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DEEP LEARNING FOR SENTIMENT BASED DYNAMIC STOCK SYMBOL ANALYSIS

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ABSTRACT

The financial markets are highly dynamic and constantly affected by a multitude of global events, ranging from political crises and global pandemics to trade competition, innovation, and scientific advancements. These disruptions reverberate through supply chains across the globe and impact the overall demand for goods and services. Research across various domains suggests that stock market behavior cannot be solely explained by predictable patterns or trends. Emotions play a significant role, influencing rational thinking and social behavior, thus making the stock market an embodiment of the collective social mood. In light of this perspective, analyzing public sentiment becomes crucial in predicting stock market movements. As the volume of textual data, such as news articles and tweets, continues to surge, they serve as valuable indicators of the prevailing public sentiment. Consequently, the proposed approach involves developing a sophisticated system capable of dynamically fetching recent tweets related to specific sectors and employing deep learning techniques, such as LSTM and GRU, for sentiment analysis. By leveraging these insights, investors can make informed decisions in the dynamic realm of financial markets.
Keywords: *Deep Learning, GRU, LSTM, Sentiment Analysis, Stock Market*

1. INTRODUCTION

Financial investors rely on information, specifically corporate financial analysis, to make trading decisions that can impact the market. The study of predicting future revenue based on stock price behaviour has influenced various research fields. Initial research suggested that stock movements lack predictable patterns or trends, making past performance an unreliable indicator of future stock value. Subsequent studies supported this idea by highlighting the impact of emotions on social behaviour and rational thinking, to such an extent that the entire stock market may be seen as a reflection of public sentiment and social mood. Based on the information presented, it can be inferred that the analysis of public sentiment has the potential to forecast stock market price movements. Johan conducted research indicating that daily fluctuations found in the closing prices of the Dow Jones Industrial Average can be influenced by changes in public mood. The study also utilized graphs to explore the correlation between tweet activity on Twitter and changes in trading volumes and stock prices. Recent studies suggest that analysing online texts found on blogs, websites, and social networks can aid in predicting financial trends, considering the continuous growth of textual data such as news articles and tweets. Numerous websites exist on the internet that publish and aggregate such financial news and articles.

Financial websites often contain numerous lengthy articles that can be challenging to process manually due to their linguistic complexity. To effectively analyse and extract valuable information from these digitized texts, modern computing methods are employed. Natural Language Processing (NLP) is a field that encompasses various computational techniques for analysing and interpreting natural language at different levels. These methodologies facilitate various tasks like emotion analysis, summarization, and keyword extraction. One notable application of Natural Language Processing (NLP) is sentiment analysis, which entails detecting and extracting subjective information from text to ascertain the attitude, polarity (positive or negative), or expressed opinion. By leveraging automated methods like sentiment analysis, investors can make more informed decisions based on the insights derived from extensive text data.

The goals of employing Deep Learning for Sentiment Analysis are centred around predicting future stock market price movements by utilizing financial news and public opinions shared on social media platforms.

These objectives involve:
• To examine the existing approaches employed in predicting stock market behaviour.
• To assess the utilization of text mining and processing techniques in analysing social media data
• To construct a predictive model for stock market prices based on sentiment analysis of social media content.
• To validate and evaluate the effectiveness of the developed stock market price prediction model.

2. LITERATURE SURVEY

2.1 Sector-level sentiment analysis with deep learning [1]

In this paper, the authors proposed a method to extract sentiment from financial news applying NLP techniques. Three applications were proposed in this domain. Initial application is related to sentiment analysis in financial news for which two computational modules were proposed. In the first phase, to detect news which was mislabeled as neutral, an ensemble model of RNNs was used. In the second stage, LSTM was used to classify news as positive/negative. In this stage, they considered mislabeled neutrals also by employing a semi-supervised learning approach. The predictive power of sentiment analysis module was then tested using an independent set of financial tweets. Their model outperformed the FinBERT model.
In the second application, they detected the sectors affected by financial news. They used a multiclass LSTM model to classify news into one of the following sectors: Commodity, Consumer goods, Energy, Financial, Healthcare, Technology.
In the third application, a hybrid model was developed by combining sentiment analysis and sector detection modules. This model achieved an accuracy of 80% and outperformed a single multiclass model in predicting sector-level sentiments.

