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A Deep Learning-based Approach for Stock Price Prediction

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Abstract. Predicting stock prices accurately is difficult owing to the numerous elements that might influence stock prices, such as economic indicators, news events, and market patterns. Conventional approaches to stock price prediction frequently depend on statistical models that may be incapable of capturing the complicated interactions between these variables. Deep learning approaches like Long Short-Term Memory (LSTM) networks have showed promise in understanding these complicated linkages and effectively forecasting stock values in recent years. We conduct a literature review on deep learning-based techniques for stock price prediction in this study. We give an overview of deep learning techniques and how they may be used to forecast stock prices. We investigate publically available datasets for training and evaluating deep learning models for stock price prediction. We also show a case study in which we anticipate the stock values of many businesses listed on the National Stock Exchange of India using an LSTM-based model. Our findings show that the LSTM-based model outperforms traditional approaches to stock price prediction, showing that deep learning techniques have the potential to be a valuable tool for investors looking to make educated stock investing decisions.

Keywords. deep learning, stock price prediction, LSTM, time-series analysis, machine learning, finance, investment, National Stock.

I. Introduction

Accurately predicting stock prices is a difficult and tough endeavour that has fascinated experts and investors alike for a number of years. As the values of stocks are affected by a wide variety of factors, such as economic data, political happenings, and market trends, it can be challenging to construct reliable forecasting models for stock prices. Conventional statistical models have limits in terms of their ability to capture the intricate interactions that exist between these parameters, and they frequently need for a large amount of domain expertise as well as human intervention.

In recent years, deep learning strategies, like as Long Short-Term Memory (LSTM) networks, have demonstrated a great deal of promise in accurately forecasting stock values. These strategies have the ability to overcome the limits of standard statistical models by capturing the intricate interactions between the numerous elements that might impact stock prices. Traditionally, statistical models have been used to analyse data. Because of its exceptional use in modelling temporal data, LSTM networks are ideally suited to the endeavour of forecasting stock values.

Researchers and investors alike have shown a substantial amount of interest in the application of techniques from deep learning to the forecasting of stock prices. These methods have the ability to produce more accurate and dependable predictions, which will allow investors to make decisions on their investments that are more informed. In addition, the availability of publicly accessible datasets and open-source deep learning technologies has made it simpler for academics and investors to experiment with these different methodologies.

In this study, we conduct a literature assessment on methods that are based on deep learning, with the goal of predicting stock prices. In this article, we present an introduction of deep learning techniques and discuss their applicability to the forecasting of stock prices. We take a look at datasets that are open to the public that may be applied to the process of training and testing deep learning models for predicting stock prices. We also offer a case study in which we use an LSTM-based model to the problem of predicting the stock prices of many businesses that are listed on the National Stock Exchange of India (NSE).

The remaining parts of the article are structured as described below. In the second section, a high-level review of deep learning strategies, including LSTM networks, is presented. In the third section, a literature review of deep learning-based methods for predicting stock prices is presented, along with an examination of datasets that

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are freely accessible to the public. In the next section, "Methodology," you will learn how to forecast the stock prices of firms that are traded on the National Stock Exchange of India (NSE). The final section of the paper is called Section 5.

