Integrating Neutrosophic Logic with Bi-directional LSTM Model for Predicting Stock Market Movements

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Abstract

In this paper, we present sentiment analysis on Twitter data by employing Neutrosophic Sentiment Analysis (NSA). NSA captures sentiments by considering three aspects: truth, falsehood, and indeterminacy, offering a more nuanced understanding of sentiment in tweets. To enhance this analysis, we integrate the results from Neutrosophic logic (NL) sentiment analysis into a Bi-directional Long Short-Term Memory (LSTM) model. This integration takes use of NL's capacity to manage uncertainty and indeterminacy in social media material, as well as the Bi-directional LSTM's capability to capture temporal relationships in sequential data. Our combined NL-Bidirectional LSTM technique attempts to increase the precision of forecasting, particularly when it comes to predicting stock market patterns based on Twitter sentiment. Through comprehensive evaluation, we demonstrate the effectiveness of this approach, highlighting its potential to address the inherent uncertainties and indeterminacies in social media data and thereby provide more reliable predictions for stock market movements.

Keywords: Neutrosophic logic; Bi-directional LSTM; Stock market prediction; Sentimental analysis

1. Introduction

Forecasting the movements of the stock market has constantly been a goal for investors looking to get an advantage in the financial markets. Traditionally, investors relied on fundamental analysis, technical analysis, and market indicators to forecast price movements. However, with the advent of large amounts of data and advances in natural language processing, sentiment analysis has emerged as a powerful approach for anticipating stock market moves.

The analysis of emotions is the process of analyzing written information, such as press releases, comments on social media, and financial statements, in order to get insights into the sentiment or opinions expressed about particular shares or the financial system as large. Investors may learn about investor emotions, market sentiment, and potential market moves by monitoring sentiment transmitted in a variety of sources.

The founding principle of opinion evaluation in the forecasting of stocks is that investor state of mind frequently impacts market movements. Price increases may result from a positive outlook as it stimulates buying, while price declines may be brought on by negative sentiment as it prompts selling pressure.By leveraging sentiment analysis, investors aim to identify shifts in sentiment that may precede changes in stock prices, this enables individuals to make better educated investing choices.

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Neutrosophic logic is a branch of formal logic that extends traditional logic to deal with uncertainty, indeterminacy, and contradictions. Introduced by mathematician and philosopher Florentin Smarandache (1) in the late 20th century, neutrosophic logic provides a framework for reasoning with vague, imprecise, or conflicting information, which is prevalent in many real-world applications.

At its core, neutrosophic logic introduces the concept of neutrosophy, which refers to the study of neutralities and the interplay between truth, falsehood, and indeterminacy. Unlike classical logic, which operates under the principle of excluded middle (where a statement is either true or false), neutrosophic logic acknowledges the existence of indeterminacy, where a statement may be partially true, partially false, or neither true nor false.

1.1 Problem statement

The inherently uncertain and dynamic nature of financial markets, traditional methods of stock market prediction often struggle to accurately forecast price movements. In order to address this challenge, this study aims to leverage neutrosophic logic as a framework for modelling uncertainty, imprecision, and contradictions in financial data. The goal is to create a prediction model that combines neutrosophic reasoning with quantitative and qualitative data to improve the correctness and dependability of stock market forecasts. By incorporating neutrosophic logic into the prediction process, the study seeks to provide investors with more robust insights into market dynamics and enhance their ability to make informed investment decisions in an uncertain and volatile environment.

2. Related Works

In terms of stock market forecast, three different approaches have been widely used employed to anticipate future price movements: Analytical analysis, Sentimental analysis, and Market microstructure analysis. Analytical analysis relies on quantitative techniques and data analysis, using mathematical models and methods for evaluating past market data and uncover any trends or patterns that might signal likely future market behavior. Market microstructure analysis delves into the dynamics and structure of financial markets, examining factors such as order flow and market liquidity to predict short-term price movements and optimize trading strategies. Sentimental analysis, on the other hand, focuses on gauging market sentiment and investor emotions via examining textual information from social media postings and news stories to assess overall sentiment surrounding specific stocks or the market. Together, these methodologies offer complementary perspectives on stock market prediction, allowing analysts to develop more comprehensive models for anticipating future price movements and market trends.

