is its role in risk management, helping investors mitigate and manage potential risks associated with their investments.

One of its primary strengths lies in enabling data driven decision-making processes, facilitating the crafting of investment strategies grounded in robust data analysis. Users benefit from real-time updates, ensuring they remain abreast of the latest market developments, fostering agility in response to dynamic market changes. Additionally, SPPS offers in-depth sector and industry analyses, furnishing valuable insights into specific sectors, thereby aiding investors in identifying potential opportunities and risks within these segments. Moreover, it grants users a broader global perspective, allowing for a comprehensive understanding of global market dynamics and their potential impact on investments.

In essence, SPPS emerges as a reliable and indispensable ally for navigating the intricate realm of stock trading. It guarantees informed decision-making, thereby providing users with a competitive advantage within the dynamic and competitive financial landscape.

RESEARCH APPROACH

The process of developing a predictive model for stock price forecasting involves several essential steps. Initially, the collection of a robust and representative dataset containing historical stock prices is crucial. This dataset may consist of various dimensions, such as 1D, 3D, or 5D, encompassing different attributes like stock price, opening and closing prices, trading volume, and sentiment scores.

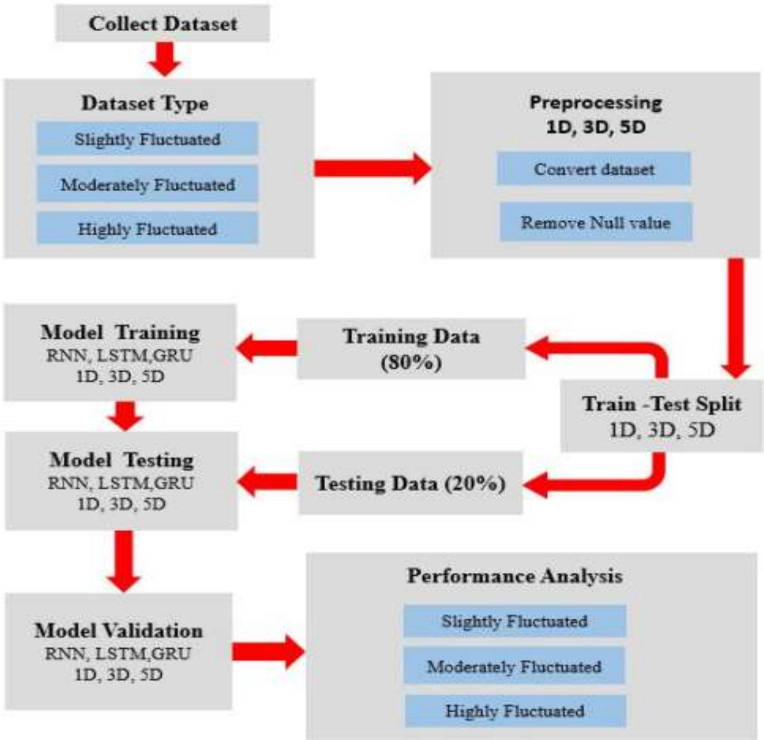
Once the dataset is gathered, preprocessing steps are undertaken to ensure its suitability for training the Recurrent Neural Network (RNN). This involves transforming the dataset into a consistent format, eliminating null values that could disrupt the model training, and normalizing the data to facilitate effective learning. Then, depending on the features of the dataset, the RNN model is trained using techniques such as Vanilla RNN, Long Short-Term Memory, Gated Recurrent Unit. The preprocessed data is fed into the model in order to extract underlying patterns from the dynamics of stock prices.

The dataset is split into a test set (20%) and a training set (80%) after the training phase to assess the performance of the model. Next, the test set is used to test the RNN model, and its prediction accuracy is evaluated using metrics like mean squared error, mean absolute error, or root mean square error.

After analyzing the model's performance, potential areas for improvement are identified, enabling refinements to the model to enhance its efficacy. This might involve retraining the model on datasets that specifically address the model's shortcomings, like data with higher volatility.

Furthermore, the model's validation is crucial to ensure it doesn't overfit the training data. Validating the model on a fresh dataset, distinct from previous training and test sets, helps confirm its generalizability and effectiveness in predicting stock prices accurately. Iterations of steps 3 through 7 are conducted iteratively, enabling continual refinement of the model until achieving satisfactory performance in accurately forecasting stock prices.

METHODOLOGY:



Several crucial processes are involved in creating a predictive model for stock price forecasting. First and foremost, it is necessary to get a solid and representative dataset of past stock values. This dataset may have several dimensions (1D, 3D, or 5D) and include different attributes (e.g., stock price, trading volume, opening and closing prices, and sentiment scores).

Preprocessing procedures are carried out once the dataset is collected to guarantee that it is appropriate for Recurrent Neural Network (RNN) training. This entails normalizing the data to promote efficient learning, removing null values that can interfere with model training, and translating the dataset into a consistent format. Next, the RNN model is trained using methods like Vanilla RNN, Long Short-Term Memory (LSTM), Gated Recurrent Unit based on the properties in the dataset. To uncover underlying patterns from the dynamics of stock prices, the preprocessed data is fed into the model.

After the training phase, the dataset is divided into a test set (20%) and a training set (80%) in order to evaluate the model's performance. Subsequently, the RNN model is tested on the test set, and metrics like as mean squared error, mean absolute error, root mean square error are used to assess the model's prediction accuracy. Analyzing the model's performance reveals potential areas for improvement, which enables model modifications to boost the model's effectiveness. To remedy this, it could be required to retrain the model on datasets that specifically address its shortcomings, including data with more volatility.

Validation of the model is also necessary to ensure that it does not overfit the training set. Testing the model on a fresh dataset that differs from the training and test sets from previous iterations is necessary to confirm its generalizability and effectiveness in accurately predicting stock values.

It is feasible to perform iterations of steps 3 through 7 on the model until it reaches sufficient performance in accurately anticipating stock values.

RESULTS

Model	R^2	MAE	MAPE	RMSE
RNN	0.94284	0.57858	2.10638	0.78400
LSTM	0.94093	0.58079	2.10279	0.79704
GRU	0.96032	0.56959	2.10013	0.78115

CONCLUSION

The final results of this study on the prediction of marble powder concrete using machine learning highlight the potential and utility of this new method in sustainable construction materials. The obtained accurate machine learning models, as reflected in the low mean square error (MSE) and root mean square error (RMSE), confirm their ability to provide accurate predictions with emphasis on compression energy input. Sensitivity analysis revealed an important role of marble powder content in influencing tensile strength. This insight is invaluable and provides a targeted understanding of the effects of marble powder on concrete properties. This not only facilitates informed decision-making by concrete mix manufacturers, but also contributes to the broader goal of sustainable construction that maximizes waste management. The inclusion of descriptive mechanisms increases the clarity of machine learning models and demystifies decision-making processes. This not only provides confidence in the reliability of the predictions, but also provides the clinician with valuable insight into the complex relationship between input parameters and compressive strength. the effective use of machine learning to predict compressive strength represents an important milestone in the pursuit of sustainable construction practices. The developed model provides engineers with a useful tool to overcome the challenges of concrete mix design with a focus on performance and environmental responsibility The use of machine learning will encompass concrete technology and holds great promise for a more sustainable and resilient future. and paves the way for continuous improvement of adaptation.

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