2.2 Predicting the effects of news sentiments on the stock market [2]

This paper suggested a method to perform sentiment analysis based on a dataset of stock-specific news articles from a reliable source in India. The dataset covered the past six months and included detailed intraday pricing data for each stock. The main text of each news article was extracted and transformed into n-grams. Initially, unigrams were used for sentiment analysis, considering individual words like 'decline' as generally negative, but also accounting for positive contexts such as 'costs declined' being positive for the company. Later, bigrams and trigrams were created to capture the polarity of individual words and the surrounding phrases, enabling a better understanding of the overall context. Stemming, which involves reducing words into their base or root forms (e.g., 'declining' to 'decline'), was applied to process bigrams and trigrams, aiding in capturing the essence of the phrases.

To overcome the lack of financial market-specific dictionaries, a customized dictionary was manually created for the pharmaceutical sector. A specialized dictionary comprising 100 words and phrases was created by the author, drawing on their expertise and thorough analysis of pharmaceutical news articles. Each entry in the dictionary was assigned a sentiment classification of positive, negative, or neutral. The n-grams generated were compared against this domain-specific dictionary, and if a match was identified, the associated words were assigned a positive or negative polarity. The occurrence frequency of positive and negative words was then calculated to generate sentiment scores. Neutral words had no impact on the scores. Based on these scores, decisions to "buy," "sell," or "hold" were made. For instance, if the cumulative sentiment score of a news article was positive and surpassed a predetermined threshold, the stock would be purchased following the release of the news. Conversely, if the overall score was negative and fell below the predefined threshold, the stock would not be bought.

2.3 Attention-emotion-enhanced-convolutional LSTM for sentiment analysis [3]

In this paper, a novel deep learning model, AEC-LSTM (attention-emotion-enhanced convolutional LSTM), is proposed for text sentiment detection, drawing inspiration from emotion intelligence and cognitive theory in neuroscience. It incorporates an emotion-enhanced LSTM (ELSTM) that leverages emotion intelligence to enhance sentiment representation. A topic-level attention mechanism is also introduced. Experimental results show that AEC-LSTM outperforms state-of-the-art models in sentiment classification.
The proposed AEC-LSTM model offers distinct advantages over other existing methods. Firstly,

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unlike current artificial neural models that overlook emotion modulation, AEC-LSTM leverages emotion modulation to enhance the learning capacity of neural units by emulating human emotion mechanisms. This inclusion of emotion modulation is a unique feature of AEC-LSTM. Secondly, while most existing attention mechanisms focus on low-level abstractions like word and phrase levels, AEC-LSTM introduces a topic-level attention mechanism that simulates higher-level attention observed in human brain recognition. This enables AEC-LSTM to acquire higher-quality sentiment representations from text sequences. Overall, AEC-LSTM stands out by incorporating emotion modulation and topic-level attention, elevating its performance compared to existing approaches.

2.4 Sentiment analysis and emotion detection on cryptocurrency related tweets using ensemble LSTM-GRU model [4]

In recent years, the cryptocurrency market has experienced an unprecedented growth rate. Similar to conventional currency, cryptocurrencies enable virtual payments for goods and services, without the need for centralized authority. Although using cryptographic techniques, cryptocurrency ensures authentic and one-of-a-kind transactions, this business is still in its infancy, and substantial concerns have been expressed concerning its use. To get an overall picture of how people feel about cryptocurrencies, sentiment analysis is particularly desirable. This study focuses on utilizing tweets related to cryptocurrencies, which are commonly used to predict cryptocurrency market values, for both sentiment analysis and emotion recognition. To enhance the effectiveness of the analysis, a deep learning ensemble model called LSTM-GRU is employed, combining long short-term memory (LSTM) and gated recurrent unit (GRU) recurrent neural network applications. The LSTM extracts features that are used to train the GRU, which is then stacked together with the LSTM. Various machine learning and deep learning techniques, along with the proposed ensemble model, are examined using term frequency-inverse document frequency (TF-IDF), word2vec, and bag of words (BoW) features. Additionally, for emotion analysis, TextBlob and Text2Emotion models are explored. The findings reveal that people predominantly express happiness when discussing cryptocurrencies, followed by sentiments of dread and surprise. The results also indicate that employing BoW features enhances the performance of machine learning models. The suggested LSTM-GRU ensemble model outperforms both traditional machine learning and state-of-the-art models, achieving accuracy ratings of 0.99 for sentiment analysis and 0.92 for emotion prediction.