In 2020,(2) Ramit Sawhney et al. developed an innovative architecture utilizing a graph neural network it deftly blends unexpected economic information, internet insights, and inter-stock relationships. This integration constructs a hierarchical temporal structure aimed at anticipating stock fluctuations. The architecture leverages tweets, historical price indicators, and corporate relationships to enhance its predictive capabilities. Unlike Stocknet, MAN-SF stands out by accurately forecasting and profiting from sudden spikes in Apple's stock price. This superior prediction is attributed to MAN-SF's advanced ability to integrate multimodal data, providing a broader and more comprehensive context. Extensive quantitative and qualitative studies on real market data demonstrate the effectiveness of MAN-SF in neural stock forecasting, highlighting its robustness and reliability in capturing and leveraging diverse data sources for financial predictions.

In 2021,(3) Nan Jing et al. suggested a combination of techniques that integrates sentiment analysis and deep learning to predict price fluctuations. This study conducted real-life experiments on six main sectors of the Shanghai Stock Exchange (SSE) at three-month intervals evaluate the approach's performance or applicability. The suggested model was contrasted with four different models—Logistic Regression, SVM, RNN, and LSTM—using the same dataset. In the final step, after collecting sentiment components and technical indicators, the LSTM model was trained with the data to forecast stock prices. The estimated outcomes were then analyzed using the Mean Absolute Percentage Error (MAPE) at both the stock and industry levels. The hybrid model demonstrated superior performance with a reduced MAPE value of 0.0449, indicating its efficacy in predicting stock prices accurately.

In 2021,(4) Trang-Thi Ho and Yennun Huang introduced an innovative platform that combines candlestick patterns with insights from online communities to predict stock movements. This approach achieved an impressive accuracy of 75.38% for predicting Apple stock movements. A three-layer Long Short-Term Memory (LSTM) model was utilized, with 30 units in the first layer and a 0.5 dropout rate in the second layer, 256 units in the second

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layer, and two units in the last compact layer. To illustrate daily stock movements, candlestick chart images were created using historical data, effectively visualizing the patterns and trends crucial for accurate stock prediction.

In 2021,(5) Pooja Mehta et al. developed an advanced algorithm to forecast stock values by incorporating sentiment analysis, news, and historical price data. They used models such as SVM, MNB, Linear Regression, Naïve Bayes, and LSTM to forecast stock market movements in the Indian social media market from 2014 to 2018 .Key sources for their data included Moneycontrol, IIFL, Economic Times, and Reuters. Among the models tested, Naïve Bayes, Linear Regression, and Maximum Entropy achieved impressive accuracies of 86.72%, 86.75%, and 88.93%, respectively. This study highlighted the significant influence of news on stock markets and demonstrated the effectiveness of deep learning techniques in making accurate stock predictions.

In 2022,(6) Krittakom Srijiranon et al., conducted a notable study in which they utilized FinBERT to analyze financial news sentiment with the aim of enhancing a model for predicting Thai stock prices over the period from 2018 to 2022. The researchers gathered data from six different news agencies, employing web scraping techniques to compile a comprehensive dataset. Their new strategy comprised integrating Empirical Mode Decomposition (EMD) and Long Short-Term Memory (LSTM) networks, which resulted in a considerable reduction in the Mean Absolute Error (MAE) of 20.82% when compared to utilizing LSTM alone. Despite this improvement, the study found that incorporating sentiment scores into the Principal Component Analysis (PCA)-EMD-LSTM model actually caused a drop in forecast accuracy. The following surprising conclusion indicates that while sentiment analysis can be a powerful tool, its integration into complex models requires careful consideration to avoid potential pitfalls. The study's findings add to the current discussion over the efficient use of machine learning techniques in financial forecasting, emphasizing both the expected benefit and problems of mixing diverse analytical methodologies.

