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NEUMANN STACKED BILATERAL DEEP LEARNING BASED BIG SENTIMENT DATA ANALYTICS

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ABSTRACT

Sentiment analysis extracts information from several text sources like, blogs, reviews, news, and so on. The purpose of sentiment analysis on big data is to classify emotions or opinions into variegated sentiments. Conventional deep learning methods have been developed to classify the tweets. However, longer sentiment analysis time was considered. To address the issue, Neumann Mutual Informative and Stacked Bilateral Deep Learning (NMI-SBDL) for sentiment investigation is proposed to research products or services before making a purchase. First, through the tweets obtained from the Sentiment140 dataset, the Knowledge Sentimental Graph is constructed. Second, computationally-efficient dimensionality reduced tweets are generated by the Neumann Mutual Information-based Feature selection algorithm. Finally, the Stacked Bilateral LSTM-based model is utilized for classifying the tweet polarity. With this robust sentiment analysis is made by the Twitter Application Programming Interface (API) with higher accuracy and lesser computation time. Experimental assessment of the proposed NMI-SBDL and existing methods are carried out with different factors using Python libraries. The results of NMI-SBDL provided for improving the sentiment analysis accuracy, precision, recall and lesser time by 13%, 6%, 6%, and 23% than the existing approaches. The paper concludes with accurate and robust sentiment analysis for big data.

Keywords: *Big Data, Sentiment Analysis, Neumann Mutual Information, Feature Selection, Stacked Bilateral, Long Short-Term Memory*

1. INTRODUCTION

Sentiment investigation is an activity that analyzes the Feeling, Mood, Affect, Emotional state and Temperament of public from written language. In the big data period, having a significant sentiment investigation mechanism is requisite in several facets, specifically learning emotions. The impact of sentiment study has gored professional and even social broadcasting in this day and age. Due to the swift evolution of social mass media, the whole world can direct their emotional state and opinions via internet. Hence, the analysis of sentiment plays a crucial role in understanding the perspectives of consumers or reviewers. Furthermore, sentiment analysis serves as a vital tool for examining collective emotions within a community.

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A fusion deep culture method that integrated the advantages of classification model and Transformer model even though eliminating the disadvantages of system model, called, robustly optimized Bidirectional Encoder Representations from Transformers BERT approach (RoBERTa) and Long Short-Term Memory (LSTM) (RoBERTa-LSTM) was proposed in [1]. The integrated method RoBERTa-LSTM was proposed for sentiment study. The robustly optimized BERT condensed the arguments into a densely packed, meaningful word embedding space. The Long Short-Term Memory model on the other hand acquired the long-distance contextual semantics in an efficient manner.

With this integrated method, improvement was originated to be observed in relations of accuracy, precision, recall and F1-score. In spite of improvements observed in relations of Correctness rate, Exactness, Sensitivity and balanced precision with the incidence of different types of data deeper and more tweet patterns cannot be formed. To address this aspect, NMI-SBDL uses Neumann Mutual Information-based Feature selection. These tweets can be utilized via Knowledge Sentimental Graph for deeply extracting and discovering extensive and new tweet patterns in a computationally efficient manner (i.e., time and accuracy). With the graph, different types of tweets are associated that in turn support richer data services than word embedding space.

Sentiment investigation for demonetization twitters employing heuristic deep neural network (SenDemonNet) was proposed in [2]. The main objective here remained in apprehending the public view on currently deployed demonetization plan utilizing SenDemonNet. First, tweet preprocessing was performed for cleaning text data. Second, with the processed tweets, feature extraction was utilizing Bag of n-grams, TF-IDF, and the word2vec methodology. Finally, classification was performed using the fusion Forest–Whale Optimization Algorithm (F-WOA) with the objective of improving the classification outcome results, therefore reaching the maximum accuracy rate.

Though improvements being found in terms of accuracy, in domains where all time instances of the input sequence are available, with an optimization mechanism the performance of information retrieval system cannot be handled for big data. To address on this issue, Stacked Bilateral LSTM-based Sentiment analysis is employed in NMI-SBDL for handling the big data (Sentiment140 dataset) for classifying the tweets. Dimensionality reduced tweets as input is utilized in the Stacked Bilateral mechanism. The hyperbolic tangent activation function is employed for measuring the tweets. The Twitter data were analyzed both in the forward direction and backward direction for enhancing the performance of information retrieval in relation with higher precision and recall.

A cross convolutional neural network-long short-term memory (CNN-LSTM) model was planned in [3] for sentiment analysis. The CNN-LSTM method was performed using dropout, max pooling, and group normalization to obtain accurate sentiment analysis results. However, it failed to enhance the accuracy. To address the issue, an integration of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM)copies was presented in [4] with the purpose of performing opinion analysis in case of long texts. With this combination model resulted in an improvement of accuracy. However, the fake information was not detected in Twitter.

To address on this aspect, movement of information has switched to numerous various media overtime. In an epoch of digitization, information and events globally are transmitted predominantly via online social media (OSN) like, Instagram, Twitter, and Facebook and so on. Though transmission of information is said to take place globally, it causes an enormous menace of information falsification being shared by some people, therefore resulting in disruption and panic.

In [5], several classification methods were designed for classifying sentiment dataset. Moreover, Random Forest was applied that in turn improved the accuracy rate. The analysis of this sentiment data has massive potentiality in transposing the mode we slog but inherent statistics extraction is still found to be demanding. A modified Convolutional Neural Network (CNN) for analyzing Twitter facts was presented in [6] to extract features. By fine tuning the network resulted in the improvement of classification accuracy. However, with the

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imbalance nature of dataset would result in either overfitting or under fitting. To address on this aspect, a hybrid method integrating Support Vector Machine (SVM) algorithm and Particle Swarm Optimization (PSO) stood designed in [7]. With this integration pattern imbalanced data issue was addressed. However, the social network reliability was not measured.

To address this aspect, the interference of counterfeit news contributors and bots results in proliferating publicity statistics as well as delicate content via network has stimulated exploration to evaluate social network reliability in an automatic manner by employing Artificial Intelligence (AI). In [8], the multilingual model for both identification in Twitter using DL methods was proposed for measuring the twitter account credibility. But it failed to consider different applications. To address the issue, a survey on sentiment classification employing DL was investigated in [9] along various evaluation measures were also conducted. Yet another work on general domain tweets was analyzed in [10]. However, the false positive rate was not measured.

To overcome the problem, a Knowledge Sentimental Graph is presented in the proposed NMI-SBDL to explicitly provide a User-Tweet pair. Additionally, instead of only selecting the essential tweets dimensionality reduction factor is considered with minimum time that in turn eliminates the edges. Therefore, reducing the graphs, we synergistically combine the dimensionality reduced tweets with anchor points for analyzing the polarity to obtain richer feature representations and significantly enhance the sentiment analysis performance, accuracy, and minimize the false positive rate.

1.1 Contributions

The principal contributions of this paper include:

- To present a detailed description of the Neumann Mutual Informative and Stacked Bilateral Deep Learning (NMI-SBDL) method that performs sentiment analysis with respect to a query term.
- To design an algorithm for implementing feature selection by employing Neumann Mutual Information-based Feature selection algorithm for discarding irrelevant tweets with dimensionality reduced computationally efficient relevant tweets associated with sentiment analysis that can be utilized as an input to classifiers.
- To offer a precise sentiment analysis classification typical to classify tweet sentiment employing Stacked Bilateral LSTM-based Sentiment analysis algorithm.
- Experiments are conducted on the benchmark Sentiment140 dataset to present judgment with the predictable and state-of-the-art sentiment analysis method. The results indicate that the proposed approach is resilient and performs competitively in terms of time, accuracy, precision, and recall.

