EFFICIENT NATURAL LANGUAGE PROCESSING USED FOR TWITTER DATA BASED ON SENTIMENT ANALYSIS

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***Abstract*: Social Media (SM) is a popular source for information retrieval. It is being used for sharing day-to-day events of our lives and the incidents occurring world-wide Twitter, in which users post instantaneous reactions to as well as opinions concerning "everything". People opinions are analyzed based on the Sentiment Analysis (SA). Most commonly Natural Language Processing (NLP) is utilized for SA. Existing works have low accuracy in sentiment classification. To trounce the difficulty, this paper proposed efficient NLP used for SA on the twitter data. Proposed system has five phases. Originally, the input data is taken from the ruby API twitter data set. Thus, the data is preprocessed utilizing Stop Word Removal (SWR), stemming, tokenization, and removal of numbers. Secondly, emoticons, non-emoticons, and lexicon features are extorted. Thirdly, the extorted features are ranked using SentiWordNet dictionary. In the fourth stage, the ranked features are classified using Modified Artificial Neural Network (MANN); the modification is done utilizing Cuckoo search (CS) algorithm. The CS algorithm is utilized for optimizing the weight for each neuron layer. Finally, the system is tested utilizing K-Fold Cross-Validation. Experimental results contrasted with the previous Modified Decision Tree (MDT) technique in respects of accuracy, recall along with F-measure, precision, average sentiment score and computation time. The proposed twitter data SA indicates better when compared with existing methods.**

***Keywords:* Big data, Natural Language Processing (NLP), Sentiment Analysis, Modified Artificial Neural Network (MANN), Cuckoo search (CS), Modified Decision Tree (MDT).**

1. INTRODUCTION

Amid the last decennia, the quantity of content that is published online has augmented extremely, chiefly owing to the broad adoption and utilization of online SM platforms [1]. SM channels, like Twitter, Facebook, give convenient as well as efficient manners for communication and also for sharing information publically [2]. A tweet might encompass just more than pure text; it might comprise, links to websites, videos, photos, other media, and short strings following a hash symbol (#), called hashtags, and usually employed to filter or promote content [3]. In particular, the social platform Twitter has turned to be a most preferred source for users to find up-to-date information. The messages published in Twitter are labeled as tweets and are restrained to 140-characters. Twitter offers exceptional conditions for social behavior analysis, and comparative historical research, among numerous other social and scientific disciplines [4]. Often twitter data is hard to understand due to the limited length of tweets along with the noise inherent in the medium. As a result, there is a variety of research in attempting to effectively identify and classify tweets [5].

As the utmost popular SM in the globe, Twitter attracts heaps of users to share opinions on numerous topics every day. On average, about six-thousands tweets are tweeted every second and also five-hundred million tweets are tweeted per day [6]. Followers of tweets receive notification connected to the actions performed by the one they follow. Typical activities of users are: posting a tweet (message), expressing like/favorite, commenting, and retweeting [7]. On account of the digital revolution, increasing communication takes place online that has stimulated text mining as well as more concretely SA research. SA, which aims to automatically extract positive and negative opinions from online text, has become the main research domains in NLP [8].

The sentiment stands as a thought, attitude, or else as judgment prompted via feeling. The Internet is essentially a resourceful place concerning sentiment information. SA studies people's sentiments towards certain entities. [9]. SA is as well termed as opinion mining, aims to ascertain people's sentiment concerning a topic by examining their posts and disparate actions on SM. Then, it comprises classifying the posts polarity into disparate opposite feelings like positive, negative et cetera [10]. Microblog sentiment computing, as well as analysis, encompasses 2 features: i) to analyze the personal emotion fluctuation in a disparate period of time, and ii) to analyze emotions of a populace in different time [11].

Sentiment classification, recognized as SA, in electronic commerce is a task of judging the opinions (positive or negative) of customers concerning products and services (paragraph, document, sentence, etc.) centered upon computational intelligence, like, Machine Learning (ML) [12]. Often, Typical SA approaches are too simplistic to productively carry out the task at hand or are excessively complex but not transparent [13]. SA application is extensive and powerful. Opinion mining or SA is widely used in areas like reviews and survey responses, online, SM, and also health care materials for applications that range from marketing to customer services to clinical medicine [14]. Also, the applications of SA includes the areas, for instance, healthcare monitoring, social event planning, election campaigning, consumer products, and awareness services [15].

Here, Section 2 offers the surveys of the associated works regarding the proposed work. In sections 3, a concise discussion about the proposed methodology is given; section 4 analyzes the Investigational outcome and section 5 will convey the conclusion of this paper.

2. LITERATURE REVIEW

Senthil Murugan Nagarajan and Usha Devi Gandhi [16] suggested a hybrid technique for the classification of SA. The combo of PSO, GA, and DT had proved to have better performance when contrasted with the other existent algorithms. That optimization technique with ML classifier gave an accuracy of over 90% for the classification of sentiment tweets into ‘‘positive,’’ ‘‘negative,’’ and ‘‘neutral’’ classes. The general accuracy obtained by this work was over 90% compared with other techniques.

