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Analysis of Real Time Twitter Sentiments using Deep Learning Models

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Abstract

Understanding attitudes regarding distinct topics and public opinions on the sentimental analysis of social media data is important. This research analyses the real-time twitter sentiments using deep learning. The major objective of the study is to create an efficient sentiment analysis algorithm to accurately ensure the sentiment polarity (positive, neutral or negative) of tweets. This study proposed a deep learning approach to capture the contextual information and complex patterns in social media data which leverages the power of neutral networks. To assess the performance of the algorithm the study relies on the evaluation of F1 score, accuracy, precision, and recall through rigorous evaluation metrics. The efficiency of the proposed approach is demonstrated by the numerical outcomes of the study. A novel contribution is provided with a specific emphasis on real-time Twitter sentiments by the study to enhance the sentiment analysis techniques for social media data. The significant implication from accurate and timely analysis of Twitter sentiments for several applications includes public opinion tracking, brand management, customer feedback analysis, and reputation monitoring. The potential to provide significant insights to researchers, organisations and business can be made from promptly addressing the sentiments expressed on real time data of twitter.

Keywords: Twitter, Sentiment Analysis, Deep Learning Models, Text Classification, Accuracy Evaluation

1. Introduction

In the previous years, to express the public opinions and sentiments on distinct fields a valuable channel for individuals has been evolved as a good source of information [1]. Twitter is a commonly used microblogging platform among these platforms, where the twitter users share their feelings, experiences, feelings and thoughts in a brief format. The huge number of user-generated information on twitter gives a different potential to turn into public opinion and sentiment. The sentiment analysis can be referred to as an opinion mining which has developed as a potent method for examining and extracting sentiment related information from social media data. This includes automatic categorization of social media posts or text documents into negative, positive or neutral sentiment categories. To analyse the sentiment, the traditional methods depend upon machine learning algorithms or rule-based techniques using handcrafted features. With the enhanced feature of deep learning, sentiment analysis has observed significant features, leading to the development of robust and more accurate models.

This research objective is to enhance sentiment analysis methods for the social media data by implementing deep learning models. Particularly, this study proposes a novel algorithm and conducts a crucial examination of its performance using standard dataset. The study provides valuable insights through the analysis of tangible numerical results into the algorithm's potential applications and effectiveness. Through the development of robust sentiment analysis techniques, this study provides insights to several fields such as public opinion analysis, customer sentiment analysis and brand monitoring. The timely and accurate insights obtained from social media can considerably advance these applications, allowing organisations and businesses based on real-time sentiments to make informed decisions. The novelty of the study lies in the comprehensive evaluation and creation of a deep learning developed particularly for real time sentiment analysis of twitter data. Through this, it considerably improves the effectiveness and the accuracy of the sentiment analysis method implemented to social media platforms.

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For the natural language, context dependence and nuances, the sentiment analysis on social media platforms is challenging, resulting in suboptimal performance from machine learning algorithms and traditional rule-based methods. Implementing deep learning in sentiment analysis develops models that dynamically adapt and learn to language complexities. By deploying word embedding and interconnected nodes, these models identify complicated patterns and improve identification of word connections. In the succeeding sections of the study, the existing literature is analysed for developing a theoretical framework, from which the details of benchmark datasets and evaluation metrics are obtained. Then, the numerical results will be presented with the discussion of implications of the results. And finally, the study emphasises the limitations and future scope in the field pertaining to real-time twitter sentiment of sentiment analysis. As a result, the study contributes valuable insights for social media text into data preprocessing techniques, highlighting the relevance of the custom cleaning functions tailored, lemmatization and noise removal. The study obtains a high accuracy in sentiment classification, by predicting and understanding sentiment polarity in real time twitter in sentiment.