1.2 Outlines

The remainder of this paper is structured as follows. Section 2 initially provides the connected work in the domain of sentiment analysis. Section 3 elaborates on the proposed Neumann Mutual Informative and Stacked Bilateral Deep Learning (NMI-SBDL) for sentiment analysis in detail. Section 4 presents the experimental settings for designing the NMI-SBDL method in specific. Section 5 grants the evaluation metrics and debate in expound. Finally, Section 6 achieves the paper.

2. RELATED WORKS

A popular social networking site Twitter tweets each second about numerous topics concerning, society, politics, sports, entertainment, and numerous more has received the attention of the research community. Keeping an eye on user postings permits one to apprehend the news that is happening globally and also assists in analyzing people's opinions to a greater extent.

A holistic approach for analyzing fluctuation concerning public opinion was presented in [11]. Yet another in-depth analysis of sentiment via public opinions and emotions was investigated in [12]. Unsupervised machine learning algorithms were employed for extracting tweets. An ensemble voting classifier was introduced for forecasting the retweetability of the posted tweets. But the time was higher.

On several social media sites, students debate and measure their day-to-day experiences in an unofficial and unintended manner. In this context, the paths taken by students provide significant implicit knowledge and offer a comprehensive and novel perspective for researchers and experts to understand students' behaviors beyond the classroom setting. An arrangement to combine one and the other qualitative study and large-scale facts mining algorithms was proposed in [13] for analyzing social data. However, the big data sentiment analysis challenges were not considered.

In order to address the issue, the implementation of judgment mining and sentiment scrutiny (OMSA) in the epoch of big data has been utilized as a convenient method in classifying the view into distinct sentiments and to be more specific measuring the public mood. A holistic systematic literature review to focus on both the technical and non-technical characteristics of OMSA was discussed in detail in [14].

The evolution of information technologies has provided new insights into intelligence via human-centric meaning and that can be as straightforward as stated by review or questionnaire. The speedy magnification rate of such large data produces several origins of subjective information. Sentiment analysis has found a place as an active topic as far as information retrieval is concerned.

The correlative acceptance of numerous Hashtags and the field possessing maximum share voice were analyzed in [15] using Jaccard similarity. With this mechanism, the accuracy rate was said to be improved. However, on convoluted training data, hybrid methods may minimize the sentiment mistakes. To address the issue, the trustability of different hybrid methods on heterogeneous datasets was provided in [16]. Beyond domains and datasets, hybrid methods were compared in analogous to single methods. With this hybrid method design accuracy was found to be improved.

In [17] the application of DL techniques for social media analytics was investigated in depth. But the accuracy was not focused. To overcome the issue, the Q-learning technique was applied in [18] for predicting Bitcoin. Simulations showed the tweets posted by users had an impact on future prices, therefore reducing spending time and CPU consumption. Nevertheless, it failed to consider the recall.

A methodical literature analysis on document-based sentiment scrutiny using DL was designed in [19]. But it failed to consider accuracy. The ensemble deep culture model was proposed in [20] to concentrate on the classification accuracy involved in the process of social media sentiment analysis. However, the features are not extracted with higher classification performance. In [21] Covid-19 Twitter was analyzed using deep learning. Here, classification between positive, negative, and neutral tweets was performed to address the precision factor. Yet another reasonable analysis of deep learning algorithms in predicting products' influential factors was analyzed in [22]. However, the classification performance was not improved.

Over the past few years, Gated Recurrent Neural Networks have found their usage in classifying the sentiment owing to their potentiality to safeguard semantics over a period of time. Despite their preservation, negation and intensification using recurrent architecture were found to be a demanding issue. In [23], sentimental relation examination using a gated recurring neural network was proposed with the purpose of capturing sentimental relations for higher classification performance. Using natural language dealing out sentiment analysis was performed in [24]. But it failed to consider large datasets with less time. A majority voting process was applied in [25] for twitter sentiment analysis employing cooperative binary cluster model. However, the preprocessing was not considered.

2.1 Problem Statement

Recent developments in sentiment analysis have led to the growth of the promotion and selling of numerous products and services via the internet using new deep learning procedures. By employing deep learning-based techniques, a classification algorithm is trained with the assistance of distinct features in tweets that can differentiate between worthiness of products and therefore contribute to business development on the overall economy and making wise decision during purchase for consumers. These features or tweets obtained from the Sentiment140 dataset are extracted and analysis is made for customer

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satisfaction. The existing deep learning-based methods [1] [2] extracted features with higher accuracy but the time involved in case of big data was not focused. Also, prediction characteristics of recall and precision were not concentrated in state-of-the-art methods, [3] [4] therefore thousands of fake products or services are mushrooming every day. Therefore, there is a requirement to design a significant method for analyzing sentiments in a precise and accurate manner and also for discarding negative tweets.

2.2 Proposed Solution

To solve above said problem, this paper presents a deep learning-based Neumann Mutual Informative and Stacked Bilateral Deep Learning (NMI-SBDL) for sentiment analysis that selects computationally efficient and dimensionality reduced tweets and enhances the precision and recall rate. The paper boon a model is to detect essential tweets with the aid of tweet information present in the Sentiment140 dataset. The proposed method selects the tweets and analyzes them to detect whether the given tweets are essential or not via a robust classification model in determining the product worthiness. Also, the accuracy and sentiment analysis performance are improved and time is minimized.

3. PROPOSED NEUMANN MUTUAL INFORMATIVE AND STACKED BILATERAL DEEP LEARNING FOR SENTIMENT ANALYSIS

Sentiment Big Data analytics is referred to as the automated interpretation and classification of tweet polarities (i.e., neutral, positive, or negative) from social media posts or huge amount of incoming data. The objective that Sentiment Big Data analytics attempts to achieve is to scrutinize people's point of view in a way that it can assist the organizations develop. It concentrates besides polarity (i.e., neutral, positive, negative) but also used to detect sentiments. In this work, a method called, Neumann Mutual Informative and Stacked Bilateral Deep Learning (NMI-SBDL) for sentiment analysis is proposed to expand accuracy in a timely manner to identify sentiment polarity. The intricate description of the NMI-SBDL method is provided followed by data collection and problem formulation.

3.1 Data Collection

The efficiency of the planned method is measured using Sentiment140 dataset extracted as ofhttps://www.kaggle.com/kazanova/sentiment140. The tweets are gathered to evaluate the tweet polarity i.e., negative, neutral, or positive on tweets extracted by utilizing the twitter Application Programming Interfaces (APIs). The Sentiment140 dataset is acquired by carrying out the following steps:

- Twitter Search Plan of action: All user tweets were extracted and stockpiled employing APIs.
- Hashtags selection: the hashtags that are related to the selected user tweet events are provided in Table 1.

Tweets collection: User tweets are stockpiled employing the tabulated hashtags. The tweets collected and extracted from distinct users based on Tweet ID are straightforwardly made accessible for further processing. The structure of the dataset is presented in Table 1.