Dario Stojanovski et. al [17] recommended a deep learning system intended for SA and also emotion identification on Twitter messages. The network was trained to utilize previously-trained word embeddings attained by means of unsupervised learning on big text corpora. The system on 3-class SA was evaluated with datasets given by the SA in the Twitter task as of the SemEval competition. Their architecture achieved similar performances to top-notch techniques and improved outcomes in the field of emotion identification in the test.

Nurulhuda Zainuddin et. al [18] projected a hybrid Sentiment Classification (SC) for Twitter by means of embedding a feature selection technique. The hybrid SC was authenticated utilizing Twitter datasets to signify disparate domains, and the evaluation with disparate classification algorithms as well demonstrated that the hybrid approach generated meaningful outcomes. The implementations demonstrated that the projected method was capable of enhancing the accuracy performance as of the existent baseline methods by means of 76.55, 71.62 along with 74.24%, correspondingly.

Muhammad Zubair Asghar et. al [19] developed a supervised white-box microblogging SA system to analyze user reviews on certain products using rough set theory (RST)-based rule induction algorithms. RST classified microblogging reviews of products into positive, negative, or else neutral class utilizing disparate rules extorted as of training decision tables utilizing RST-centric rule induction algorithms. Experimental results exhibited that the developed method was excellent, regarding accuracy, coverage along with the number of rules utilized.

Heba M. Ismail et. al [20] defined a fully automated as well as domain-autonomous method for constructing feature vectors as of Twitter text corpus for ML-SA centered on a fuzzy thesaurus and also sentiment replacement. Experimental results demonstrated that the sentiment replacement yielded up to thirty-five reductions on the dimensionality of the feature space. Including the fuzzy thesaurus resulted in the best accuracy contrasted with the baselines with an augmentation of more than 3%. Comparable outcomes were attained with a bigger data-set, the STS-Gold, representing the projected method's robustness.

Marco Furini and Manuela Montangero [21] transformed the SA procedure into a game. Certainly, the game was considered with a reasoned approach and a game was developed that involved users in categorizing the polarity (for instance, positive, negative, neutral) as well as the sentiment (like, sadness, joy, surprise) of tweets. To assess the proposal, a dataset of about 52,877 tweets was used and validated the outcomes through 2 disparate methods: ground-truth as well as manual assessment. The obtained result illustrated that the game approach was effective in gauging people sentiments along with highlighted that the contestants liked to play the game.

3. PROPOSED METHODOLOGY

In the proposed work, the efficient natural language is processed in following stages as; first the input twitter data is pre-processed utilizing SWR, tokenization, along with Stemming to distill un-structured to a structured format. Second, extort the Features from the resulted word after preprocessing. The Features are Emoticons, Non-Emoticons, and Lexicon. Third, Rank all the featured words. Next, MANN classifies the data centered on the extracted features ranking value as positive, negative or else neutral for the SA. The proposed MANN weight parameters are optimized employing CS algorithm. The proposed simulation outcome indicates better performance when compared with the existent methods. Finally, the result was tested utilizing K Fold Cross-Validation method. The proposed block diagram is shown in below fig 1.