2. Literature Review

A real time cryptocurrency prediction platform was proposed on the basis of twitter sentiment. The study used a spark based architecture to determine the fault tolerant ability. Online learning and sentiment analysis are supported by the proposed predictive method. As a result of implementation and evaluation, the study found that the KryptoOracle has the potential to enhance the decision making process and can provide valuable insights depending upon large financial data volumes [16]. Cloud computing is a comprehensive technology for citizens, businesses and government. In their study, they analysed the dataset which was generated by emerging fields on twitter. The study built three classifiers to examine the sentiments of tweets, where these classifiers outperformed with best accuracy rate for predicting the sentiment through the tweets data by implementing Support vector machine and Naive Bayes algorithm. The study's findings demonstrated that most of the predicted emotions were sadness, happiness and anger. Among the predicted tweets 6.5% were found irrelevant [17]. A study was conducted using ensemble based deep learning models towards COVID-19 in India and European countries to help their state run administrations in controlling, observing, and controlling the spread of Covid-19. The study proposed a sentiment analysis system to examine the real time tweets that are associated with pandemic. The results of the study demonstrated that the proposed model accomplished 95.2% and 97.28% of accuracy in categorising the people's sentiments particularly from India and Europe [18].

In another study, the objective was to create a model which can evaluate if a tweet is ham or spam. This study used convolutional neural network, recurrent neural network, stochastic gradient descent, logistic regression, decision tree, multinomial naive bayes, bidirectional long short-term memory and long short-term memory for the sentiment analysis. The performance of each classifier examined which elements removed from the tweets can be sufficiently used to distinguish in the event that a specific tweet is spam or not and make a learning model that will connect tweets with a specific opinion [19]. Polaris was proposed as a framework for foreseeing and analysing people's sentiment for events examined in the real time data of tweets. The study showed both sentiment analysis and trajectory analysis so that the people can get the foresight of their sentiments. Similarly they have improved the accuracy in analysing the sentiments and forecasting them by deploying the most recent deep learning method [20]. Web-based entertainment is an important instrument for estimating emotions, however understanding it is demanding because of language diversity and data generation [21]. This paper has analysed political Ayodhya tweets utilising artificial intelligence machine learning algorithms to categorise polarity. Further, the study suggests that the emotions from social media can be predicted through enhanced data analysis and proper understanding of social media [21].

A methodology was proposed which includes preprocessing and characterization steps, making a corpus and utilising different algorithms such as random forest, logistic regression, decision tree, and Bernoulli NB. This study outperformed on training data by implementing linear regression in the study [22]. To undertake sentiment analysis on contemporaneously Twitter data from the election for president in 2019, a study used the technique of machine learning random forest modelling for sentiment classification as well as a feature-selection model word2vec. Word2vec with Random Forest fundamentally upgrades sentiment examination precision contrasted with conventional strategies like TF-IDF and BOW, which can further develop quality by considering logical semantics, improving artificial intelligence and emotion analysis accuracy [23]. A comparative analysis was carried out for artificial intelligence strategies like support vector machine, Maximum entropy classification and Naive Bayes for sentiment analysis, for evaluating their precision and accuracy in emotion analysis [24]. For classification of twitter data, a study deployed random forest, logistic regression, Naive Bayes and decision tree [25]. The findings of the study demonstrated that the logistic regression model has the highest F-score and accuracy. A technique was suggested which captures individual tweets employing Twitter application programming interfaces then applies a text classification algorithm to categorise them as good, poor, or neutral. The programme then classifies the reviews based on sentiment ratings [26].

2.1. Research gap

The research gap recognized in the existing studies features possible regions for headways and unique contributions in sentiment analysis. These incorporate constant cryptographic cryptocurrency prediction with adaptation to internal failure, improved sentiment categorisation for cloud-based examination, Coronavirus opinion investigation and speculation, spam discovery with multimodal highlights, thorough opinion and direction investigation, upgraded artificial intelligence based political feeling investigation, enhanced opinion investigation systems, high level procedures for political decision opinion investigation, correlation of simulated intelligence techniques for feeling investigation, ideal classifier determination, and computerised survey grouping for web-based entertainment. These gaps highlight opportunities for additional turn of events and investigation in emotion examination, enveloping parts of adaptation to non-critical failure, high level AI procedures, more extensive speculation, multimodal examination, and the mix of arising advances to improve sentiment prediction precision and relevance. Further examination concerning these regions could assist with growing more refined group models or profound learning methods for feeling expectation.

3. Methodology

3.1. Data collection and data description

This study's dataset was derived from Twitter and comprises real-time Twitter data. The table 1 gives a comprehensive summary of the data, enabling those to comprehend the structure and elements. Every record in the table is associated with a single tweet and includes details such as the Tweet ID, Date and Time, Query Tag, Username, and Tweet Text. The table shows the first 3 rows of the dataset.