Table 1: Structure of Sentiment140 data collection

S. No	Information	Description
1	Tweet size	1,600,000 tweets
2	Tweet annotation	0 – negative; 2 – neutral, 4 – positive
3	Field size	6 fields
4	Used Hashtags	@nationwide class no, it's not behaving at all, I'm mad, why am I here? because I can't see you all o…

1.1 Issue Articulation

In this segment, we initially express the job of the proposed method in a mathematical manner by constructing a Knowledge Sentimental Graph (KSG). The Knowledge Sentimental Graph interlinks data that are in the form of unstructured in to a meaningful manner. The KSG is a triple '(E, R, F)' where '$E = \{e_1, e_2, \dots, e_m\}$' represents the entity set, '$R = \{r_1, r_2, \dots, r_k\}$' represents the relationship set and finally 'F' denotes the relationship between entities respectively. Let us consider we have a User-Tweet pair '(U, T)', where '$U = \{U_1, U_2, \dots, U_m\}$' means the '$m$' users tweeted and '$T = \{T_1, T_2, \dots, T_n\}$' means the '$T$' tweets that has been made by the corresponding users.Then, the User-Tweet pair '(U, T)' here represents the entity set, the relationship between User-

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Tweet are denoted relationship set and finally, the relationship between these two forms the fact. The objective of the proposed method remains in predicting tweet polarity '$y \in \{0,2,4\}$', where '0', '2' and '4' means the negative, neutral and positive sentiment polarities, separately. The development of KSG relies on its entities (alternatively called nodes) and their interactions with other elements, represented in the form of a diagram. Every entity (referred to as nodes or users) has the capability to exchange information with other entities (nodes or users). Figure 1 shows simple KSG structure where two nodes or users denote distinct entities.

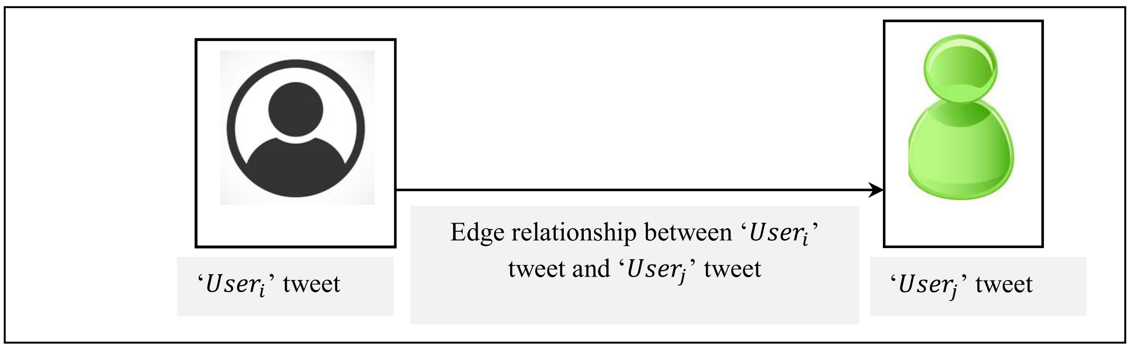


Figure 1: KSG structure with two entities and its relationship

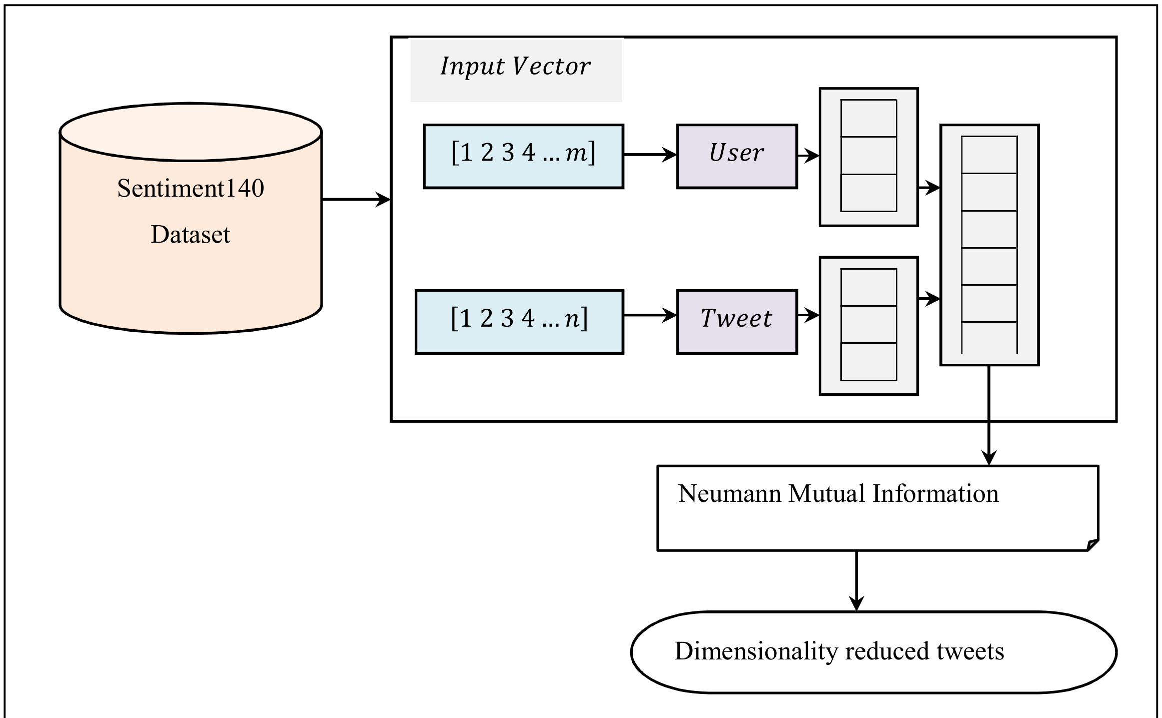
As shown in the above figure, there is an association among these dual nodes or users that signifies their rapport. The primary node or user 'i' denotes the subject whereas the second node or user 'j' denotes the object, and their relationship (i.e., between user 'i' and user 'j') is referred to as the predicate.

1.2 Pre-Processing

The pre-processing of the fresh tweets extracted by using the APIs necessitates elimination of characters that do not assist in detecting Sentiment. Some of the unwanted characters range from HTML characters to special character "@",URL, and hashtags, case sensitive, long words elimination, stop word elimination.

1.3 Neumann Mutual Information-based Feature selection

With the processed tweets essential features or tweets have to be selected by reducing the dimensionality so that accuracy can be improved with minimum error rate. In this work, the Neumann Mutual Information-based Feature selection norms for Knowledge Sentimental Graph (KSG) graphs are utilized. This criterion is applied after KSG construction and preprocessing for the tweets in the training process. With the application of dimensionality reduction eliminates the edges, therefore reducing the graphs size. Figure 2 shows the construction of Neumann Mutual Information-based Feature selection model.