2.5 Tweet sentiment analysis for cryptocurrencies [5]

A significant number of cryptocurrency traders depend on Twitter tweets as a valuable resource for making their daily trading decisions. In this study, the authors focused on whether sentiment analysis for cryptocurrency might be automated. They picked one cryptocurrency (NEO) alternative coin for the study and gathered pertinent data. The gathering and preparation of the data were crucial parts of the study. First, Twitter was used to download the daily NEO hashtag tweets over the previous five years. The tweets were subsequently filtered to remove any references or mentions unrelated to NEO. They manually assigned labels for positive, negative, and neutral emotion to a portion of the tweets. Using the labeled data, we conducted training and testing of a Random Forest classifier, achieving a test set accuracy of 77%. In the subsequent stage of the study, they examined whether a correlation existed between the daily sentiment expressed in tweets and the price of NEO. Notably, positive relationships were observed between the tweet volume and daily prices, as well as between the values of other cryptocurrencies. The data collected during the study are openly shared and made accessible to others. A sentiment analyzer used the Python scikit-sklearn module to follow a common path for the suggested training. The tweets were first transformed into parameterized token counts using the CountVectorized technique. The TF-IDF (term frequency-inverse document frequency) was then used. Likewise, divide the 1200 tweet dataset into 20% test data and 80% train data. 200 estimators were the maximum allowed number as well. Here, the optimal parameters in the training set are sought using the GridSearchCv object from the Scikit-Learn toolkit. As a result, they achieved results of 82% accuracy on the training set and 77% accuracy on the test set.

In the existing systems, various deep learning models have been developed for sentiment analysis in worldwide share market. Most of these systems focus on English language-based sentiment analysis for predicting market trend. Here, we propose a system to analyze sentiments based on tweets in Indian languages.

3. METHODS

3.1. Long Short-Term Memory (LSTM)

Created to address the issue of long-term dependency, this design allows for the retention of information over extended periods. It employs three distinct gates for this purpose: the forget gate, input gate, and output gate.

Forget Gate: The forget gate is responsible for eliminating information that is deemed unhelpful in the cell state. It uses the previous cell and the current cell as inputs, multiplies them using weight matrices, and adds a bias. An activation function is then applied to the result, generating a binary output. If the output is 0, the specific piece of information is discarded. Conversely, if the output is 1, the information is retained for potential future utilization.

Input Gate: Gives the cell state additional useful information. The sigmoid function controls information and filters the values that are retained. The 1tanh function creates a vector from the input of the previous cell and the current cell with an output range of -1 to +1 that encompasses all possible values from the input of the previous cell and the current cell. Then, to extract the valuable information, the vector's values and the controlled values are multiplied.

Output Gate: Gleans pertinent information from the active cell state for output presentation. Applying the tanh function to the cell results in the creation of a vector. By utilizing the sigmoid function in conjunction with inputs from the previous and current cells, information is effectively controlled and filtered based on which values should be retained. To transmit data as both input and output to the subsequent cell, the values of the vector and the controlled values are multiplied together.

3.2. Gated Recurrent Unit (GRU)

Created to get around the fading gradient issue. Information is transferred using the hidden state once the cell state has been deleted. Uses the reset gate and the update gate, two distinct gates, for this process.

Reset Gate: The reset gate plays a crucial role in determining which information is retained or discarded from the memory, as well as deciding the extent to which the previous hidden state information should be preserved. In the case where the gate value is close to 0, the GRU tends to forget the prior hidden state and relies more on the current input. Conversely, if the gate value is close to 1, the GRU incorporates the previous hidden state significantly into the new hidden state.

Update Gate: The update gate is used to control the flow of information into the memory and determine how much of the fresh input must be utilized to update or change the hidden state. It is represented as a vector and makes decisions about which data to retain and which data to discard. The output from the sigmoid function indicates the amount of information to be retained from the previous hidden states.

3.3. System Architecture

The proposed architecture aims to implement a system for predicting recent trends in share market based on the sentiments from tweets collected from news channels particularly for Indian scenario. As seen in Fig.1., the collected news dataset is used to train an GRU-LSTM ensemble model [1] to classify input data into neutral or non-neutral sentiment. Further, neutrals are removed to train another LSTM model to classify texts into binary (positive or negative) sentiment. The first ensemble model is used to classify the neutral datapoints in the dataset into neutral or non-neutral. This is done with the assumption that some of the neutrals in the dataset may have been misclassified as so. The datapoints that are still classified as neutral are discarded and not further used in the system. Semi-supervised learning is performed on the LSTM model with the newly classified data in order to improve its performance.