Table 1. Tweet Dataset

Tweet ID	Date and Time	Query Tag	Username	Tweet Text
1467810369	Mon Apr 06 22:19:45 PDT 2022	NO_QUERY	_TheSpecialOne_	*@switchfoot http://twitpic.com/2y1zl - Awww, that's a bummer. You shoulda got David Carr of Third Day to do it. ;D*
1467810672	Mon Apr 06 22:19:49 PDT 2022	NO_QUERY	scotthamilton	*is upset that he can't update his Facebook by texting it... and might cry as a result School today also. Blah!*
1467810917	Mon Apr 06 22:19:53 PDT 2022	NO_QUERY	mattycus	*@Kenichan I dived many times for the ball. Managed to save 50% The rest go out of bounds*

A Python function for noise removal in text data is designed for cleaning tweets, preprocessing input text to remove irrelevant elements like links, mentions, punctuation, and stopwords. Lemmatization reduces words to base form, and a custom function called "cleaned()" handles misspellings or abbreviations [4, 5, 12].

3.2. Deep learning Model development

The model consists of a pretrained embedding layer, two Bidirectional LSTM layers, and a Dense layer with a sigmoid activation function. It captures contextual information through word mapping, Bidirectional LSTM processing, and binary classification. Training is done using binary cross-entropy and the Adam optimizer. The proposed deep learning model is a sequential model that contains bidirectional LSTM layers to analyse sentiment in text data. The model initiates with the embedding model that can convert the input words to sequential vector representations depending upon the pre-trained word vectors. The vocabulary size of this layer is 20,000 and 50 as the embedding dimension. The succeeding bidirectional LSTM layer examines the integrated sequential model in both backward and forward directions, this helps the model to effectively capture long term dependencies and contextual information [3].