As exposed in the directly above diagram with the Sentiment140 dataset providing as input, initially, input vector is formulated (i.e., user-tweet pair). Next, with the input vector is subjected to average quantum to produce dimensionality reduced tweets. Let us first formulate the input vector as given below.

$$IV = \begin{bmatrix} U_1T_1 & U_1T_2 & \dots & U_1T_n \\ U_2T_1 & U_2T_2 & \dots & U_2T_n \\ \dots & \dots & \dots & \dots \\ U_mT_1 & U_mT_2 & \dots & U_mT_n \end{bmatrix} \quad (1)$$

From the above equation (1), the input vector 'IV' is formulated based on the 'm' users and 'n' tweets. The Neumann Mutual Information between User-Tweet pair '(U,T)' for a probability distribution of two users 'U_i', 'U_j' is mathematically stated as given below.

$$Prob\ (U_i) = \sum_{U_j} Prob\ (U_i, U_j) \quad (2)$$

$$Prob\ (U_j) = \sum_{U_i} Prob\ (U_i, U_j) \quad (3)$$

Let us consider a quantum system that can be split into two portions, 'U_i' and 'U_j', with the purpose of making independent measurements to be made on either portion. Then, the state space of the entire quantum is formulated as given below.

$$H_{U_iU_j} = H_{U_i} \otimes H_{U_j} \quad (4)$$

From the above state space of the entire quantum, let us consider '$\rho^{U_iU_j}$' the user density matrix, then the corresponding operation for user 'U_i' density matrix is represented as given below.

$$\rho^{U_i} = Tr_{U_j} \rho^{U_iU_j} \quad (5)$$

In a similar manner, the corresponding operation for user '$\rho^{U_iU_j}$'density matrix is mathematically represented as given below.

$$\rho^{U_j} = Tr_{U_i} \rho^{U_iU_j} \quad (6)$$

Finally, the average quantum mutual information with dimensionality reduced tweets in the corresponding state space is mathematically formulated as given below.

$$DRT = SS(\rho^{U_iU_j} || \rho^{U_i} \otimes \rho^{U_j}) \quad (7)$$

As given in the above equation (7), for every edge, average quantum mutual information is measured, and if found to be smaller than threshold, then the edge is discarded and on contrary, the edge is retained for further processing. The virtual code representation of

Neumann Mutual Information-based Feature selection is given below.

Input: Dataset 'DS', Features '$F = \{F_1, F_2, \dots, F_n\}$', entity '$E = \{e_1, e_2, \dots, e_m\}$', relationship set '$R = \{r_1, r_2, \dots, r_k\}$', Tweets '$T = \{T_1, T_2, \dots, T_n\}$'
Output: Computationally-efficient dimensionality reduced tweets
Step 1: Initialize 'm', 'n', 'k' Step 2: Begin Step 3: For each Dataset 'DS' with Features 'F' Step 4: Formulate the input vector as give in equation (1) Step 5: For each User-Tweet pair '(U, T)' Step 6: Evaluate probability distribution of two users 'U_i', 'U_j' as given in equations (2) and (3) Step 7: Model state space of the entire quantum as given in equation (4) Step 8: Evaluate user 'U_i' density matrix as given in equation (5) Step 9: Evaluate user 'U_j' density matrix as given in equation (6) Step 10: Return dimensionality reduced tweets 'DRT' as given in equation (7) Step 11: End for Step 12: End for Step 13: End

Algorithm 1: Neumann Mutual Information-based Feature selection

As outlined in the algorithm immediately above, given the dataset and features as input, the initial step involves formulating the input vector based on the Knowledge Sentimental Graph. Second, for each User-Tweet pair, probability distribution of two user's tweets separately is obtained. Next, state space of the entire quantum with respect to User-Tweet pair is formulated with which the density matrix is obtained separately for each user. Finally, average quantum mutual information is evaluated to obtained dimensionality reduced tweets.

1.4 Stacked Bilateral LSTM-Based Sentiment Analysis Using Dimensionality Reduced Tweets

In this section, we introduce a sentiment analyzer for Twitter sentiment classification in social media posts based on Stacked Bilateral Long Short-Term Memory (LSTM). The LSTM architecture enables the network to capture long-term relationships through the use of forget and remember gates, allowing the cell to decide whether to retain or discard tweets based on their strength and relevance. The Stacked Bilateral in our work represents the analysis of sentiments in both the forward and backward direction for robust representation and are then stacked, therefore producing the final output for classification. Figure 3 shows the structure of Stacked Bilateral LSTM-based Sentiment analysis model.

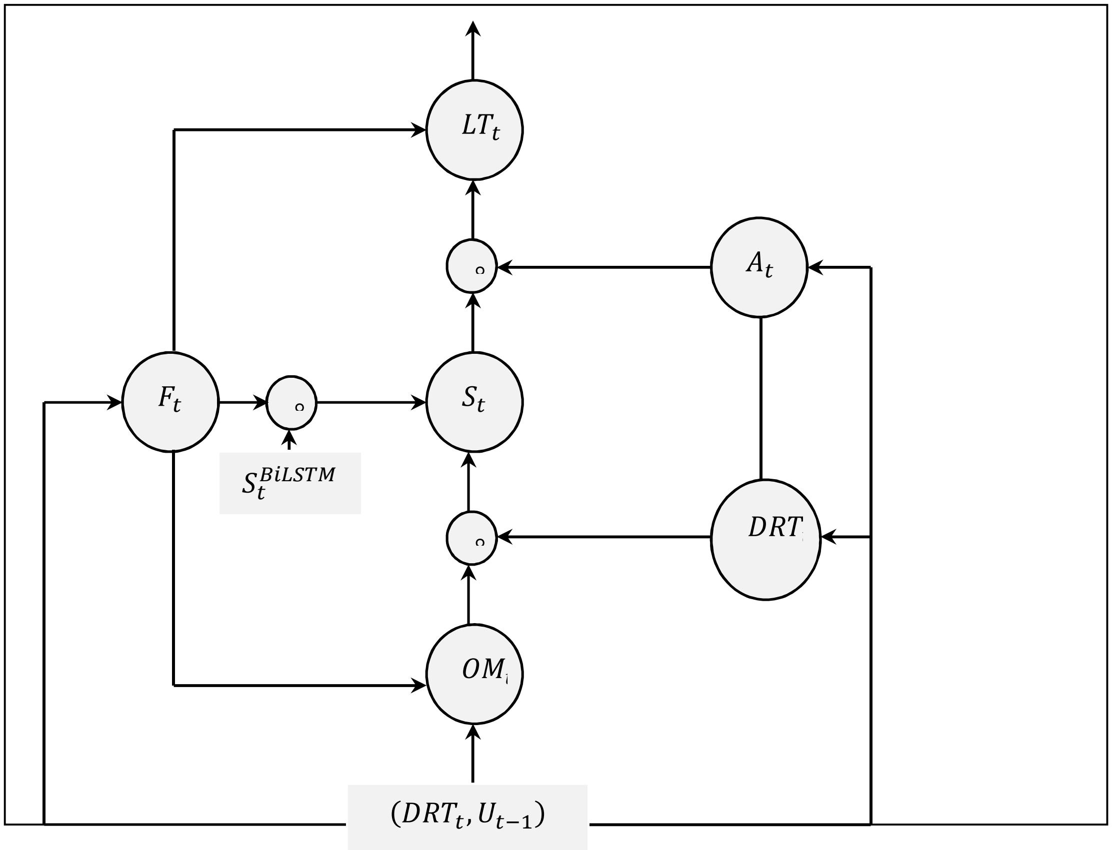


Figure 3: Stacked Bilateral LSTM cell gates-based sentimental analysis

As shown in the above figure, with the social media twitter post as discussed above is initially tokenized according to Knowledge Sentimental Graph and then dimensionality reduced tweets are generated. With the generated tweets are then fed as input into the embedding layer that translates the tweet tokenish into the crypto tweet implanting. The LSTM is ultimately trained by utilizing the sequence of crypto tweets as input. A fully connected layer is employed to process the output of the LSTM, and it is activated with the sigmoid function to produce the final output estimates. The labels of the posts used for training were categorized and encoded as negative ('0'), neutral ('2'), and positive ('4') respectively.