The final trained LSTM model is then used in client-server architecture that pulls tweets dynamically from the Twitter API based on keyword input from the client. The tweets pulled are sent to a translation pipeline in order to translate all texts into English. The translated texts are passed through to the trained LSTM model to classify into Positive or Negative. This classification data is then collated to form a simple pie graph that shows the percentage of Positive and Negative tweets each regarding the input stock symbol. This can be used by the end user to arrive at a conclusion whether or not to invest or trade with said symbol.

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4. DATASET

The quality and quantity of the data acquired can affect the accuracy and efficacy of the analysis, making data collecting an important step in sentiment analysis. A programme called StockNewsAPI offers financial news stories from various news organizations, financial blogs, and company press releases. In the financial market, sentiment analysis can be performed using the data gathered by StockNewsAPI.

1. Titles and body of news articles can be included in the data gathered by StockNewsAPI. These constitute the bulk of the information gathered. They offer the text that will be subjected to sentiment analysis.
2. Source: The author and publisher of the news piece are identified by the source. This can be used to check the news's dependability and believability.
3. Date and time: The analysis is contextualized by the date and time the article was published. Monitoring industry trends and happenings is helpful.
4. Ticker symbols: You may identify the companies discussed in the article by looking up their ticker symbols, which can serve as a starting point for additional study.
5. Category: The news article's category informs readers about the news's genre, such as earnings reports, mergers and acquisitions, or changes to the law.

To forecast the tendencies of the financial market, sentiment analysis can be done using the data gathered from StockNewsAPI. Investors might learn more about how the market is going to perform by examining the sentiment of financial news items. Positive sentiment can indicate an upward trend, while negative sentiment can signal a decline.

5. RESULTS AND DISCUSSION

Technical Analysis methods for stock market predictions face a number of challenges in today's market scenario since emotion plays an important role in the price of financial instruments. This may be due to the increased presence of retail traders in the Indian market. High accuracy sentiment analysis of publicly shared data can be used to analyze popular opinion on a particular stock symbol and use that to guide decision making in the market.
The results of our evaluation indicate that our model performs well in classifying the sentiment of tweets regarding any particular stock symbol. We found that the model was able to classify tweets into a positive or negative label with an accuracy of 90.6%. The accuracy of LSTM is 90.5% and the accuracy of GRU is about 90%. Table 1 shows the performance evaluation parameters of LSTM and Table 2 demonstrates the performance evaluation parameters of GRU.