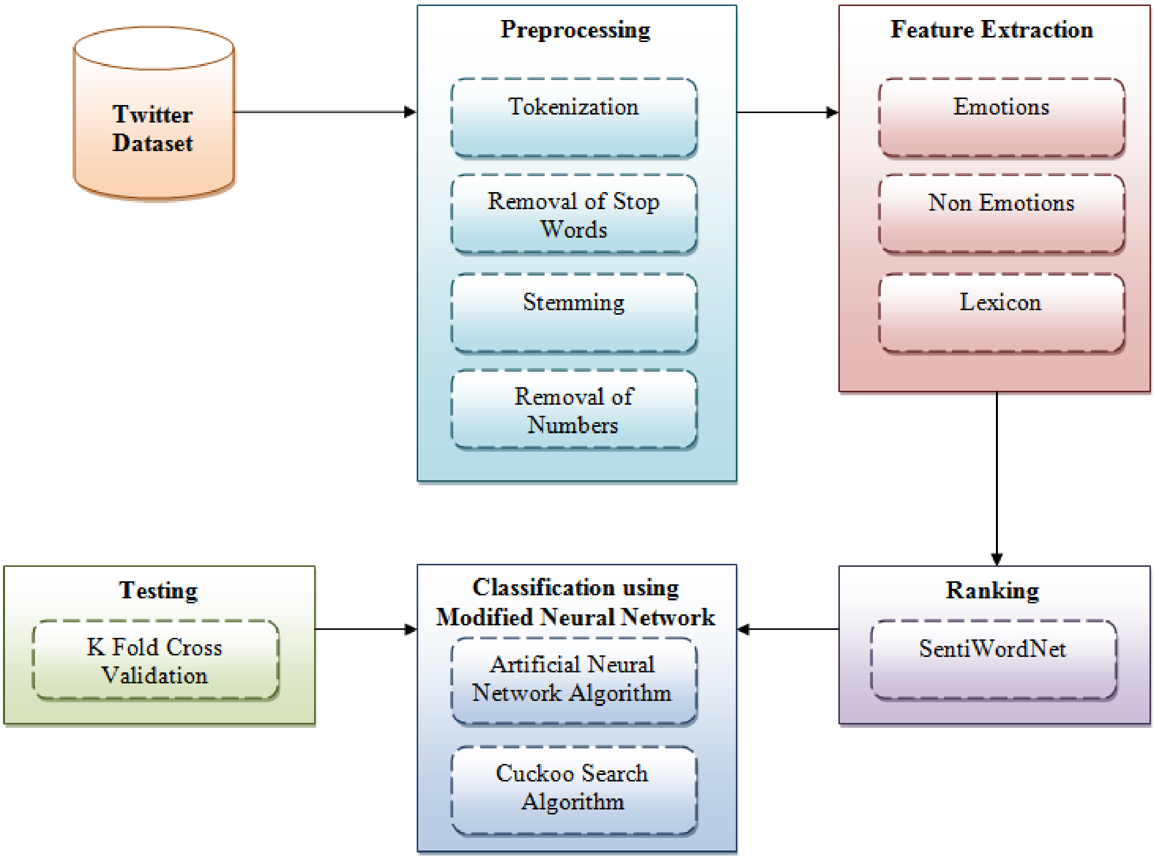

Figure 1: Block diagram for the proposed system

3.1 Preprocessing

Initially, the input was taken as of the database. Input data is preprocessed to distill un-structured to structured format using tokenization where the values are split as a word, and the unwanted words are removed.

3.1.1 Tokenization

Data splitting has been the way toward parting the total information into little-isolated portions. In the preprocessed stage, the huge information is isolated into petite portions that empower straightforward for ascertaining the information highlights. This step is followed by tokenization. The process of swapping a sensitive one with a non-sensitive correspondent is called as token. A token encompasses no extrinsic meaning. Tokenization is done to split the values as words. Then, unwanted words are removed using SWR. The input data after applying the tokenization is given in Eq (1),

$$P_t = \{D_1, D_2, D_3, ...D_n\} \tag{1}$$

Where, P_t denotes the tokenized data and $i = 1,2,......., n$.

3.1.2 Stop Word Removal

Subsequent to finishing the tokenization process, removing the unwanted words as of the data-set is called SWR. SWR and stemming are a common method in indexing. Stop words are words with a high frequency that have small semantic weight as well as are unlikely to assist the retrieval process. Stop word removes the commonly utilized word. Common practice in information retrieval is to drop it as of index. In the proposed SA of twitter data, the stop words don't have any information related to emotions. Therefore, it must be removed. A Few of the frequently utilized stop words are "a", "me", "of", "the", "he", "she", "you". The tokenized data after applying the SWR is given in equation (2),

$$S_r = \{P_1, P_2, P_3.....P_n\} \tag{2}$$

Here, the preprocessed dataset after removing the stop words is indicated as S_r.

3.1.3 Stemming

Stemming is done utilizing WordNet. This step removed the suffix like 'ing' and 'ed' from words. Stemming does help in improving retrieval performance. All these splitting, SWR and stemming methods comprised the pre-processing phase.

3.1.4 Removal of Numbers

The sentences that are present in the database contain numbers. These numbers don't have great significance in the SA. Numbers don't contain any information that is related to emotions or sentiments. Hence, in the preprocessing step, numbers are also eliminated.

3.2 Feature Extraction

After completing the preprocessing phase, the features are extorted from resultant data. Feature extraction is a part of the big data analysis. This starts as of an initial set of gauged data and constructs the derived values planned to be informative as well as for non-redundant, facilitating the following learning and generalization steps. In this proposed SA methods, Emoticons, Non-emoticons, and Lexicon features are extracted which is delineated in below section.

3.2.1 Emotion Features

The pictorial illustrations of facial expressions utilizing punctuation as well as letters are called as emoticons and also this used as an emotion features. The purpose of emoticons is to express the user's mood. Emoticons are extremely common in many forms of SM, and they are reliable carriers of sentiment. The preprocessed dataset after removing the stop words (S_r) is given as the input to the emotion features extraction and it is given in equation (3),

$$F_1 = E_f = \{S_1, S_2, S_3 \ldots\ldots S_n\} \tag{3}$$

The emotion feature (E_f) is extracted as of the pre-processed data set S_r is denoted in equation (3) using table 1 and it is taken as a feature F_1. Emoticons can well be utilized to demonstrate positive or negative emotion that could well be an indicator of whether an individual is in a depressive mood. Positive words are love, great, good, thanks and negative words are hate, shit, tired and hell. Some of the emoticons and their meaning, polarity, and the strength are expressed in table 1,

Table 1: Emotion features

Emoticon	Meaning	Polarity	Strength
:D	Big grin	Extremely positive	1
BD	Big grin with glasses	Extremely positive	1
XD	Laughing	Extremely positive	1
\m/	Hi 5	Extremely positive	1
☺,=),☺	Happy, smile	Positive	0.5
:*	kiss	Positive	0.5
😐	Straight face	Neutral	0
:\	undecided	Neutral	0
☹	sad	Negative	-0.5
</3	Broken heart	Negative	-0.5
B(	Sad with glasses	Negative	-0.5
:'(	crying	Extremely negative	-1
X-(	angry	Extremely negative	-1

3.2.2 Non Emoticon Features

The Non-Emoticon features denoted the non-emotion symbols that exist in the Twitter dataset. Each of these features has a particular meaning. The non-emoticon features are the icons other than the emotion icon. This includes the verbal information that is present in different sentences in the Twitter dataset. The preprocessed dataset subsequent to removing the stop words (S_r) is given as the input for the non-emotion features extraction and it is given in equation (4),

$$F_2 = N_f = \{S_1, S_2, S_3 .....S_n\} \tag{4}$$

The non-emotion feature (N_f) is extracted as of the pre-processed data set S_r is denoted in equation (4) and it is taken as a feature F_2.