Let us consider the new contribution acknowledged by the neuron at time instance 't' be denoted as 'DRT_t' Then, the input 'DRT_t' is the dimensionality reduced data agreed through the input gate via hyperbolic tangent activation role. At this time instance 't', the neuron encompasses both the long-term memory 'LT' (i.e., 'LT_{t-1}') and the operating memory 'OM' (i.e., 'OM_{t-1}') from prior time instance 't'. On one hand the dimensionality reduced tweets in the long termmemory refers to the tweet instances that are used for the whole training process and on the other hand, the dimensionality reduced tweets in the operating memory refers to the tweet instances that are utilized in a preferential manner. With these 'DRT_t', 'LT_{t-1}' and 'OM_{t-1}', forget gate is constructed that establishes the tweets to be retained and tweets to be discarded. The forget gate is mathematically stated as given below.

$$F_t = \sigma(W_F DRT_t + U_F OM_{t-1}) \tag{8}$$

From the above equation (8), forget gate at time instance 't', 'F_t' is evaluated based on the sigmoid activation function 'σ', weights 'W_F' analogous to input dimensionality reduced tweets 'DRT_t' and weights 'U_F' analogous to operating memory 'OM_{t+1}' respectively. Next, the neuron evaluates essential tweets 'LT'' from 'DRT_t', and is mathematically obtained as given below.

$$LT' = \varphi(W_{LT} DRT_t + U_{LT} OM_{t-1}) \tag{9}$$

From the above equation (9), 'φ' denotes the hyperbolic tangent initiation function. In precedence with the inclusion of 'LT'', to the memory cell, the neuron estimates the tweets that are useful for saving 'S' in the memory cell. The neuron here while saving the estimated tweets in the memory cell is read only in one forward direction. In our work, both forward direction and backward direction are taken into considered and the outputs are stacked together. This is mathematically expressed as given below.

$$S_t = \sigma(W_S DRT_t + U_S OM_{t-1}) \quad (10)$$
$$S_t^{BiLSTM} = S_t^{forward} \oplus S_t^{backward} \quad (11)$$

With the above resultant tweets saved in the memory as evaluated in (10) and (11), the tweets in the long-term memory are updated as given below.

$$LT_t = F_t \circ LT_{t-1} + S_t^{BiLSTM} \circ LT_t \quad (12)$$

From the above equation (12), '$\circ$' denotes the element-wise growth applied for the tweets presents in the long-term memory for sentiment analysis. Finally, the operation memory 'OM' at instance 't' is updated as given below.

$$A_t = \sigma(W_t DRT_t + U_t OM_{t-1}) \quad (13)$$

$$OM_t = A_t \circ \varphi(LT_t) \quad (14)$$

From the above equations (13) and (14), the anchor point 'A_t' is a tertiary vector that will regulate the significance of tweets. The neuron here by applying hyperbolic tangent on long-term memory accomplishes element-wise multiplication with the 'A_t' for updating tweets in operation memory 'OM_t'. Upon successful updates performed in both the long-term memory and operation memory at instance 't', the neuron (i.e., user) will identify what tweets to be outputted to other neurons to enhance learning process. The complete procedure is said to be iterated until no more input data is present in the neuron. The pseudo code illustration of Stacked Bilateral LSTM-based Sentiment analysis is given below.

Input: Dataset 'DS', Features '$F = \{F_1, F_2, \dots, F_n\}$', entity '$E = \{e_1, e_2, \dots, e_m\}$', relationship set '$R = \{r_1, r_2, \dots, r_k\}$', Tweets '$T = \{T_1, T_2, \dots, T_n\}$'
Output: Robust sentiment analysis
Step 1: Initialize dimensionality reduced tweets 'DRT' Step 2: Initialize 'm', 'n', 'k' Step 3: Begin Step 4: For each Dataset 'DS' with Features 'F' and dimensionality reduced tweets 'DRT' Step 5: Formulate forget gate as given in equation (8) Step 6; Evaluate essential tweets using hyperbolic tangent activation function as given in equation (9) Step 7: Evaluate tweets that are useful for saving in the memory cell both in the forward and backward direction as given in equations (10) and (11) Step 8: Update tweets in long term memory as given in equation (12) Step 9: Evaluate the anchor point for analyzing the polarity as given in equations (13) and (14) Step 10: If '$A_t = 0$' Step 11: Then tweet polarity is negative Step 12: Return polarity result Step 13: End if Step 14: If '$A_t = 2$' Step 15: Then tweet polarity is neutral Step 16: Return polarity result Step 17: End if Step 18: If '$A_t = 4$' Step 19: Then tweet polarity is positive Step 20: Return polarity result Step 21: End if Step 22: End for Step 23: End

Algorithm 2: Stacked Bilateral LSTM-based Sentiment analysis

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As outlined in the algorithm above, the goal is to enhance the ratio of accurately predicted positive observations and improve the proportion of pertinent tweets acquired for sentiment analysis. To achieve this, an LSTM-based neural network with a Stacked Bilateral mechanism is devised. Through the application of the Stacked Bilateral mechanism, the input-dimensionality-reduced tweet undergoes processing in the neural network from the start to the end and then iteratively from the end to the start. This approach accelerates the learning and analysis of sentiment, leading to an improvement in the network's accuracy in correct sentiment analysis and a reduction in incorrect sentiment analyses.

4. EXPERIMENTAL SETUP

Within the realm of extensive sentiment data analysis, the openly accessible Sentiment140 dataset is employed. This dataset encompasses 1,600,000 tweets extracted using the Twitter API. The tweets are categorized with annotations such as '0 = negative,' '2 = neutral,' and '4 = positive,' making them suitable for sentiment detection. Refer to Table 2 for specific details regarding the dataset.

Table 2: Details of Sentiment140 dataset

S. No	Information	Description
1	Tartet	Tweet split (0 = negative, 2 = neutral, 4 = positive)
2	Ids	Tweet ID
3	Date	Tweet date
4	Flag	Query
5	User	User that tweeted
6	Text	Tweet text

With the aid of the above features, four performance metrics, accuracy, time, precision and recall rate are exploited to measure the presentation of our proposed method, Neumann Mutual Informative and Stacked Bilateral Deep Learning (NMI-SBDL) for sentiment analysis comparing with conventional methods, Robustly optimized Bidirectional Encoder Representations from Transformers BERT approach (RoBERTa) and Long Short-Term Memory (LSTM) (RoBERTa-LSTM) [1], SenDemonNet [2] and other state-of-the-art sentiment analysis methods CNN-LSTM[3] and CNN-BiLSTM [4]. The procedures were implemented using Python, a high-level, general-purpose programming language.

5. DISCUSSION

5.1 Performance Analysis of Sentiment Analysis Accuracy

The primary parameter required for sentiment analysis using twitter is the accuracy rate. In other words, sentiment analysis accuracy states to the statistical measure of how well a twitter training sentiment analysis test correctly identifies or excludes a condition.

$$SA_{acc} = \sum_{i=1}^{n} \frac{T_{AC}}{T_i} * 100 \qquad (15)$$

Derived from the equation (15), the accuracy of sentiment analysis, denoted as 'SA_acc,' represents the percentage ratio of sample tweets accurately assessed or classified as 'T_AC' to the total sample tweets involved in the simulation process denoted as 'T_i.' It is measured in terms of percentage (%). Table 3 summarizes the sentiment analysis accuracy involved in the sentiment analysis using two conventional methods, RoBERTa-LSTM [1], SenDemonNet [2], state-of-the-art methods, CNN-LSTM [3]and CNN-BiLSTM [4] respectively.