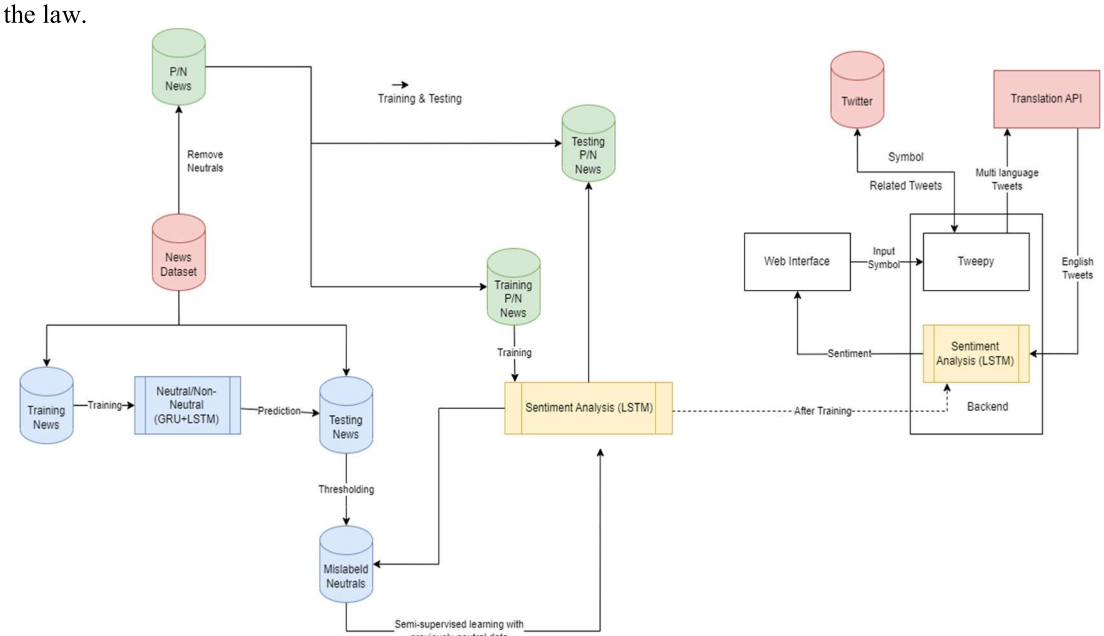

Figure.1: System Architecture

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Table 1: LSTM Results

	Precision	Recall	F1-Score
Negative	0.911	0.899	0.905
Positive	0.901	0.912	0.906

Table 2: GRU Results

	Precision	Recall	F1 Score
Negative	0.898	0.903	0.901
Positive	0.902	0.898	0.900

Fig.4 shows the user interface page where the user can input or give the keyword searching for. Also the user can decide the number of tweets to pull to the model for testing; here the range is in between 100 to 1000. Fig.5 shows the output after clicking Perform Sentiment Analysis button. The system shows a range of tweets to the users. Fig.6 shows the tweets in English which are translated from different languages. Table 3 shows the actual and indicated stock values. Fig. 7. shows the sentiment distribution for ADANIENT, Fig 8. shows the sentiment distribution for BAJAJFINSERV, Fig. 9. shows the sentiment distribution for ICICIBANK and Fig. 10. Shows the sentiment distribution for ITC. In Fig.11., performance of existing algorithms with proposed model is shown. The proposed model has higher accuracy than existing algorithms.