3.2.3 Lexicon Features

Lexicon features which map a total of words as per the words are positive or negative. Put it differently, the lexicon is a system of rules that permit for the combo of those words into meaningful phrases. Lexicon features were designed centered on the intuition that sentiment/emotion bearing words recognized by lexicons can form helpful knowledge to signify documents aimed at sentiment classification. In this study, the lexicon feature is extracted specifically oriented for SA of Twitter messages. The preprocessed dataset after removal of the stop words (S_r) is given as the input for the lexicon features extraction and it is given in equation (5),

$$F_3 = L_f = \{S_1, S_2, S_3 .....S_n\} \tag{5}$$

The emotion feature (L_f) is extracted as of the pre-processed data set S_r is denoted in equation (4) and it is taken as a feature F_3.

3.3 Ranking

In this phase, ranking of the words count upon the meaning using SentiWordNet. SentiWordNet is constructed in a 2-stage approach: primarily, WordNet term relationships like a synonym, antonym along with hyponymy are examined to expand a core of seed words and as well known a priori to take positive or else negative opinion bias. Subsequent to a fixed count of iterations, a sub-set of WordNet is attained with a positive or else negative label. In this proposed work, the features are ranked centered on the meaning that is provided in this dictionary.

3.4 Classification Utilizing Modified Neural Network

The ranked features were classified using MANN. In this SA work, Artificial Neural Network (ANN) is utilized for classification. The weight values are optimized using well-known CS algorithm. ANN is trainable algorithms which can learn to solve intricate problems as of the training data which comprises a set of pairs of inputs and desired outputs (targets). It comprised of a set of neurons (signified by functions) connected to others organized in disparate layers in which each layer composed of neurons. The issue to be solved is signified by input patterns, which is sent via the layers. The information is mapped via the corresponding synaptic weights. The weight value is optimized using CS which is delineated in below section. The structure of ANN is displayed in fig.2,

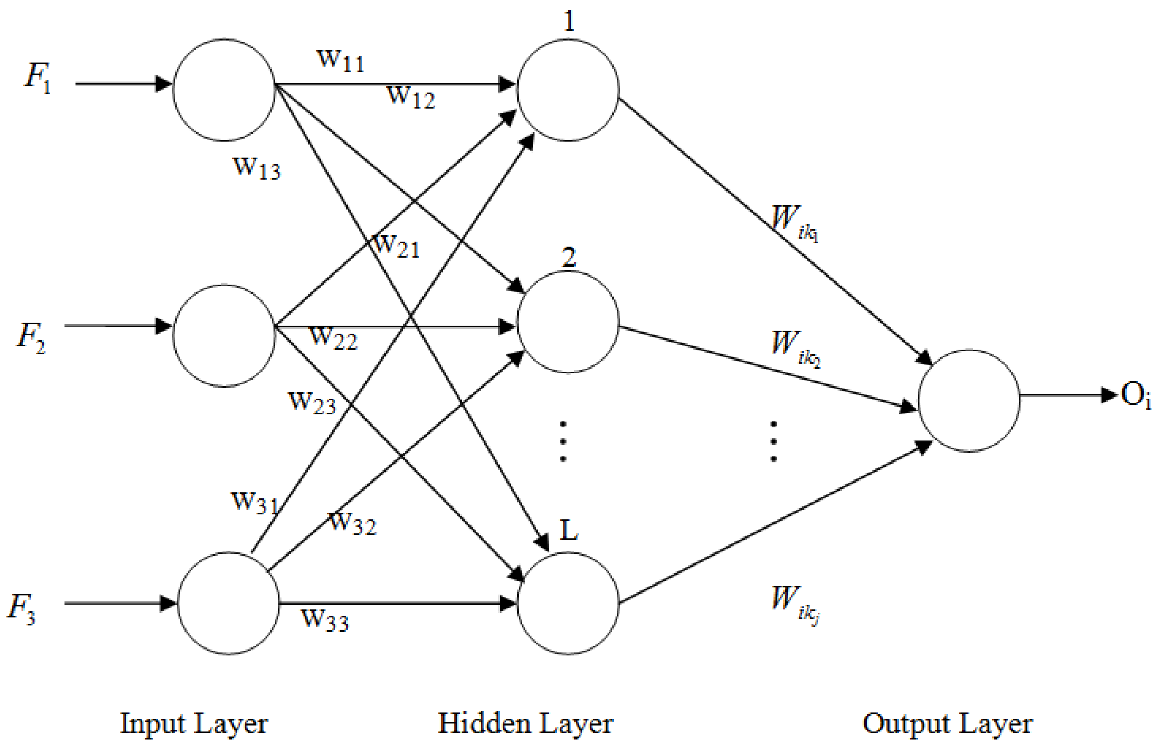

Figure 2: Structure of ANN

The algorithm of ANN steps is described in below section,

Step 1: Generate arbitrary weights within the interval [0, 1] and assign it to the hidden layer as well as the output layer neurons. Maintain a unity value weight for all neurons of the input layer.