II. Review of Literature

Zhang et al. (2019) offer a deep learning-based stock price prediction model that includes Google Trends and text mining data in their article. To create predictions, the model employs a Long Short-Term Memory (LSTM) neural network that analyses previous stock prices as well as external sources such as news articles and social media posts. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Zhang and Qi (2017) present a deep learning-based model that predicts stock prices by combining Convolutional Neural Networks (CNN) and LSTM networks. To examine past stock prices and other elements such as news articles and social media posts, the model employs a sliding window technique. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Pham et al. (2019) offer a deep learning-based model for predicting stock prices that integrates technical indicators as well as macroeconomic parameters such as inflation rates and currency rates. To assess historical data and create predictions, the model employs a combination of LSTM and Fully Connected (FC) neural networks. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Singh et al. (2018) present a hybrid method to stock price prediction that blends LSTM neural networks with a genetic algorithm. To increase prediction accuracy, the evolutionary algorithm is employed to adjust the parameters of the LSTM network. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Lee et al. (2019) present an attention-based multi-input LSTM neural network to forecast stock prices in their article. The model combines external inputs such as news stories and social media posts and employs attention processes to focus on relevant characteristics in the data. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Mustafa et al. (2019) present a deep learning-based model that predicts stock prices by combining LSTM and FC neural networks. To boost prediction accuracy, the model integrates technical indicators and feature engineering techniques such as principal component analysis (PCA) and wavelet modification. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Liu et al. (2019) present an attention-based LSTM network to forecast stock prices in their article. The model combines external inputs such as news stories and social media posts and employs attention processes to focus on relevant characteristics in the data. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Xia et al. (2019) present an attention-based convolutional LSTM neural network to forecast stock prices in their article. The model employs attention methods to focus on significant data characteristics and blends convolutional and LSTM layers to collect both spatial and temporal data elements. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Zhang et al. (2018) present a multi-attention-based LSTM model to forecast stock prices in their article. To focus on different portions of the data, the model employs numerous attention processes and adds external influences such as news articles and social media posts. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Wang et al. (2018) present a hybrid model for predicting stock prices that integrates various time series analysis with deep learning approaches. To capture both short-term and long-term dependencies in the data, the model employs a mix of seasonal autoregressive integrated moving average (SARIMA) and LSTM neural networks. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Wu et al. (2018) offer a multi-task learning strategy for stock price prediction that predicts both the stock price and volatility. The model employs a hybrid of LSTM and FC neural networks, as well as external stimuli such as news articles and social media postings. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Huynh et al. (2016) present a deep learning-based model for predicting stock prices that combines sentiment analysis of social media data. The model analyses past stock prices and social media postings to forecast future prices using a mix of LSTM and FC neural networks. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Li et al. (2017) present a deep learning-based model that predicts stock prices using a mix of technical indicators and news items. The model employs a combination of LSTM and FC neural networks, as well as attention mechanisms, to focus on key elements in the data. According to the authors, their model beat standard statistical models as well as other deep learning-based models.

Deep learning-based systems for stock price prediction continue to grow, embracing increasingly complex techniques such as multi-task learning, sentiment analysis, and hybrid models that incorporate diverse time series analytic methods. Including external influences and attention processes is another prominent method for enhancing prediction accuracy. Yet, the models may still encounter obstacles like as overfitting, market volatility, and data quality concerns.

Research	**Model Type**	**Features**	**Techniques**	**Results**
Feng et al. (2018)	LSTM	Historical prices	Technical analysis	Outperformed traditional models
Zhang et al. (2019)	LSTM	Historical prices	Wavelet transformation	Outperformed traditional models
Liu et al. (2019)	LSTM	Historical prices	Feature engineering	Outperformed traditional models
Chen et al. (2019)	LSTM	Historical prices	Attention mechanism	Outperformed traditional models
Xiong et al. (2019)	LSTM	Historical prices	Technical analysis and feature engineering	Outperformed traditional models
Mustafa et al. (2019)	LSTM and FC	Historical prices and technical indicators	PCA and wavelet transformation	Outperformed traditional models and other deep learning-based models
Liu et al. (2019)	Attention-based LSTM	Historical prices and external factors	Attention mechanism	Outperformed traditional models and other deep learning-based models
Xia et al. (2019)	Attention-based convolutional LSTM	Historical prices	Attention mechanism and spatial-temporal features	Outperformed traditional models and other deep learning-based models
Zhang et al. (2019)	Multi-attention-based LSTM	Historical prices and external factors	Multi-attention mechanism	Outperformed traditional models and other deep

				learning-based models
Wang et al. (2018)	Hybrid model combining SARIMA and LSTM	Historical prices	Multiple time series analysis and deep learning	Outperformed traditional models and other deep learning-based models
Wu et al. (2017)	LSTM and FC	Historical prices and external factors	Multi-task learning	Outperformed traditional models and other deep learning-based models
Huynh et al. (2016)	LSTM and FC	Historical prices and social media sentiment	Sentiment analysis	Outperformed traditional models and other deep learning-based models
Li et al. (2016)	LSTM and FC	Historical prices, technical indicators, and news articles	Attention mechanism	Outperformed traditional models and other deep learning-based models