Table 3: Comparative analysis of sentiment analysis accuracy using Proposed NMI-SBDL, RoBERTa-LSTM [1], SenDemonNet [2], CNN-LSTM [3] and CNN-BiLSTM [4]

Number of Tweets	Sentiment analysis accuracy				
	NMI-SBDL	RoBERTa-LSTM	SenDemonNet	CNN-LSTM	CNN-BiLSTM
1000	97.5	94.5	93	92.7	91.5
2000	97.15	93.15	91	90.15	88.55
3000	96.85	92	91.15	89.15	85
4000	96.35	91.75	90	87	83.15
5000	96	91.35	88.35	85.25	80
6000	95.15	91	86	82	78.55
7000	95	88	84.35	80.25	75
8000	93.25	87.55	83	78	73
9000	93	87	81.55	75.35	72.55
10000	91	86.25	78	72	70

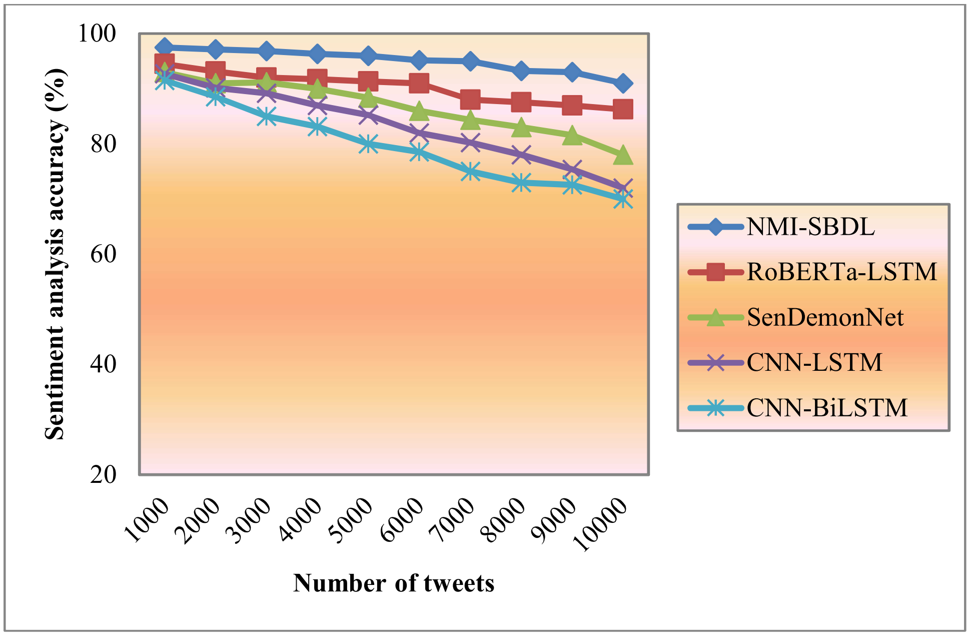

Figure 4: Graphical representation of sentiment analysis accuracy

Figure 4 portrays the relative performance of twitter sentiment studyof two conventional methods, RoBERTa-LSTM [1], SenDemonNet [2], state-of-the-art methods, CNN-LSTM [3]and CNN-BiLSTM [4] respectively in relations of accuracy. From the figure it is contingent that the sentiment analysis accuracy in the y-axis and number of tweets in the x-axis are both found to be in reverse proportional with each other. To be more specific, growing the number of tweets causes decreases in the sentiment analysis accuracy and vice versa. But simulations accomplished with 1000 tweet samples the sentiments accurately evaluated using NMI-SBDL method was found to be 97.5%, 94.5% when used with [1], 93% when used with [2], 92.7% when used with [3] and 91.5% when used with [4]. From this result, the sentiment analysis accuracy was found to be improved using NMI-SBDL method when compared to [1], [2], [3] and [4]. The reason behindhand the development was due to the employment of Knowledge Sentimental Graph for each User-Tweet pair that evaluates space of the entire quantum. Finally, by employing average quantum mutual information dimensionality reduced tweets were obtained with which the classification is made for further processing. This in turn progresses the sample tweets accurately being estimated using NMI-SBDL method. As a result, the sentiment analysis accuracy using NMI-SBDL method was said to be improved by conventional methods by 5% in comparison to [1] and 10% in comparison to [2], improved by state-of-the-art methods by 15% in comparison to [3] and 20% in comparison to [4] correspondingly.

5.2 Performance Analysis of Sentiment Analysis Time

The evaluation of tweet polarity extracted through the tweet API is reported to require a short amount of time. In other words, sentiment analysis time refers to the time used up in acquiring the user's tweets and analyzing the same based on the tweet polarity. This is mathematically formulated as given below.

$$SA_{time} = \sum_{i=1}^{n} T_i * Time\ [A_t] \qquad (16)$$

From the above equation (16), sentiment analysis spell 'SA_{time}' is estimated based on the user tweet samples intricate for analyzing sentiments 'T_i' and the time consumed in arriving at the anchor point 'A_t' is a tertiary vector that will determine the significance of tweets '$Time\ [A_t]$'. This is restrained in terms of milliseconds (ms). Table 4 recaps the sentiment analysis time tangled in the sentiment analysis using two conventional methods, RoBERTa-LSTM [1], SenDemonNet [2], state-of-the-art methods, CNN-LSTM [3]and CNN-BiLSTM [4] respectively.

Table 4: Comparative analysis of sentiment analysis time using Proposed NMI-SBDL, RoBERTa-LSTM [1], SenDemonNet [2], CNN-LSTM [3] and CNN-BiLSTM [4]

Number of Tweets	Sentiment analysis time (ms)				
	NMI-SBDL	RoBERTa-LSTM	SenDemonNet	CNN-LSTM	CNN-BiLSTM
1000	250	320	370	440	500
2000	315	355	395	465	515
3000	335	385	425	495	535
4000	385	405	448	550	590
5000	415	440	515	585	625
6000	435	455	585	625	650
7000	485	515	615	655	685
8000	525	585	635	685	735
9000	550	600	680	730	780
10000	600	625	715	755	815