Step 2: the hidden layer's output is calculated utilizing the below Eq.

$$H_o = b_i + \sum_{i=1}^{L} F_i W_i \tag{6}$$

In which b_i denotes the bias value, F_i refers the input feature values from the extracted features, W_i indicates the weight value of the given input features.

Step 3: To find the last output unit using a hidden unit is multiplied with the weight of the hidden layer output, which is given in the below Eq.

$$O_i = b_i + \sum_{i=1}^{m} H_o W_{ik_j} \tag{7}$$

Where, H_o is the hidden unit and W_{ik_j} is weights of the hidden layer and O_i denotes the output unit.

The activation function for the output layer is estimated as

$$Active\,(O_i) = \frac{1}{1+e^{-O_i}} \tag{8}$$

Step 4: Recognize the learning error as offered beneath

$$E_r = \sum Z_i - O_i \tag{9}$$

In which, E_r signifies the error rate, Z_i denotes the target output value as well as O_i signified as the actual output value. To achieve the best output value, the weigh is needed to be optimized using the CS algorithm.

3.4.1 Cuckoo Search Algorithm (CS)

This is centered upon the breeding behavior of the cuckoo bird. It encompasses 3 basic optimization rules.

1) Every cuckoo lays 1 egg at a particular time as well as places it at a randomly picked host nest.

2) The best nests with good quality eggs were taken to the following generations.

3) The total available host nests are set, in addition, the host may find out the alien egg which was placed by a cuckoo with a probability $P_a \in [0,1]$ as well construct a new solution.

In this proposed technique, the weight is optimized in each layer of ANN using CS algorithm. The optimization algorithm steps are explained as below,

Step 1: Introduce an arbitrary population of n host nests $(W_i = 1,2,3,....n)$.

Step 2: Attain a cuckoo by Levy flight behavior equation which is defined as follows,

$$C_i(t+1) = C_i(t) + \alpha \oplus Levy(\lambda), \alpha > 0 \quad (10)$$

$$Levy(\lambda) = t(-\lambda), 1 < \lambda < 3 \quad (11)$$

Step 3: compute its fitness function F_i. The fitness is the difference in solutions and the new solution is swapped by the arbitrarily selected nest.

Step 4: compute the threshold value (T_h) from F_i and separate the data on low priority (LP) and high priority (HP) grounded on the T_h. This value can be considered in the process that is calculated as

$$T_h = \frac{W * (1-\alpha)}{T} \quad (12)$$

Where, W is the average weight, T signifies the total weight, α signifies a value as of 0-1.

Step 5: choose a HP nest amongst the host nests like j and computes its fitness F_j.

Step 6: If $F_i < F_j$, then replace j by means of a new solution else allow j be the solution.

Step 7: the worst nest is removed and new ones are constructed at new sites utilizing Levy flights.

Step 8: Keep the current optimal nest, jump to Step (2) if $CurrentIteration(I) < \max imumiteration(I_{\max})$.

Step 9: Find the optimal solution. Cuckoo is exposed by means of the host bird at a probability $p_a \in [0,\ 1]$.

This optimization process is continued in each layer of the Neural Network and results in the efficient classification.

3.5 K-Fold Cross Validation

This is the last step that is involved in the implementation of the proposed work. This is done to assess the results in a statistical manner. This step determines the level of accuracy of the predictive model. The aim of cross-validation is to test the ability of the proposed system to envisage new data which are not utilized in the estimation process.

4. RESULT AND DISCUSSION

The proposed SA system is done on the JAVA platform. The proposed system's performance was analyzed utilizing some performance metrics, like F-Measure, recall, accuracy, precision, computational time and average sentiment score. The performance measure is described as follows,

4.1 Performance Analysis

Performance analysis is performed by evaluating some performance metrics.

Precision: Also termed as positive predictive value stands as the fraction of retrieved instances which are pertinent, or else is the percentage of chosen items that are correct.

$$precision = \frac{a}{a+b} \tag{13}$$

Recall: Also recognized as sensitivity stands as the fraction of pertinent instances which are retrieved or else it is the percentage of right items which are selected.

$$recall = \frac{a}{a+d} \tag{14}$$

F-Measure: A metric that combines precision along with recall metrics, it is basically the weighted harmonic mean or can be considered as a combined measure that evaluates the trade-off, precision, recall.

$$F\_Measure = 2.\frac{(precision)(recall)}{precision + recall} \tag{15}$$

Accuracy: Accuracy is a performance measure which denotes how close the proposed system is to the target value. It is a gauge that ascertains the total predictions which are done to the total predictions which are made. The system's accuracy is determined using the following mathematical expression.

$$accuracy = \frac{a+c}{a+b+c+d} \tag{16}$$

Where a denotes the true positive, b denotes the false positive, c refers the true negative, and d signifies the false negative.