In 2022,(7) Pedro Harder and Bledar Fazlija highlighted the use of advanced Natural Language Processing (NLP) algorithms for sentiment analysis to enhance stock price predictions. They emphasized that these models can be applied in various contexts, leveraging sentiment scores to inform risk-based strategies and identify sustainable investment opportunities. Their work underscores the versatility and effectiveness of sentiment analysis in the financial sector, demonstrating how integrating these advanced algorithms can provide valuable insights and improve decision-making processes in the realm of stock market investments.

In 2022,(8) Paraskevas Koukaras et.al., developed a model to predict stock movements by utilizing data from Twitter and StockTwits. They discovered that VADER and Support Vector Machine (SVM) were the most successful tools, with a the F-score of 76.3% and an AUC of 67%. The researchers employed TextBlob and VADER for sentiment analysis, revealing distinct performance metrics across different datasets. On the 'StockTwits with TextBlob' dataset, SVM had the greatest F-score of 68.7% and the highest AUC of 53.3%. This study highlights the potential for combining social media sentiment monitoring with machine learning algorithms to improve the predictability of stock market forecasts.

In 2023,(9) Michele Costola et al., investigate the influx of news related to COVID-19 influenced the formation of market expectations. From January to June 2020, they examined 203,886 online items concerning COVID-19 that were posted on three news websites: MarketWatch.com, NYTimes.com, and Reuters.com. In this online articles are give the sentiment score using the FINBERT model. According to these findings, emotion and market returns have a statistically significant and favorable association. In particular, there is a highly significant and inverse link between realized volatility and sentiment ratings and volumes from the New York Times. Regarding variations in the Dow Jones Industrial Average trading volumes.This analysis anticipates stock market changes. Investors may be able to analyze hazards while handling their investment portfolios while significant uncertainty, particularly in the early stages of a future pandemic.

3. Proposed Model

Combining sentiment analysis with stock market prediction using neutrosophic logic and a bi-directional LSTM involves using nuanced sentiment scores (true, false, indeterminate) and financial indicators as inputs. The Bi-LSTM model processes these features bidirectionally, capturing temporal dependencies to predict market movements more accurately. In the proposed model is explained in figure1

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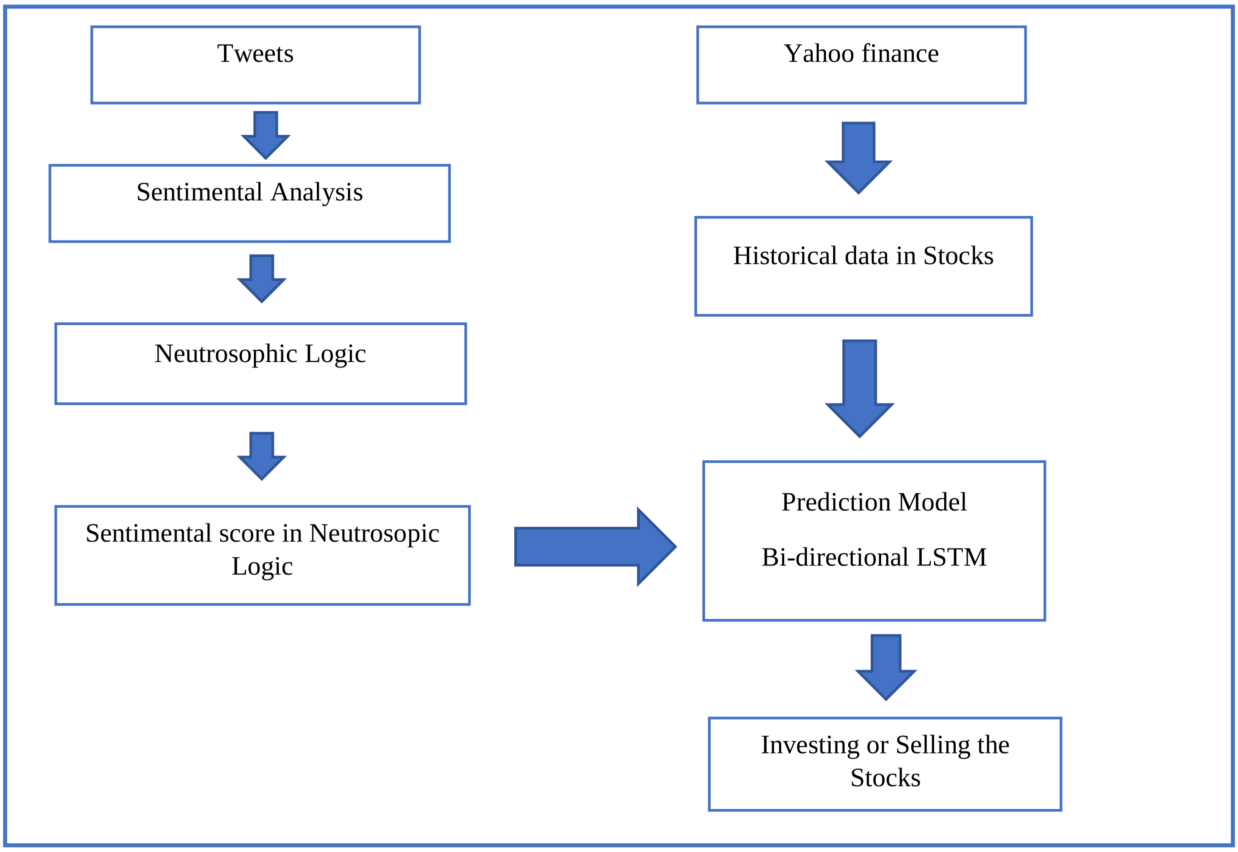