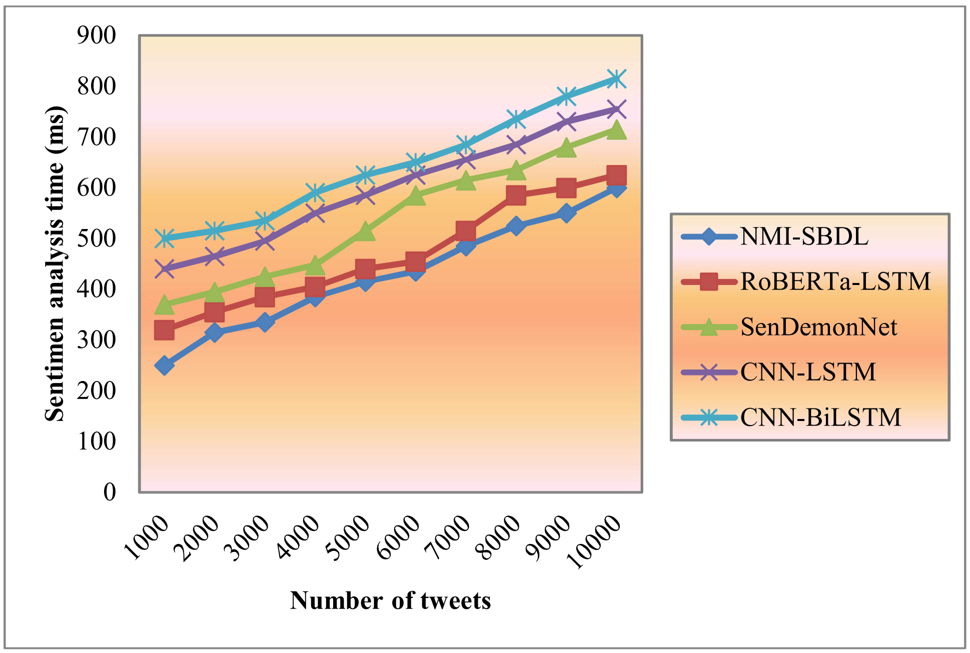

Figure 5: Graphical representation of sentiment analysis time

Figure 5 illustrates the comparative efficiency of Twitter sentiment analysis among two conventional approaches, RoBERTa-LSTM [1] and SenDemonNet [2], as well as two state-of-the-art methods, CNN-LSTM [3] and CNN-BiLSTM [4], with respect to sentiment analysis time. The y-axis represents sentiment analysis time, and the x-axis displays the number of tweets. The figure indicates a direct proportionality between the number of tweets and the performance of sentiment analysis. Specifically, an increase in the number of tweets correlates with improved sentiment analysis performance for Twitter, consequently leading to an increase in sentiment analysis time. In simulations conducted with 1000 tweets, the time required for analyzing Twitter sentiment using the NMI-SBDL method was observed to be 250 ms, 320 ms for [1], 370 ms for [2], 440 ms for [3], and 500 ms for [4]. From this result, the sentiment analysis time was observed to be comparatively lesser using [1], [2], [3] and [4]. The enhancement can be attributed to the inclusion of Bayes Linear Regression before the actual feature selection process. With this type of regression, the proposed method utilizes a Neumann Mutual Information between User-Tweet pair for a probability distribution of two users for

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estimating the independent measurements. As a result, the sentiment analysis time for capturing user tweets and detecting sentiment using the NMI-SBDL method is decreased by 9% when compared to [1], 21% when compared to [2], 29% when compared to [3], and 34% when compared to [4], respectively.

5.3 Performance Analysis of Precision

The precision rate is defined as the ratio of relevant instances (i.e., analyzed relevant tweets) to retrieved instances (i.e., retrieved tweets) in sentiment detection. Mathematically, this is expressed as follows:

$$P = \frac{TP}{TP+} \tag{17}$$

From the above equation (17), the precision rate 'P' is evaluated on the basis of the true positive instances 'TP' (i.e., positive tweets detected as positive tweets) and the false positive instances 'FP' (i.e., positive tweets detected as negative tweets) respectively. Table 5 summarizes the prediction rate involved in the sentiment analysis for the sample tweets using two conventional methods, RoBERTa-LSTM [1], SenDemonNet [2], state-of-the-art methods, CNN-LSTM [3]and CNN-BiLSTM [4] respectively.

Table 5: Comparative analysis of precision using proposed NMI-SBDL, RoBERTa-LSTM [1], SenDemonNet [2], CNN-LSTM [3] and CNN-BiLSTM [4]

Number of Tweets	Precision				
	NMI-SBDL	RoBERTa-LSTM	SenDemonNet	CNN-LSTM	CNN-BiLSTM
1000	0.96	0.94	0.92	0.9	0.88
2000	0.94	0.92	0.91	0.89	0.87
3000	0.93	0.91	0.9	0.87	0.86
4000	0.93	0.91	0.88	0.86	0.84
5000	0.91	0.89	0.86	0.85	0.83
6000	0.91	0.87	0.86	0.84	0.82
7000	0.9	0.87	0.84	0.83	0.82
8000	0.89	0.86	0.83	0.83	0.81
9000	0.87	0.85	0.83	0.82	0.81
10000	0.87	0.83	0.83	0.81	0.8

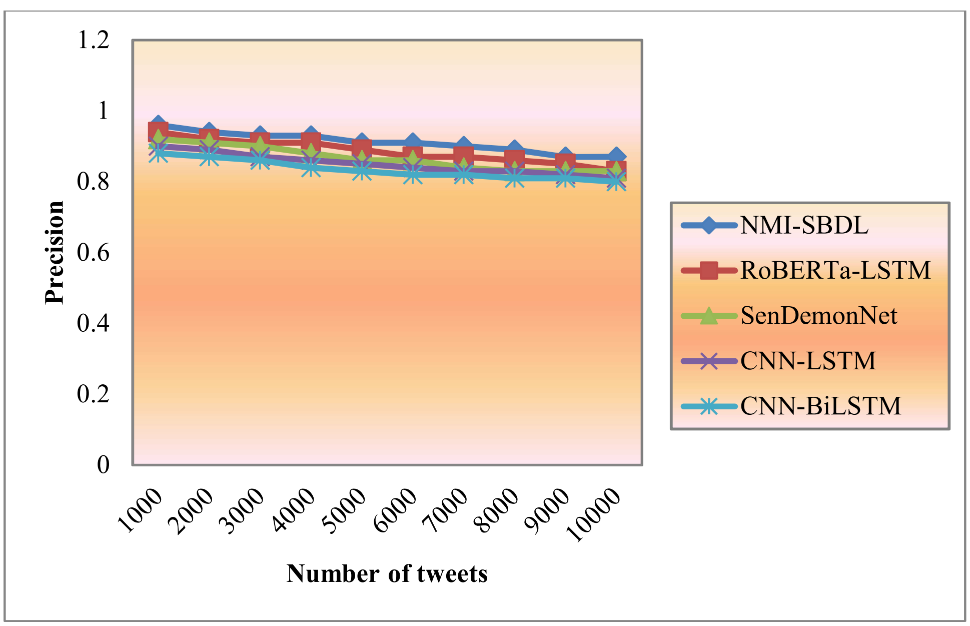

Figure 6 :Graphical representation of precision

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Figure 6 given above illustrates the graphical representation of precision for 10000 distinct sample tweets to detect sentiment. From the above figure it is inferred that the precision rate was found to be comparatively higher using NMI-SBDL method upon comparison with two conventional methods [1], [2], and state-of-the-art methods [3] and [4]. The increase in the precision rate using NMI-SBDL method was lesser than [1], [2], [3] and [4]. The reason behind the minimization of false prediction results was due to the application of Stacked Bilateral LSTM cell for sentiment analysis. By applying this mechanism, traversal for sentiment analysis using the tweets were made both in the forward direction and backward direction. Therefore, for classification both the long short term memory results in addition to operation memory results were utilized for analysis purpose. As a result, the precision rate using NMI-SBDL method was found to be comparatively better by the conventional methods, [1] by 3% and 5% when compared to [2] and better by state-of-the-art methods by 7% compared to [3] and 9% compared to [4] respectively.