Computational time: this is the time duration taken from the beginning of the first task to the ends of the last task. It is exhibited in the following equation,

$$E_T = P_E - P_S \tag{17}$$

Where, E_T referred to as the computational time, P_E is the ending time, P_S denotes the starting time.

Average Sentiment Score: The statistical of the sentiment score is calculated by the equation (18),

$$A_S = \frac{1}{N}\sum_{i=1}^{N} u_i \tag{18}$$

Where, A_S signifies the average sentiment score, u_i implies the words.

4.2 Comparative Analysis

The performance of the proposed twitter data SA using ANN is weighted against the existing MDT technique that is discussed below,

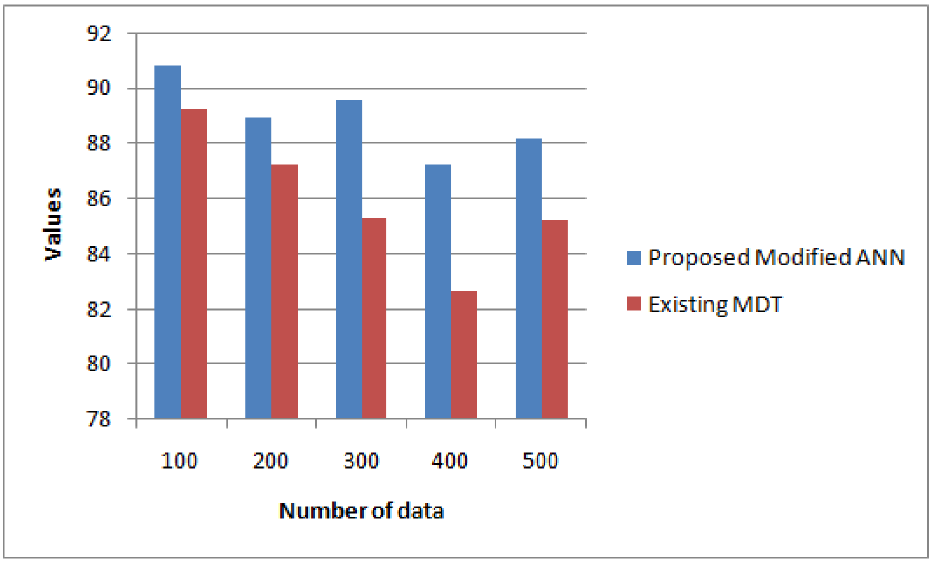

Figure 3: Compared the performance of the Modified ANN with the existing MDT based on the precision measure.

Discussion: Above fig.3 shows the comparison of the proposed MANN with the existent MDT in term of precision. The performance is varied relying upon the number of data. As of the fig.3, it is apparent that for 100 data, the proposed system attains 90.86 precision, but the MDT has 89.3 precision. Similarly, the precision measure varies for different data. For 200 data, MANN is 88.96, existing is 87.30. For 300, the proposed system is augmented to 89.63 when weighted against the 200 data. Thus, it can well be said that the proposed MANN performance is better when weighted against the existing system.

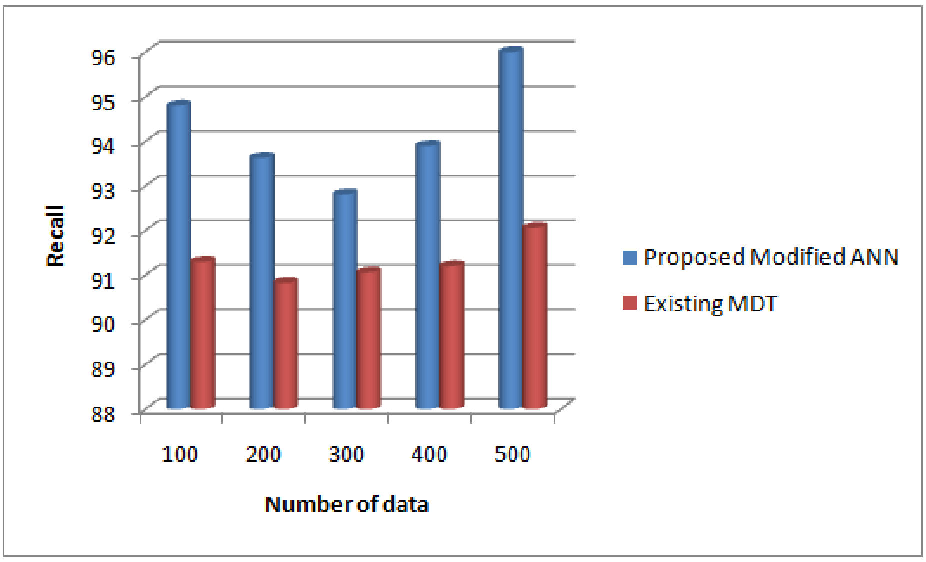

Figure 4: Comparison graph based on a recall measure

Discussion: The above fig.4 illustrates the performance of the proposed SA using MANN classification with the existing MDT classification technique based on the recall measure. Here, for 100 data the proposed system has obtained 94.80 recalls, the existing system obtained 91.30 recalls. For 200 data, the proposed MANN has 93.63 recall values, the existing system has 90.83. For 400 data MANN has provided 93.9 recall, existing has 91.2 recalls. Henceforth from this graph, it is apparent that the proposed SA using MANN classification method is better when compared with the existing system.