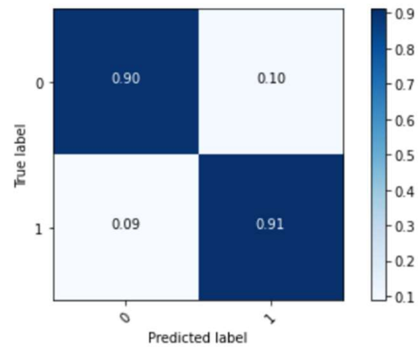

Figure 2: Normalized Confusion Matrix for LSTM

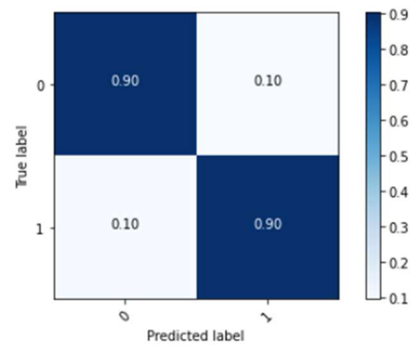

Figure 3: Normalized Confusion Matrix for GRU

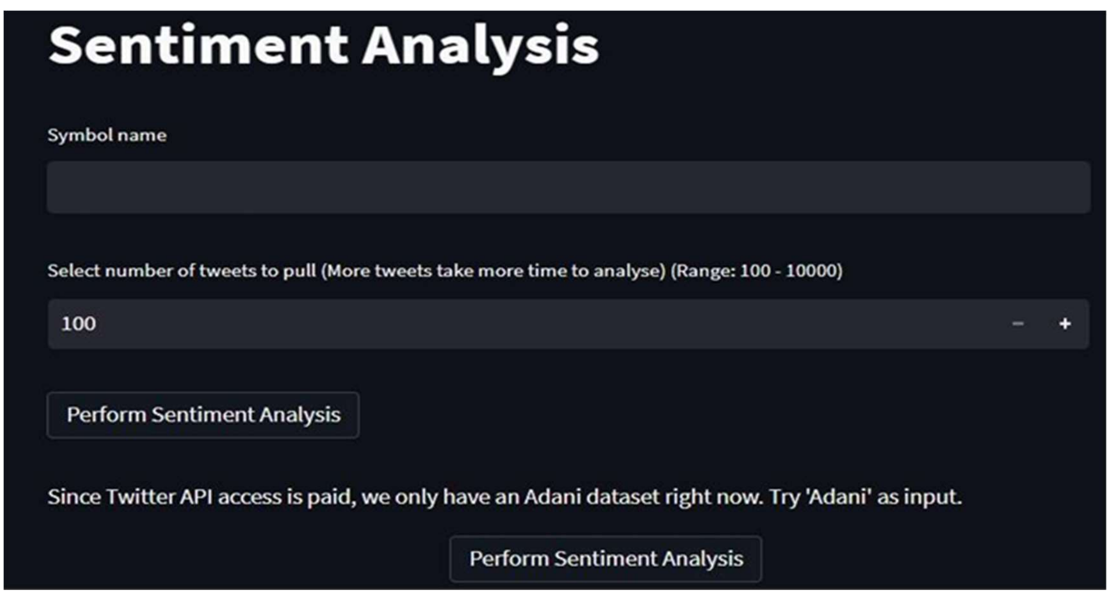

Figure 4: User Interface

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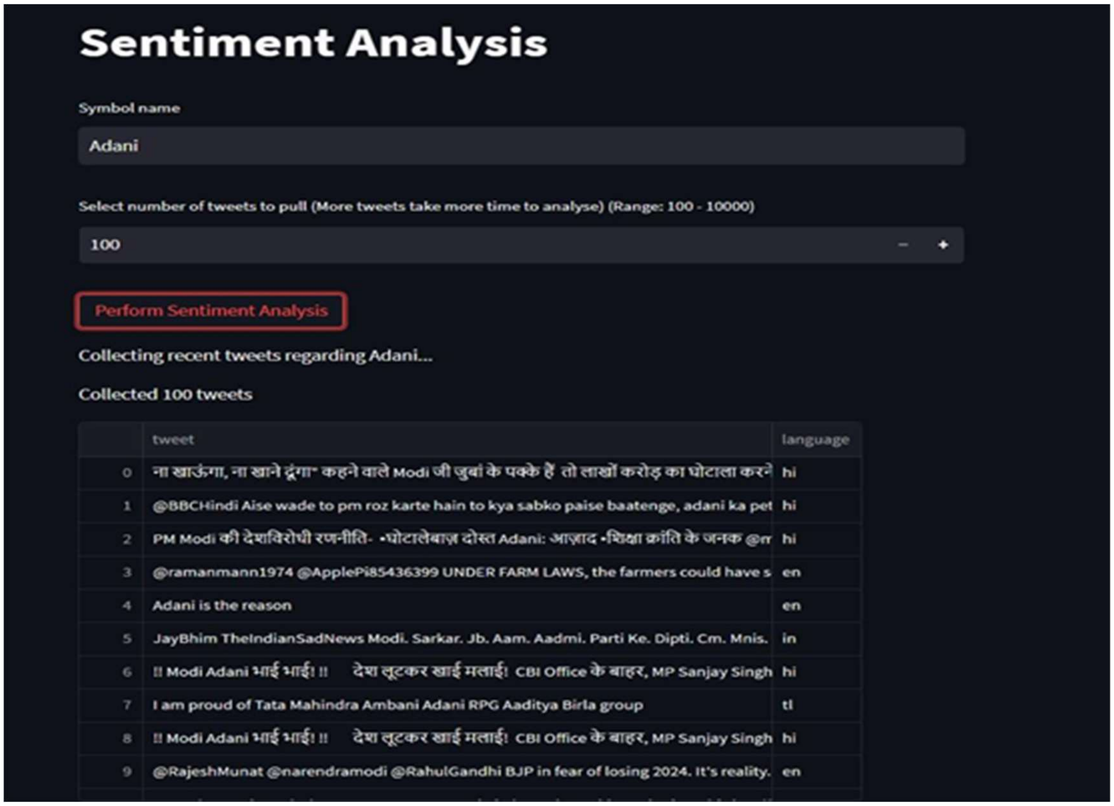