5.4 Performance Analysis of Recall

Finally, recall is measured that refers to the ratio of relevant instances (i.e., relevant tweet detection) that were retrieved.

$$R = \frac{TP}{TP+FN} \tag{18}$$

From the above equation (18), recall rate 'R' is evaluated based on the true positive instances 'TP' and the false negative instances 'FN' respectively. Table 6 displays the corresponding results of recall rate using two conventional methods, RoBERTa-LSTM [1], SenDemonNet [2], state-of-the-art methods, CNN-LSTM [3]and CNN-BiLSTM [4] respectively.

Table 6 : Comparative analysis of recall using proposed NMI-SBDL, RoBERTa-LSTM [1], SenDemonNet [2], CNN-LSTM [3] and CNN-BiLSTM [4]

Number of Tweets	Recall				
	NMI-SBDL	RoBERTa-LSTM	SenDemonNet	CNN-LSTM	CNN-BiLSTM
1000	0.94	0.92	0.90	0.88	0.86
2000	0.92	0.90	0.89	0.87	0.85
3000	0.91	0.89	0.88	0.85	0.84
4000	0.91	0.89	0.86	0.84	0.82
5000	0.89	0.87	0.84	0.83	0.81
6000	0.89	0.85	0.84	0.82	0.80
7000	0.88	0.85	0.82	0.81	0.80
8000	0.87	0.84	0.81	0.81	0.79
9000	0.85	0.83	0.81	0.80	0.79
10000	0.85	0.81	0.81	0.79	0.78

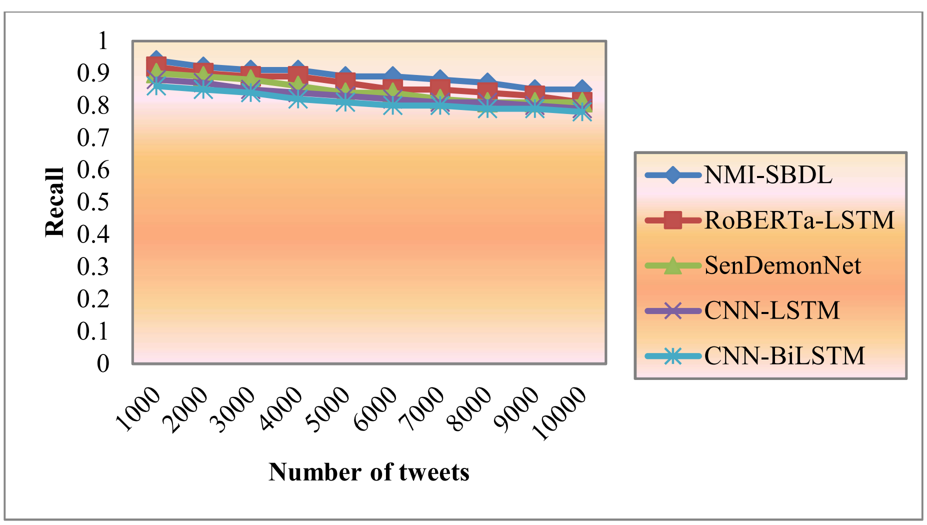

Figure 7: Graphical representation of recall

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Figure 7 given above illustrates the recall rate for different numbers of tweets ranging between 1000 and 10000 employing the six different fields acquired from table 2 separately. Also, a linear trend is observed i.e., increasing the numbers of sample tweets causes an increase in the false negative rate. This is due to the reason that by increasing the sample tweets size, false negative rate increases and on the other hand, true positive rate increases. However, the false negative rate using NMI-SBDL method was found to be comparatively lesser than the two conventional methods, [1] and [2] and two state-of-the-art methods, [3] and [4] respectively. The reason behind the minimization of false negative rate was owing to the Stacked Bilateral LSTM-based Sentiment analysis algorithm for sentiment analysis based on the tweets obtained. With this algorithm, an integration of LSTM-based neural network and Stacked Bilateral mechanism is performed. Moreover, by applying Stacked Bilateral mechanism dimensionality reduced tweet is fed via neural network from beginning to end and then from end to beginning, therefore analyzing the sentiment faster. Due to this accurate sentiment analysis made by the network was improved and on the other hand, wrong sentiment analysis made by the network was reduced concurrently. This in turn improves the recall rate using NMI-SBDL method by 3% compared to [1], 5% compared to [2] and 7% compared to [3] and 9% compared to [4] respectively.

5.5 Comparison With State-Of-The-Art Methods

The study results are discussed with proposed NMI-SBDL and state-of-the-art methods such as RoBERTa-LSTM [1], SenDemonNet [2], CNN-LSTM[3], and CNN-BiLSTM [4] using Sentiment140 dataset based on various parameters, such as sentiment analysis accuracy, sentiment analysis time, precision and recall. Table 7 provides a detailed comparison of the proposed and state-of-the-art methods.

Table 7: Comparative analysis of proposed with state-of-the-art methods

Parameter	NMI-SBDL	RoBERTa-LSTM [1]	SenDemonNet [2]	CNN-LSTM [3]	CNN-BiLSTM [4]
Sentiment analysis accuracy (%)	95.12	90.25	86.66	83.18	79.73
Sentiment analysis time (ms)	429.5	468.5	538.3	598.5	643
Precision	0.91	0.88	0.86	0.85	0.83
Recall	0.89	0.86	0.84	0.83	0.81

Table 7 shows the comparative results of sentiment analysis accuracy, sentiment analysis time, precision, and recall for proposed NMI-SBDL and state-of-the-art methods such as RoBERTa-LSTM [1], SenDemonNet [2], CNN-LSTM [3] and CNN-BiLSTM [4]. By observing the above table, the results of sentiment analysis accuracy, precision, and recall using the proposed NMI-SBDL are highly increased than the other existing methods. The reason for the higher sentiment analysis accuracy is to apply the Stacked Bilateral LSTM-based Sentiment analysis algorithm to categorize the tweet polarity. Then the activation function returns the classification results and minimizes the incorrect false negative rate. In this way, tweets are correctly classified hence it improves accuracy, precision, and recall. Also, the sentiment analysis time of the proposed NMI-SBDL is greatly reduced by 429.5 ms than the other works. The sentiment analysis accuracy, precision, and recall of NMI-SBDL are achieved as 95.12%, 0.91, and 0.89 which is observed as the highest value than the other methods.

6. CONCLUSION

In this paper, a significant sentimental analysis method using Neumann Mutual Informative and Stacked Bilateral Deep Learning (NMI-SBDL) is proposed. Various stages in the design encompass feature selection and classification. Initially, tweets are collected from diverse users and fed as input to the Neumann Mutual Information-based Feature Selection algorithm. Secondly, computationally efficient dimensionality reduced tweets are obtained with the Neumann Mutual Information mechanism for

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minimizing computation time. Subsequently, the tweets with reduced dimensionality are utilized as input, the tweets are classified by employing Stacked Bilateral LSTM-based Sentiment Analysis algorithm with maximum precision and recall.

The comprehensive experimental evaluation is implemented for NMI-SBDL and conventional method using Python and applied to the Sentiment140 dataset. The results confirm that the NMI-SBDL method yields superior outcomes in performance metrics, such as 23% sentiment analysis time, 13% accuracy, 6% precision, and 6% recall, in comparison to both conventional and state-of-the-art methods. The proposed NMI-SBDL is shown to be effective in accurately identifying tweets, reducing computation time, and contributing to the overall improvement of sentiment analysis performance. In the future, need to develop the algorithm to acquire higher accuracy with the use of deep learning and optimization approaches.

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