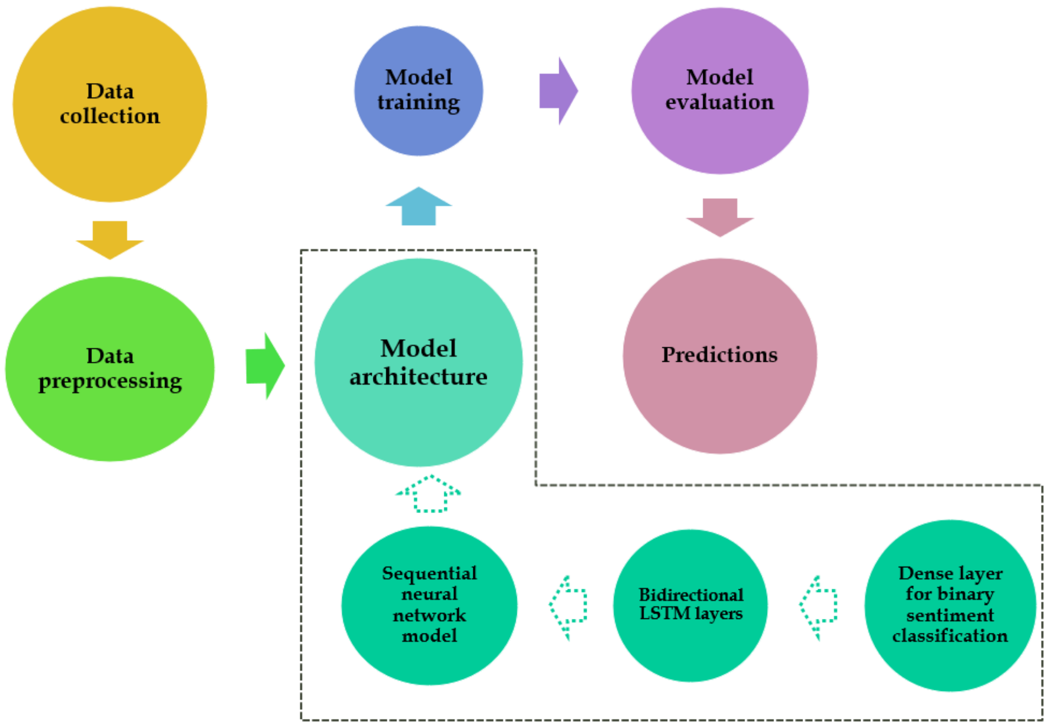

Figure 1. Overview of the proposed model

The overview of the proposed model is illustrated in figure 1. The data collection involves real time twitter data with Tweet ID, Date and Time, Query Tag, Username, and Tweet Text. Then the data is preprocessed for removing URLs, mentions, punctuation, and stopwords and handling abbreviations and misspellings. Then comes the most important segment; model architecture, which constructs a sequential neural network model to incorporate a pre-trained embedding layer. For capturing the context the two Bidirectional LSTM layers are added with a Dense layer for binary sentiment classification. Then the model is compiled with an optimizer and loss function, a result the model is evaluated by accuracy metric. Then the model is trained to analyse the accuracy, F1 score, recall and precision. Finally, the training model is applied to predict the negative and positive sentiments.

The following is the pseudo code of the model:

Defining model architecture

Compiling the model: loss='binary_crossentropy', optimizer='adam', metrics=['accuracy']

Training the model using the preprocessed dataset:

Initialising batch size and number of epochs

Evaluating the trained model on validation dataset:

Calculating accuracy, precision, recall, F1-score, and confusion matrix

Predicting sentiment on custom data using the trained model

Interpreting model performance and accuracy

On a sequence of length 25, this layer operates on 256 units. The second Bidirectional LSTM layer further refines the representations and outputs a condensed representation of size 256. In the end, a dense layer with a single unit and a sigmoid activation function is utilised to perform binary classification, predicting the sentiment polarity [1]. The model has a total of 20,577,843 parameters, out of which 577,793 are trainable and the remaining 20,000,050 are non-trainable (due to the pre-trained word vectors). The model is constructed by utilising the binary cross-entropy loss function and the Adam optimizer, while accuracy serves as the evaluation metric. In summary, this deep learning model with pretrained embeddings and Bidirectional LSTMs is designed to analyse sentiment in text data by capturing contextual information and predicting sentiment polarity accurately [8].

3.3. Model training

The significance of high quality of training data in preparing features affects models positively. To additionally work on the model's performance, presenting regularisation procedures can help forestall overfitting and improve speculation. Expanding the quantity of epochs during model preparation empowers it to procure a more profound comprehension of intricate patterns and potentially enhance its accuracy [11,13]. Besides, preparing the model on a bigger and more different dataset improves its capacity to deal with many linguistic styles, settings, sentiments, and opinions. By consolidating these improvements and using bigger, cleaner datasets, there is the possibility of accomplishing considerably higher correctnesses and more robust sentiment analysis abilities [15].

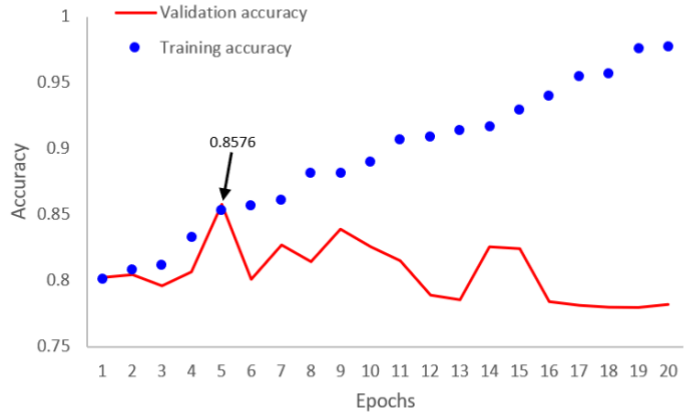

Figure 2. Epoch vs Accuracy

The validation accuracy achieved in the fifth epoch was considered since it is a considerable performance gain for the model. The fifth epoch obtains 85.7% as its validation accuracy, which has been marked with an arrow on the plot. The points are the epoch obtained and the line graph is the validation accuracy.