Figure 5: After clicking Perform Sentiment Analysis button

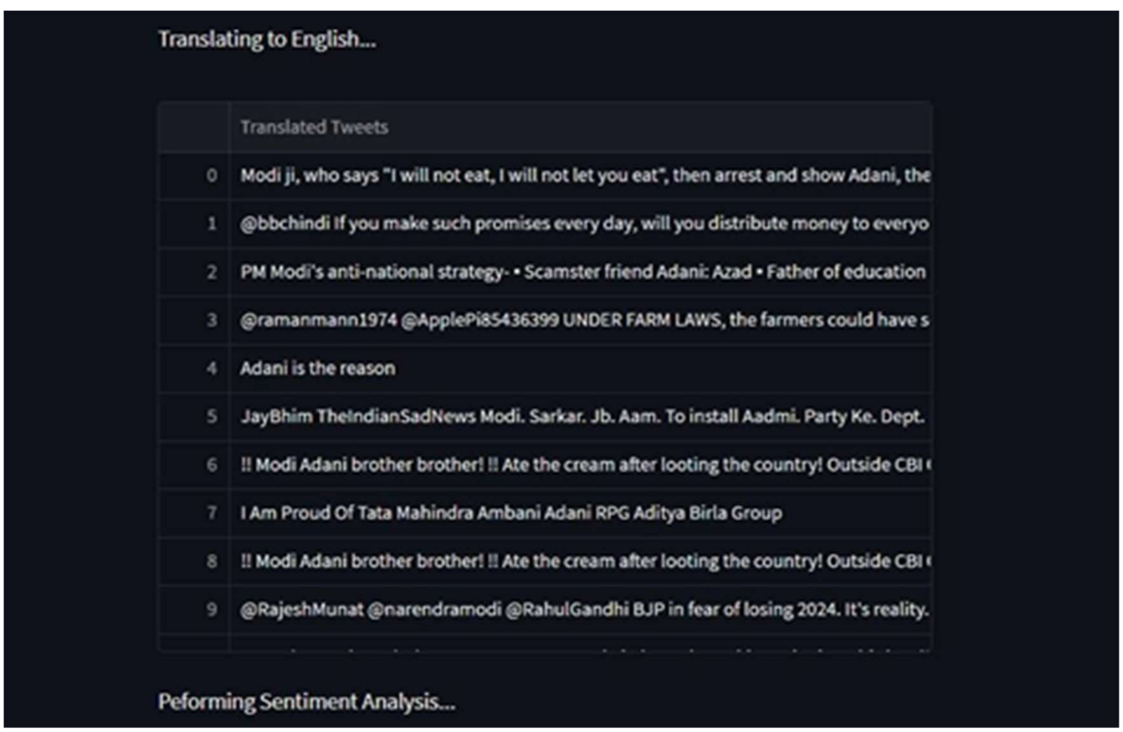

Figure 6: Translating Tweets

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Table 3: Actual and indicated stock values

Stock Symbol	Proposed Model Positive	Proposed Model Negative	Indication	Stock price actual gain/loss in Feb, 2023
ITC	85%	15%	Positive	+6.91%
ICICIBank	52.8%	47.2%	Neutral	+2.76%
BajajFinServ	67.5%	32.5%	Positive	+3.83%
AdaniEnt	21%	79%	Negative	-54.14%