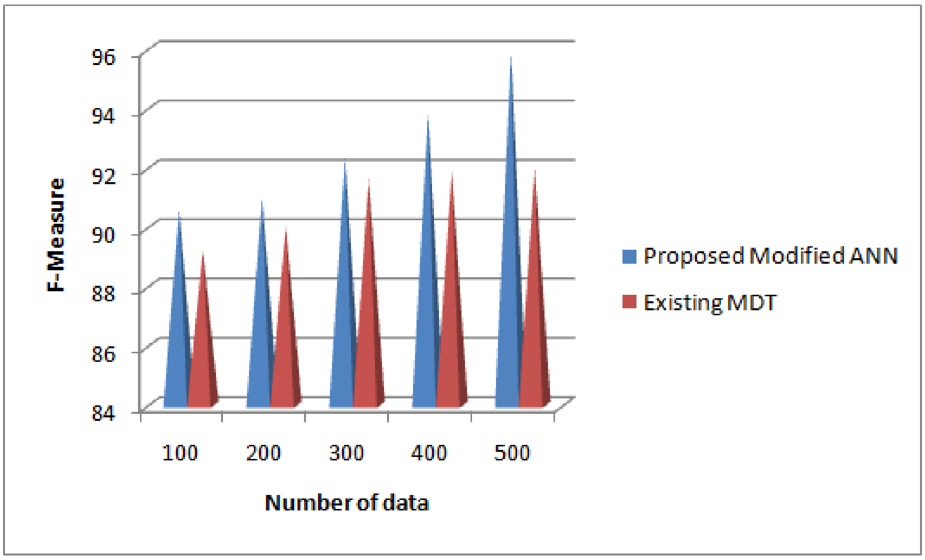

Figure 5: Demonstrate the performance of the proposed modified ANN with the existing MDT in term of F-Measure

Discussion: Figure.5 demonstrates the performance of the proposed work with the existent system based on F-Measure. F-Measure value is obtained from the combo of precision with the recall value. From the previous fig discussion, it is clear that the proposed MANN is better, so here it can be concluded that the F-Measure performance is also high for the proposed system. For 100 data, the proposed system has 90.6 and the existing system has 89.2. For 200 data, f-measure is 91 for the proposed system but the existing system has slightly lesser when compared with the proposed method. Similarly, for 300 data, the proposed achieves 92.84 f-measure and 91.6 for the existing system. Hence from this comparison, the proposed is better when compared with the existing system.

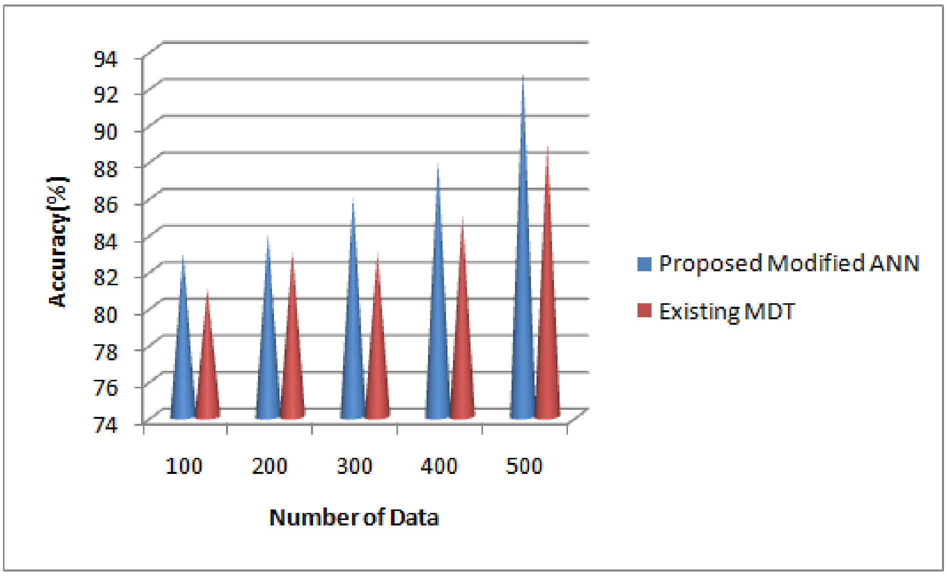

Figure 6: Accuracy comparison of the proposed with the existing system

Discussion: Fig.6 compared the proposed MANN system with the existent MDT regarding accuracy. Accuracy is an important performance measure for any sort of system. Here, accuracy performance is varied depending on the number of data. For 500 data analysis, the proposed MANN achieve 93% accuracy, Existing MDT algorithm has obtained 89% accuracy. For 400 data, the proposed work provides 88% accuracy and the existing system has obtained 85% accuracy which is lesser than the proposed system. For 300 data analysis, the proposed system has 86% accuracy but the existing has 83%. From over all data variation, the proposed SA classification using MANN has better accuracy when compared with the existing MDT.