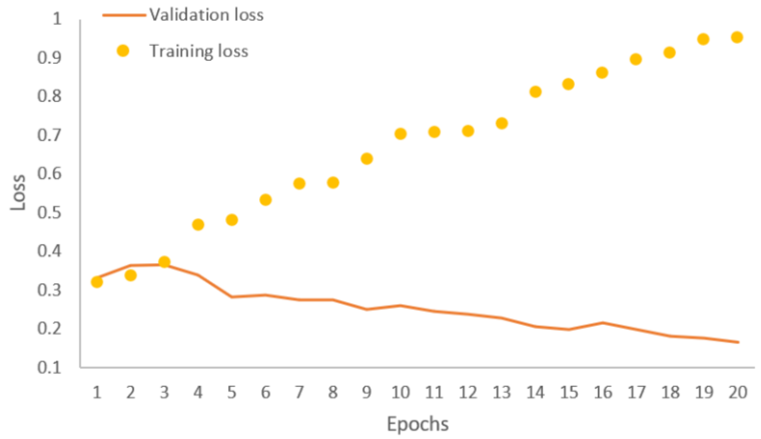

Figure 3. Epoch vs Loss

The figure 2 and 3, are the plots obtained after evaluating the validation accuracy. In figure 3 the validation loss is increasing with the hike of epochs. This phenomenon occurs when the model learns the training data very well, this can also be termed as overfitting. This also signifies that the point has started memorising idiosyncrasies and noise in the training set. In conclusion, this conveys that the model can outperform on the training data.

4. Results and Discussions

The confidence values returned by the model further provide insights into the certainty of sentiment classifications. After the successful training of the proposed system, the sentimental analysis model can be used to test the custom data obtained from the real time twitter dataset. 0 to 1 is the range of output produced by the model where 0 indicates negative sentiments and 1 indicates positive sentiments. The major advantage of this proposed model is that it can understand the relationships between words. For example, it identifies that adding a word like "not" in front of a positive word "happy" would entirely contradict the meaning [7]. Furthermore the deep learning model also demonstrates its ability to accurately predict the sentiment of the word "uniquet" was not available in the provided training dataset, but that word is strongly correlated with the word "worry" which has been used very frequently, enabling the deep learning model to allocate a positive sentiment to it correctly. This illustrates the efficiency of the model and word embedding capability to generalise to undetected words. This study uses deep learning models as the hyperparameters like preprocessing setting or environment and training parameters for simulating the findings of the study. Table 2 demonstrates the confusion matrix of the deep learning based model which has the capability to enable accurate prediction of twitter sentiments.

Table 2. Confusion matrix

		Predicted positive	**Predicted negative**
		Positive (1)	Negative (0)
Actual positive	Positive (1)	True positive	False negative
Actual negative	Negative (0)	False positive	True negative

The "true negative" of the model predicts a negative sentiment whereas the actual sentiment was also expected to be negative. When the actual sentiment was indeed positive and predicted as positive then the model depicts "true positive". When the model fails to understand the positive sentiment and predicts it as "negative sentiment", this case gives a "false negative" output. Similarly, when the model mis-classifies the sentiment and produces "positive sentiment" and the actuarial sentiment is negative then it implies "false positive". These kinds of values are further used to calculate several evaluation metrics like Precision, Accuracy, F1 score and Recall. To assess the viability of our proposed deep learning-based opinion examination model for constant Twitter feelings, an intensive evaluation was directed. The model's exhibition was estimated utilising generally used benchmark datasets inside the sentiment analysis research society [10]. Table 3 shows the assessment measurements got from our investigation. With a precision of 0.85, the model exhibited its capacity to accurately group 85% of the tweets. Besides, the Precision score of 0.87 exhibited the model's fitness in precisely distinguishing positive and negative feelings. The recall score of 0.83 demonstrates that the model successfully found a large number of the positive and negative feelings. Moreover, the F1 score of 0.85 demonstrates a fair presentation among precision and recall.

Table 3. Model Evaluation Metrics

Metric	**Value**
Precision	0.87
Accuracy	0.85
F1 score	0.85
Recall	0.83

We recognize specific constraints of our review, for example, the dependence on the Twitter Programming interface for information assortment, which might present predispositions or impediments concerning the inclusion and representativeness of the information. The viability of opinion investigation models can differ contingent upon the specific points and spaces of the dissected tweets [3]. The human annotators' subjectivity in naming tweets with feeling extremity might present some level of comment commotion.