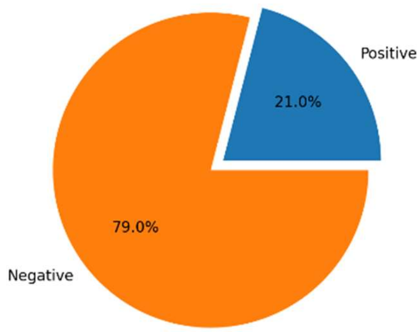

Figure 7: Sentiment distribution for ADANIENT

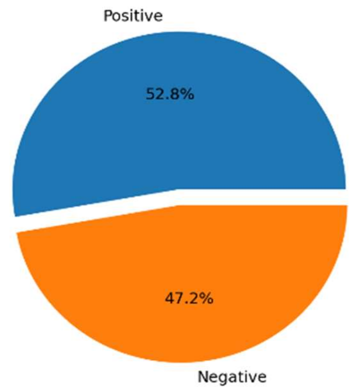

Figure 9: Sentiment disstribution for ICICI

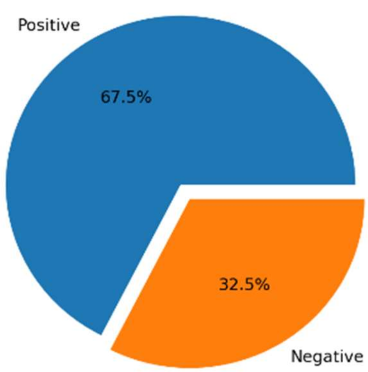

Figure 8: Sentiment distribution for BajajFinserv

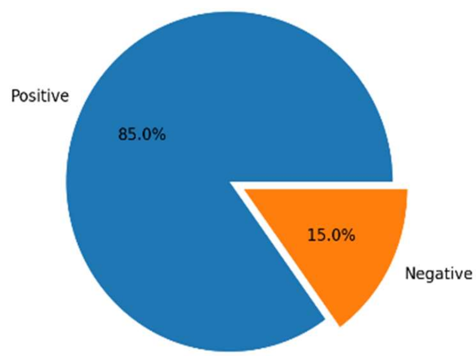

Figure 10: Sentiment distribution for ITC

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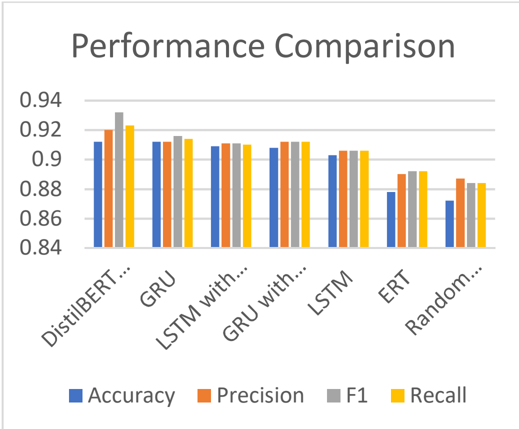

Figure 11: Performance Comparison

6. CONCLUSION

Financial news is increasingly valuable for investors to gauge market sentiment, necessitating accurate and swift comprehension of these texts. Both the academic and industrial sectors are actively investigating computational approaches to automatically extract valuable information from financial news. This research paper presents three applications of natural language processing (NLP) within this specific field. After evaluating various machine learning algorithms, deep learning methods consistently outperformed others in all applications.

The initial application centers around conducting sentiment analysis of financial news. The proposed approach involves the development of two computational modules: one for preliminary label augmentation and another for performing actual sentiment analysis. An ensemble of recurrent neural networks (RNNs) is employed to identify news that may be mislabeled as neutral. Long short-term memory (LSTM) models are then utilized to classify news as positive or negative, incorporating semi-supervised learning to handle mislabeled neutrals. The sentiment analysis module demonstrates superior predictive performance compared to FinBERT, a state-of-the-art pre-trained language model, when tested on an independent set of financial tweets. The findings of the study indicate a well-balanced performance across all sectors, highlighting the effectiveness of deep learning in accurately predicting the sectors affected by the sentiment expressed in the news.

The sentiment analysis and sector detection models are integrated into a hybrid system, which serves various purposes including evaluating overall market sentiment trends and analysing the behaviour of sector exchange-traded funds (ETFs). The predictions generated through sector-level sentiment analysis can be explored as potential indicators for forecasting price trends of sector ETFs. Furthermore, the study proposes investigating the trade-off between the time to execute and predictive performance of the sentiment analysis, particularly in the context of algorithmic trading profits. Additionally, the potential improvement of sentiment analysis results through the inclusion of Attention Mechanisms and Convolutional Neural Network (CNN) layers in the system is explored.

With information specific to individual sectors, this model facilitates a deeper knowledge of sentiment within particular industries. Businesses in certain industries, legislators, and investors may find this to be of special use. Businesses may proactively manage their operations, reputation, and investments by using sector-based sentiment research to uncover new risks and possibilities within their industry. By assessing market sentiment towards particular industries and the firms that make up those industries, investors can utilize sector-based sentiment research to make better informed investment decisions.

The availability of pertinent data sources inside share market sectors is crucial for the success of this model. The degree of variation in the quality and bias of data sources across different industries might result in biased or erroneous sentiment analysis outcomes. Market sentiment is shaped by new trends, technologies, and laws that are continually emerging in many industries. This also influences the accuracy of this model.

A more thorough knowledge of sentiment can be obtained by integrating several modalities, such as text, photos, videos, and audio into sector-based sentiment analysis. Investigating multimodal sentiment analysis methods suited to share market industries are future opportunities in this field. Sector-specific sentiment can be very dynamic, impacted by a range of things including news stories, market patterns, and seasonal variations. Understanding changing sentiment patterns and making wise decisions needs research into temporal sentiment analysis techniques, which record and examine sentiment trends over time within particular sectors.

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Authors' Contribution

The authors confirm contribution to the paper as follows: study conception and design: Lakshmi K.S, Paul Joshi; data collection: Santa Maria, Divya James; analysis and interpretation of results: Lakshmi K.S, Paul Joshi, Divya James, Liyan Grace Shaji, Santa Maria; draft manuscript preparation: Divya James, Liyan Grace Shaji, Santa Maria. All authors reviewed the results and approved the final version of the manuscript.

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