Figure 1: Sentimental anlaysis in Neutrosophic logic

3.1 Data collection

We are utilising the StockNet benchmark dataset (10). This dataset includes tweets as well as historical stock market data for many stocks. The period from December 31, 2014 to December 31, 2015. This dataset is useful for applications like using sentiment analysis of financial news and news sentiment to anticipate stock prices, event studies on the influence of news events, and temporal research of the effects of news on stock prices. The tweets were gathered from Twitter using NASDAQ symbols such as AAPL (Apple). When historical data for the same time period was gathered from Yahoo Finance

3.2 Data preprocessing

Several phases are needed. To ensure text integrity, start by replacing certain Twitter features like mentions, hashtags, and URLs with placeholders. For ultimate uniformity, delete any special letters or punctuation and convert the content to lowercase. Separate the text's words and sentences into tokens, and eliminate frequent stopwords that do not help emotion categorization. Address emojis and emoticons by converting them to textual descriptions and deleting emoticons, which may not have a direct impact on sentiment analysis. To ensure consistency, consider using stemming or lemmatization to reduce words to their base form. Finally, convert the text to a numerical representation suited for machine learning models, guaranteeing that the data is ready for sentiment classification tasks.

3.3 Advanced Sentiment Analysis with Neutrosophic logic

Neutrosophic logic is a specific methodology that incorporates the neutrosophy notation into standard sentiment analysis methodologies. Neutrosophy is concerned with indeterminacy and uncertainty, supplementing the conventional polarities of positive, negative, and neutral thoughts with varying degrees of doubt. In this approach, attitudes are assessed not just as positive, negative, or neutral, but also in terms of their degree of truth, indeterminacy, and falsehood. This provides for a more sophisticated comprehension of thoughts that may be confusing or conflicting. Neutrosophic sentiment analysis is especially effective in situations where ideas or feelings are complicated, or if the sentiment presented does not fit cleanly into traditional categories. It offers a systematic approach to dealing with uncertain and imprecise sentiment data, providing insights into varied levels of sentiment strength and uncertainty.

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3.4 Handling Ambiguous Sentiments in Social Media with Neutrosophic Logic

Neutrosophic logic improves this procedure by introducing a three-dimensional framework that accounts for the degrees of truthfulness (positive sentiment), uncertainty (uncertainty or ambiguity), and falsehood (negative sentiment).In the Neutrosophic logic, sentiment analysis can handle a wider range of linguistic expressions, including those with contradictory or vague sentiments, making it particularly useful for analyzing social media posts, reviews, and other user-generated content where sentiments are frequently mixed and not explicitly stated