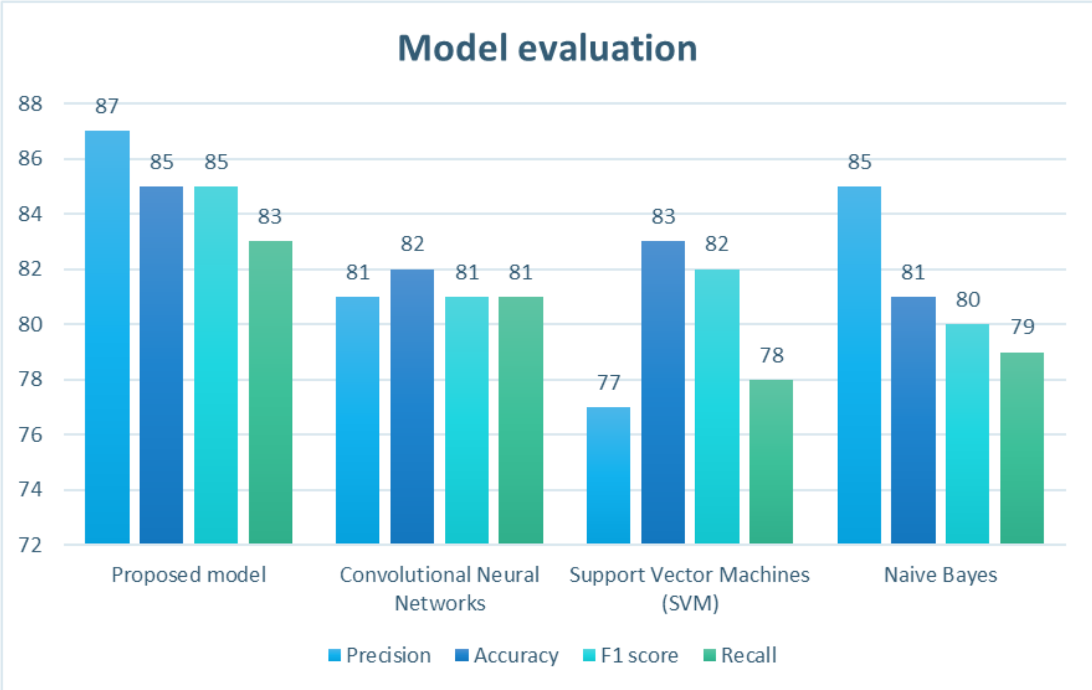

Figure 4. Model evaluation on the basis of Precision, Accuracy, F1 score and Recall.

The figure 4 contains a bar graph illustrating the performance of the different algorithms such as Convolutional Neural Networks, Support Vector Machines (SVM) and Naive Bayes. From figure 4, it can be noted that the deep learning based approach model (proposed model) has outperformed with evaluation metrics of other algorithms. The study deployed the same preprocessing procedures and datasets for accurate comparison. In addition to this, it should be noted that the selection of algorithms completely depends upon the objective of the sentimental analysis and the nature of the data used. Despite these factors, this comprehensive comparison provides a more accurate understanding of the performance of the proposed model.

The significant effect of word embeddings in boosting the capabilities of models is an important discovery from the study. A fundamental revelation from the examination underlines the outstanding impact of word embeddings in helping the model's abilities. By changing over words into thick vectors inside a multi-layered system, word embeddings really catch semantic affiliations and context oriented bits of knowledge, permitting the model to recognize nuanced opinions. The capacity of the model to accurately order feelings for concealed words exhibits the adequacy of word embeddings in speculation [1]. The bidirectional LSTM layers likewise assume an urgent part in catching the consecutive conditions in tweets. These layers empower the model to think about both past and future settings, working with a superior comprehension of the opinion communicated in a tweet. The bidirectional idea of the LSTM permits the model to use data from both going before and succeeding words, prompting further developed feeling investigation precision [14]. Moreover, our review features the significance of adjusting the preprocessing steps. The evacuation of commotion, like URLs, makes reference to, and stopwords, fundamentally works on the nature of the info information. Moreover, custom cleaning capabilities that handle incorrect spellings and contractions can additionally upgrade the model's exhibition. It is fundamental to adjust the preprocessing steps in view of the particular use case and target space to streamline opinion examination results [15].