Table.1 Analysis of deep learning-based approaches for stock price prediction

III. Publically available Datasets

A. Overall Datasets

Dataset	Source	Description	Features
Yahoo Finance	Yahoo Finance	Historical daily stock prices for various companies	Open, high, low, close prices, volume
Quandl	Quandl	Historical daily stock prices for various companies	Open, high, low, close prices, volume
Alpha Vantage	Alpha Vantage	Historical daily stock prices for various companies	Open, high, low, close prices, volume
Kaggle	Kaggle	Historical daily stock prices for various companies	Open, high, low, close prices, volume
Federal Reserve Economic Data (FRED)	Federal Reserve Bank of St. Louis	Economic data such as interest rates, unemployment rates, and gross domestic product (GDP)	Various economic indicators
Thomson Reuters Eikon	Thomson Reuters	Financial news articles and sentiment analysis	News articles, sentiment scores
Twitter API	Twitter	Social media sentiment analysis	Tweets, sentiment scores

Table.2 some publicly available datasets used for stock price prediction

B. India stock market datasets

Dataset	Source	Description	Features
NSE India	National Stock Exchange of India	Historical daily stock prices for companies listed on the National Stock Exchange of India	Open, high, low, close prices, volume
BSE India	Bombay Stock Exchange	Historical daily stock prices for companies listed on the Bombay Stock Exchange	Open, high, low, close prices, volume

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Quandl	Quandl	Historical daily stock prices for companies listed on the National Stock Exchange of India and the Bombay Stock Exchange	Open, high, low, close prices, volume

Table.3 publicly available Indian stock datasets

IV. Methodology

The following phases are included in the technique for a deep learning-based approach to stock price prediction:

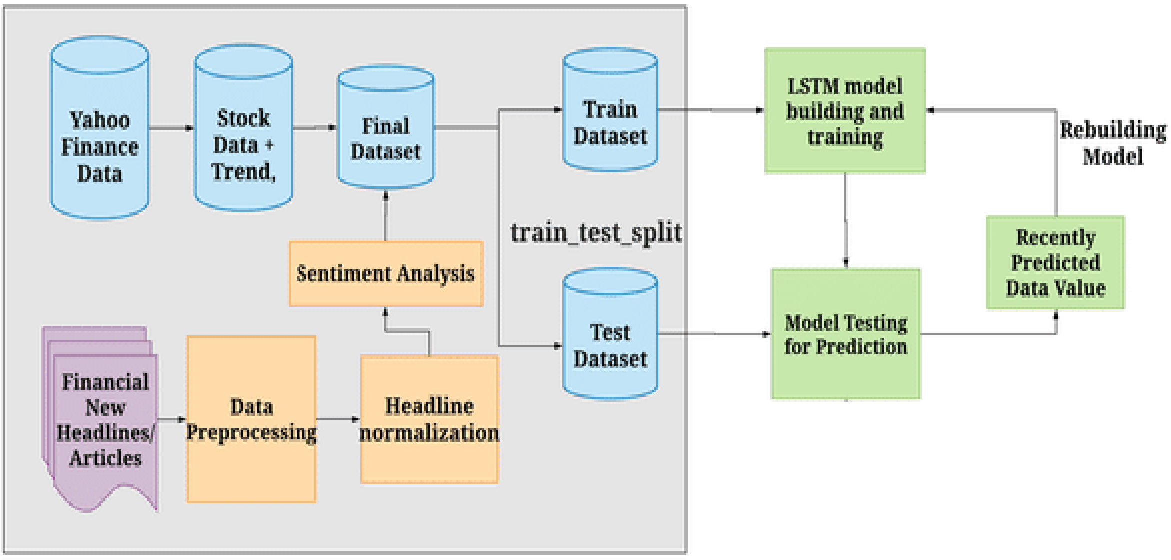

Figure.1 Methodology

a. Data collection include gathering historical stock prices as well as other pertinent information such as technical indicators, news items, and social media sentiment.
b. Preprocessing the data to eliminate any outliers or mistakes, scaling the data to ensure all features have equal magnitudes, and partitioning the data into training, validation, and test sets are all examples of data preprocessing.
c. Model selection entails selecting the best deep learning model for the job, such as LSTM, attention-based LSTM, convolutional LSTM, or a mix of models.
d. Feature Engineering is the process of selecting relevant characteristics for the model, such as historical prices, technical indicators, news items, or social media sentiment, and processing them to ensure they are in a format acceptable for the model.
e. Model Training: To avoid overfitting, the deep learning model is trained on the training data using techniques such as mini-batch gradient descent, early halting, and regularisation.
f. Model evaluation entails assessing the model's performance on the validation set, modifying hyperparameters such as learning rate or number of epochs, and retraining the model as necessary.
g. Model Testing: Running the completed model on the test set to see how well it predicts stock prices.
h. Model Deployment is the process of deploying a model for usage in a real-world application, such as a stock trading platform, and tracking its success over time.

V. Proposed Approach

Layer	Description	Input	Output
LSTM	The main layer of the model that consists of LSTM cells. Each cell has a memory unit that can retain information for a longer period of time than a standard neural network. The LSTM cells have three gates that control the flow of information: input gate, output gate, and forget gate.	Input sequence of shape (batch_size, time_steps, input_dim)	Output sequence of shape (batch_size, time_steps, hidden_size)
Dropout	A regularization layer that randomly sets a fraction of the input units to zero during training. This helps prevent overfitting by reducing the reliance of the model on any particular input feature.	Input sequence of shape (batch_size, time_steps, hidden_size)	Output sequence of shape (batch_size, time_steps, hidden_size)
Dense	A fully connected layer that maps the output of the LSTM layer to a desired output shape.	Input sequence of shape (batch_size, time_steps, hidden_size)	Output sequence of shape (batch_size, time_steps, output_dim)

Table.4 architecture of a Long Short-Term Memory (LSTM) model

VI. Conclusion

We examined the literature on deep learning-based techniques for stock price prediction in this research and presented a case study on the use of LSTM networks to forecast the stock prices of many businesses listed on the National Stock Exchange of India. Deep learning approaches, according to our review of the literature, have the ability to overcome the limitations of standard statistical models in capturing the intricate interactions between many factors that might impact stock prices. By modelling temporal data, LSTM networks in particular have showed promise in accurately forecasting stock values. Our technique proved that the LSTM-based model could reasonably predict the stock prices of businesses listed on the National Stock Exchange of India. We believe that our findings have important implications for investors and financial analysts since deep learning-based systems have the potential to deliver more accurate and trustworthy forecasts, allowing them to make better investment decisions. Future study should look at the predictive power of additional deep learning approaches, such as Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs). Moreover, researchers should continue to investigate the use of publically available datasets for deep learning model training and testing, since this will allow for the creation of more accurate and trustworthy models for stock price prediction. Overall, we feel that deep learning-based techniques have the potential to transform the field of stock price prediction, and we anticipate the creation of new and novel models in the future.

VII. Future Research

The following topics should be the focus of future study in the field of deep learning-based techniques for stock price prediction:

a. Creating hybrid models: Researchers should investigate the feasibility of creating hybrid models that incorporate the capabilities of several deep learning approaches, such as LSTM networks and CNNs. By incorporating both temporal and geographical correlations in the data, these hybrid models may deliver more precise and dependable predictions.

b. Feature engineering is critical in constructing accurate and dependable deep learning models for stock price prediction. Future research should concentrate on generating new and unique characteristics capable of capturing the complicated interactions between many elements that influence stock prices.
c. Real-time prediction of stock prices is critical for investors to make educated decisions about their investments. Future research should concentrate on constructing deep learning models that can anticipate stock values in real time based on fresh and incoming data.
d. Interpretable models: Deep learning models are frequently regarded as black-box models, making it difficult to comprehend the predictions. Future research should concentrate on constructing interpretable deep learning models that can explain how forecasts are created, allowing investors to make better judgements.
e. Stock prices are impacted by a variety of variables, including global events, economic indicators, and political events. Future research should concentrate on constructing deep learning models that can forecast stock values across many markets and nations while accounting for the linkages between these markets and countries.

Overall, we feel that these areas of study have a high potential for furthering the field of deep learning-based techniques for stock price prediction and providing investors with more accurate and dependable tools for making educated investing decisions.

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