3.4.1Neutrosophication

In the Crisp, inputs are transformed into neutrosophic sets using three triangle membership functions (MFs): truth, indeterminacy, and falsity functions in equations (1,2, and 3).These functions represent different sentiment levels, with truth corresponding to positive sentiment, indeterminacy to uncertainty, and falsity to negative sentiment. The inputs are scaled from 0 to 1 and classified as small (S), middle (M), or large (L) degrees of truth. Indeterminacy and falsehood levels are categorized as small-middle (S-M) and middle-large (M-L).

$$\mathrm{T}(x) = \begin{cases} \alpha\left(\frac{x-a_1}{a_2-a_1}\right) & (a_1 \le x \le a_2) \\ \alpha & (x = a_2) \\ \alpha\left(\frac{a_3-x}{a_3-a_2}\right) & (a_2 \le x \le a_3) \\ 0 & otherwise \end{cases} \tag{1}$$

$$\mathrm{I}(x) = \begin{cases} \frac{(a_2-x+\theta(x-a_1))}{(a_2-a_1)} & (a_1 \le x \le a_2) \\ \theta & (x = a_2) \\ \frac{(x-a_2+\theta(a_3-x))}{(a_3-a_2)} & (a_2 \le x \le a_3) \\ 1 & otherwise \end{cases} \tag{2}$$

$$\mathrm{F}(x) = \begin{cases} \frac{(a_2-x+\beta(x-a_1))}{(a_2-a_1)} & (a_1 \le x \le a_2) \\ \beta & (x = a_2) \\ \frac{(x-a_2+\beta(a_3-x))}{(a_3-a_2)} & (a_2 \le x \le a_3) \\ 1 & otherwise \end{cases} \tag{3}$$

In the neutrosophic set $\langle (a_{1,} a_{2,} a_3);\ \alpha, \theta, \beta \rangle$, In maximum truth membership degree is α , minimum indeterminancy degree is θ, and the minimum falsity degree is β. In the $\alpha, \theta, \beta \in [0,1]$ and the $a_1 \le a_2 \le a_3$ assumptions is based on their [11,12,13]. In this eqn(1,2,3) are used to from the membership function in figure(2).

3.4.2 Rule inference

In this phase, Mamdani control systems are employed to combine the two inputs: positive score and negative score. This control system, now applied in neutrosophic-based analysis, effectively integrates these inputs to produce a balanced and comprehensive output. By leveraging neutrosphic logic principles, the Mamdani control system can handle the inherent uncertainties, indeterminacies, and ambiguities in the input data, which are characteristic of neutrosophic sets.(14) and the rule of mamdani control system in table(1).

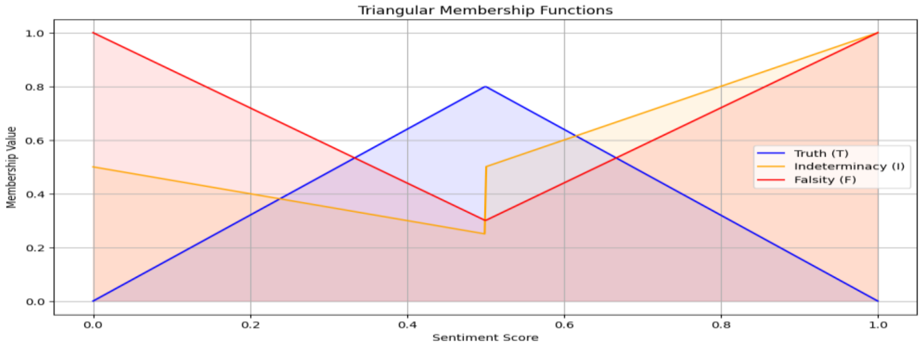

Figure 2. Triangle membership function

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Table 1: Madani control system rule