Although our profound learning model shows empowering results, recognizing specific constraints is significant. The adequacy of the model is extraordinarily reliant upon the type and comprehensiveness of the preparation information. Any predispositions or uneven characters in the preparation information might actually block the model's ability to apply its learnings to different situations or populaces. Cautious curation and adjusting of the preparation information can assist with moderating such predispositions. Additionally, the model's precision might shift when applied to various dialects or spaces [10]. The concentrate essentially centres around opinion investigation of English tweets, and the model's presentation could contrast when applied to different dialects or explicit spaces with extraordinary phonetic qualities. The translation of feeling investigation results ought to be done warily. While our model gives certainty values, taking into account the abstract idea of feelings and the chance of misinterpretation is fundamental. Feeling examination is a difficult errand, and the model's forecasts ought to be utilised as a device to help human judgement instead of a conclusive measure [2]. To sum up, our examination grandstands the viability of utilising profound learning models to dissect feelings in Twitter information. By utilising word embeddings and bidirectional LSTM layers, the model shows the capacity to fathom unpretentious varieties in feeling and really handle new jargon. Notwithstanding, it is pivotal to know about limits connected with information inclinations, language conditions, and the abstract idea of opinions. Further exploration can investigate strategies to address these restrictions and extend the pertinence of opinion examination models to various dialects and spaces.

This study provides practical implications for organisations and businesses to obtain valuable insights for public sentiment, customer opinions and brand perceptions. This proposed methodology can be deployed in distinct fields like public relations, marketing and reputation management which allows well informed decision making and prompt responses to the consumer’s sentiments. Using deep learning the study advances sentiment analysis in social media data this illustrates the effectiveness of bidirectional LSTM layers and word embeddings in real time twitter dataset, allowing generalizability and negation to unfamiliar words. This feature allows the developed model to create advanced sentiment analysis techniques to accommodate various research in computational linguistics, social media analysis and opinion mining.

5. Conclusion and Future Research Directions

To analyse the real-time twitter data and perform sentiment analysis, this study has emphasised on deep learning models. The major objective of the study was to develop a highly efficient algorithm capable of identifying the sentiment polarity (negative, positive or neutral) of tweets. By elevating the advantages of neutral networks and training on a huge data of real time tweets, the study created a deep learning based-method which identified the contextual information and complex patterns available in social media data. The findings of the study illustrated the effectiveness of the proposed deep learning based-method in accurately categorising sentiments from twitter. The proposed approach obtained high performance and accuracy in overcoming the limitations of the informal and short nature of twitter. To understand the correlation among the words and to predict accurately, the model enables the use of word embeddings even for words which had not been experienced at the time of training. This inturn leads to exhibit the ability of the proposed model to provide a generalised informative insight. The findings acquired from this study improves the enhancement of sentiment analysis approach relevant to social media data, particularly considering the real time twitter sentiments feature. For various applications such as public opinion tracking, brand management, customer feedback analysis and reputation monitoring. The proposed model developed a valuable opportunity to obtain important insights, allowing business, researchers and business to make insightful decisions and immediate response to the progressing sentiments posted on twitter. On the successful implementation of the proposed model, there exists few limitations like consideration of irony, sarcasm, and context based sentiments, these can be improved through the implementation of more advanced techniques.

5.1. Limitations and future scope

The sentiment analysis of real-time Twitter data using deep learning models is subject to certain limitations. These limitations encompass dataset bias, generalizability across other platforms, management of language variations, limited emotion recognition, absence of real-time annotation, and ethical considerations. Dataset bias, generalizability to other platforms, and the need for tailored approaches are all factors that need to be addressed. Additionally, the study's focus on real-time Twitter sentiments may not accurately capture the dynamic nature of sentiments, making it difficult to accurately capture the temporal aspect. Addressing these limitations and exploring further research avenues will contribute to the advancement of sentiment analysis techniques for social media data. By addressing the capabilities and the challenges for real-time twitter data of sentiment analysis. The practical applications of social media analysis in advanced fields can be considered in future research. Future research on real-time tracking, comparative analysis, multilingual sentiments, domain-specific adaptation, user specific sentiment analysis and fine grained analysis can be

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emphasised in the study. This intends to solve privacy issues, and bias as well as enhance the sentiment analysis algorithms for focused insights.

6. Declaration

6.1. Author Contribution

Conceptualization: R.A.; Methodology: R.A.; Software: R.A.; Validation: R.A.; Formal Analysis: R.A.; Investigation: R.A.; Resources: R.A.; Data Curation: R.A.; Writing Original Draft Preparation: R.A.; Writing Review and Editing: R.A.; Author has read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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