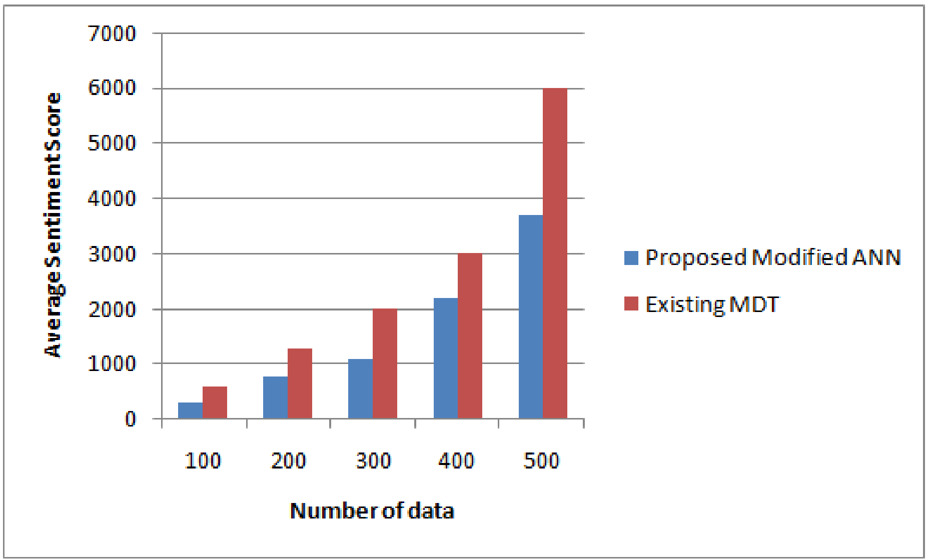

Figure 7: Comparative analysis of average sentiment score

Discussion: Above fig.7 exhibits the analysis of average sentiment score. This value represents the polarity of sentiments. The MDT algorithm shows a gradual increase in the average score. This is because of the misclassification in SA. The proposed MANN has very few classifications, consequently, the average sentiment score is lower than the other methods that are taken for comparison.

Table 2: Analysis of computational time

Number of Data	Proposed Modified ANN	Existing MDT
100	80	90
200	100	150
300	300	400
400	480	600
500	1020	1500

Discussion: Above table.2 reveals the analysis of computational time. The computational time is varied depending upon the amount of data to be taken. The proposed has taken 80 seconds for analysis of 100 data, but the existent system took 90 seconds. For 200 data, the proposed MANN has occupied 100 seconds for the data analysis process which is 50 seconds less than the existing system. For 300 data, the existing MDT has occupied 400 seconds which is 100 seconds greater than the proposed MANN. For 400 data, the proposed MANN has taken 480 seconds for execution, but the existing method takes 600 seconds. For 500 data, the proposed method has taken 1020 seconds for execution; the existing system has taken 1500 seconds. The comparison graph proves that the proposed MANN computational time is lesser than the existing MDT. The graphical illustration of the proposed work is exhibited in fig.8,

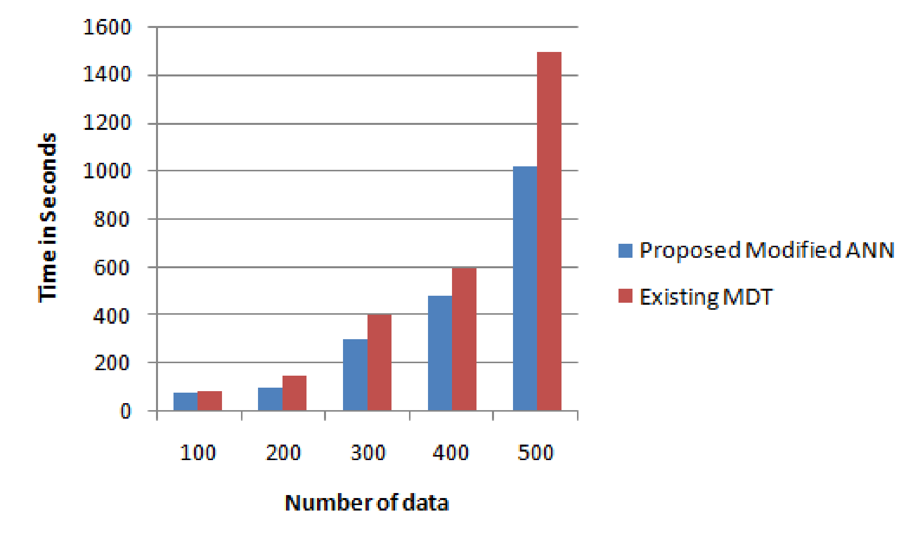

Figure 8: Demonstrate the performance of the proposed MANN with the existing MDT based on computational time.

5. CONCLUSION

Here, an efficient NLP is proposed which is utilized for SA on the twitter data. The proposed system's performance was analyzed using Ruby Twitter API dataset. Here, to classify the ranked features using MANN, the modification is done by the CS algorithm. Using this algorithm, each layer weight is optimized for obtaining the best solution. The performance analysis has revealed that the proposed work has given a low computational time, and also has given a high accuracy. The comparison outcome illustrates that the proposed MANN technique has specified higher precision, F-Measure, recall, and accuracy. Hence, the proposed MANN technique has more effectively classified the people opinion from the dataset than the existing MDT technique.

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