Rules	Positive Score	Negative score	Output
R1	Small	Small	Neutral
R2	Middle	Small	Positive
R3	High	Small	Positive
R4	Small	Middle	Negative
R5	Middle	Middle	Neutral
R6	Large	Middle	Positive
R7	Small	Large	Negative
R8	Middle	Large	Negative
R9	Small-Middle	Small-Middle	Negative- Neutral
R10	Middle-Large	Middle-Large	Positive-Neutral
R11	Small-Middle	Middle-Large	Negative-Neutral
R12	Middle-Large	Small-Middle	Positive-Neutral
R13	Small-Middle and Small-Middle	Small-Middle and Small-Middle	Negative- Neutral
R14	Middle-Large and Middle-Large	Middle-Large and Middle-Large	Positive-Neutral
R15	Small-Middle and Middle-Large	Small-Middle and Middle-Large	Negative-Neutral
R16	Middle-Large and Small-Middle	Middle-Large and Small-Middle	Positive-Neutral

3.4.3 Deneutrosophication

Deneutrosophication use the centroid approach to turn neutrosophic information into a crisp value. The centroid approach determines the center of gravity of the aggregated neutrosophic set, yielding a precise number that represents the overall evaluation based on the neutrosophic analysis. The centroid technique formula is provided by

$$\mathrm{COA} = \frac{\sum_{i=1}^{n} \mu(x_i).x_i}{\sum_{i=1}^{n} \mu(x_i).} \qquad (4)$$

Where COA is the centre of Area (centroid), $\mu(x_i)$is the membership function of the neutrosophic set at point x_i and n is the totalquantity of units in the neutrosophic set.

In using the eqn(4) to get the crsip value to ensures that the final result is not just a simple arithmetic combination but a sophisticated synthesis that captures the qualitative aspects of the input scores. Through this method, Mamdani control systems, combined with deneutrosophication using the centroid method, improve the accuracy as well as dependability of neutrosophic-based evaluation, transforming it into an effective decision-making tool.

3.5 Predicting Bi-Directional LSTM model

A Bi-Directional Long Short-Term Memory (Bi-LSTM) model represents a sophisticated artificial neural network design that excels in detecting context and interdependence within linear input sequences. This design extends typical Long Short-Term Memory (LSTM) networks by analysing incoming data sequences having both backward

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and forward orientations, resulting in a more complete grasp of the data. This bidirectional technique is especially useful for natural language processing (NLP) applications, where the setting of both previous and subsequent items within a series is critical for effective interpretation (15,16). Figure 3 illustrates the construction of a bidirectional LSTM.

3.5.1 Understanding LSTM Networks

Before delving into the details of Bi-LSTM, it is critical to grasp the principles of a regular LSTM network. LSTM networks are a form of Recurrent Neural Network (RNN) that is intended to capture relationships that last forever and alleviate the issue of decreasing gradients, which is common in regular RNNs. An LSTM unit comprises of a cell, an input gate, an output gate, and a forget gate. Those elements control the movement of data, permitting a network to keep or delete information as needed.

LSTM units:

Forget Gate: Chooses which data from the cell state to remove.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

Which new data should be stored in the cell state is determined by the input gate.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

Candidate Cell State generates an assortment that contains novel possibility entries.

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Update Cell State: Combines the new candidate values with the previous state to update the cell state.

$$C_t = f_t . C_{t-1} + i_t \cdot \tilde{C}_t$$

Output Gate: Selects the output by using the most recent cell state.

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

Hidden State: The outcome for this specific time step is the hidden state.

$$h_t = o_t \cdot tanh(C_t)$$

3.5.2 Bi-Directional LSTM Architecture

A Bi-Directional LSTM improves this design by adding an intermediate stage that handles the data entered series in reverse order. This means that any phase in the process is assessed in two directions: forward (from t=1 to t=T) and backward (from t=T to t=1). The outputs of these two layers are then combined to provide a more complete representation of the sequence.

The structure of a Bi-Directional LSTM can be visualized as follows:

The input sequence is processed in its natural order by the forward layer.

$$\overrightarrow{h_t} = LSTM\ (x_t, \overrightarrow{h_{t-1}}, \overrightarrow{C_{t-1}})$$

The backward layer handles the provided input data in the opposite direction.

$$\overleftarrow{h_t} = LSTM\left(x_t, \overleftarrow{h_{t-1}}, \overleftarrow{C_{t-1}}\right)$$

Combined Output: Concatenates the outputs of the forward and backward layers.

$$h_t = \left(\overrightarrow{h_t}, \overleftarrow{h_t}\right)$$

This bidirectional technique enables the model to absorb context from both previous and future states,making it particularly effective for tasks where understanding the relationship between elements in both directions is crucial. For instance, in sentiment analysis, the sentiment of a word might depend on the context provided by both preceding and following words.

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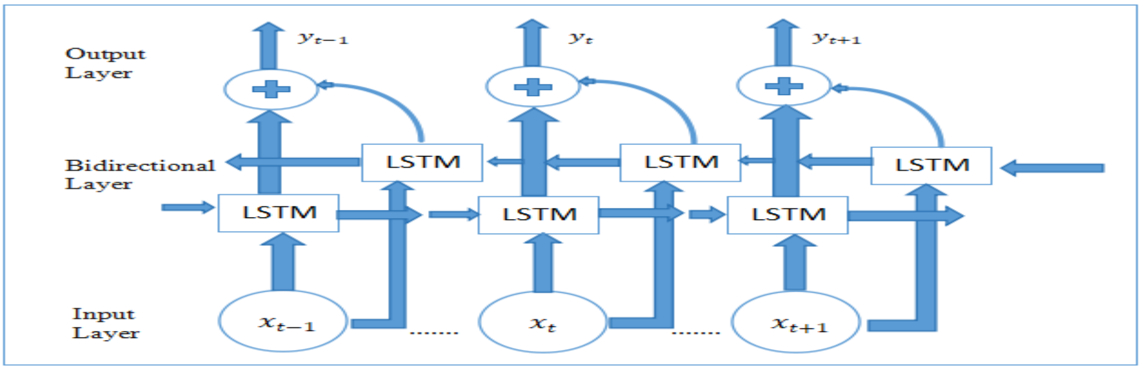

Figure 3. Bi-directional Model architecture

4. Result analysis and discussion

The primary purpose of the initial tests is to see if the emotional state of the data collected from Twitter has a substantial influence on the outcome of the bidirectional LSTM-based forecasting model. This model had been trained and evaluated on a dataset that included past stock prices as well as sentiment scores from Twitter. The difference in accuracy in Table 2

Table 2: Accuracy difference in with and without NL

Model	**Accuracy**
With using the NL	67.46%
Without using the NL	55.75%

In this paper Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), and Bidirectional LSTMs differ in their architecture and capabilities. RNNs, with their simple structure, are suitable for capturing short-term dependencies but often suffer from the vanishing gradient problem. LSTMs address this issue by using memory cells and gating mechanisms, making them capable of learning long-term dependencies and handling more complex sequential tasks. Bidirectional LSTMs enhance this further by processing data in both of forward and reverse directions, permitting them to gather information from the past, present and future, making them excellent for jobs requiring a thorough grasp of sequences, such as automated translating and sentiment evaluation. In the three models used the NL to compare the findings in Table 3.

Table 3: comparison of Neutrosophic logic in RNN, LSTM and Bi-directional LSTM models

ModelName	Accuracy	F1 Micro	F1 Macro	Precision	Recall
RNN	45.71%	0.4571	0.4554	0.4849	0.4571
LSTM	51.43%	0.5143	0.4996	0.5200	0.5143
Bi-Directional LSTM	67.46%	0.6746	0.6723	0.7010	0.6746

5. Conclusion and future works

Integrating Neutrosophic Logic with a Bi-directional LSTM model for predicting stock market movements has demonstrated promising results, improving the model's capabilities to handle uncertainty and capture both past and future contexts, leading to more robust predictions. Neutrosophic Logic improves the model's capacity to manage imprecision and indeterminacy, making the predictions more reliable in the inherently uncertain domain of stock market forecasting. Future work should focus on refining this integration through parameter tuning and optimization, as well as exploring different architectures and configurations to maximize performance. Expanding the datasets to include more diverse and extensive market data, along with incorporating additional significant aspects such as fiscal data, geopolitical developments, and social media sentiment, could further increase the model's efficiency and generalizability. Additionally, comparing the performance of this integrated approach with other advanced prediction models across various financial forecasting problems would provide valuable insights.

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