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DEEP LEARNING TECHNIQUE BASED TEXT EMOTION CLASSIFICATION SYSTEM USING GENETIC ALGORITHM TECHNIQUE

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ABSTRACT

In today's era the research area of emotion detection has becomes trendy field of research. The data in text form is the very easy way to communicate among interaction of human-machine through the social networking sites, is one of the schemes to share users views. Recognition of human's emotion through analyzing textual documents is useful and essential, but sometimes difficult because of the fact that it is not necessary to use emotion words directly in textual expressions. In this research, a deep learning technique based Text Emotion Classification (TEC) System using Genetic Algorithm (GA) as an optimization technique is presented. Initially, a lexicon dictionary is prepared based on the emotional words and different processes such as pre-processing, feature extraction, optimization and classification has been applied to classify the textual emotion. The test data has been trained using deep learning scheme named as Deep Neural Network (DNN) with optimization technique based on GA with a novel fitness function. The emotion; happy, sad and angry are identified as per the shared data on the social media platform. Most of the state-of-the-art in the previous research on textual emotion mining is mainly focused on without utilizing the feature selection concept, so we introduce the concept of feature selection using the GA and passes an input to DNN. At the last, we compare the performance of the proposed TEC system with existing work proposed by Chatterjee et al. terms of precision, recall and F-measure and we observed that the system got better emotion classification accuracy.

KEYWORDS: Data Mining, Textual Emotion Classification System, Lexicon Dictionary, Feature Selection, Genetic Algorithm, Deep Neural Network.

1. INTRODUCTION

The use of facial as well as textual emotion recognition or classification on social media platform is growing. Now a day's researchers are interested in the area of textual emotion recognition which involves recognition of emotion from words of a sentence based on their polarity, due to this the communication among machine and human increases. The traditional emotion recognition or classification can be performed based on the many areas such as text, speech, image and facial expressions, but out of them recognition of emotion from textual data is in high demand in the modern social media dependent world [1]. Recognition of emotion from the textual data is mostly used because it makes possible to modify ideas through emotions [2]. The data in textual form has revealed to be the primary communication instrument in interaction between humans and machines, and the use of social networking sites is one of the solutions to customer opinions. This communication is gradually improving in order to render it as human and genuine as possible. An emotional estimate is taken from the text files, information collected by users on blogs such as Facebook, Twitter etc. together with the audio and feelings are obtained from it. Because text may be in form of written or spoken, is the unique way to convey one's feelings and emotions, designing effective emotion identification systems is the best quality [3].

Analysis of textual data, also known as data mining, aims to determine people's sensitivities of a posts on social media platform based on words polarities. It can categorize the polarity of the posts into dissimilar opposite emotions, namely; happy, sad and angry [4] and to identify the polarity of the textual data, lexicon based approached is available techniques. Lexicon based text data analysis is designed to estimate the polarity of a text file from the semantic direction of a word or phrase in a text file. The lexicon-based textual emotion recognition approach is constructed by utilizing dictionary-based approach where a database is already designed according to the text data polarities [5]. In the classification of emotions from the textual data, machine or deep learning techniques also play a vital role. The general architecture of deep learning based Text Emotion Recognition (TEC) system is shown in Fig. 1.

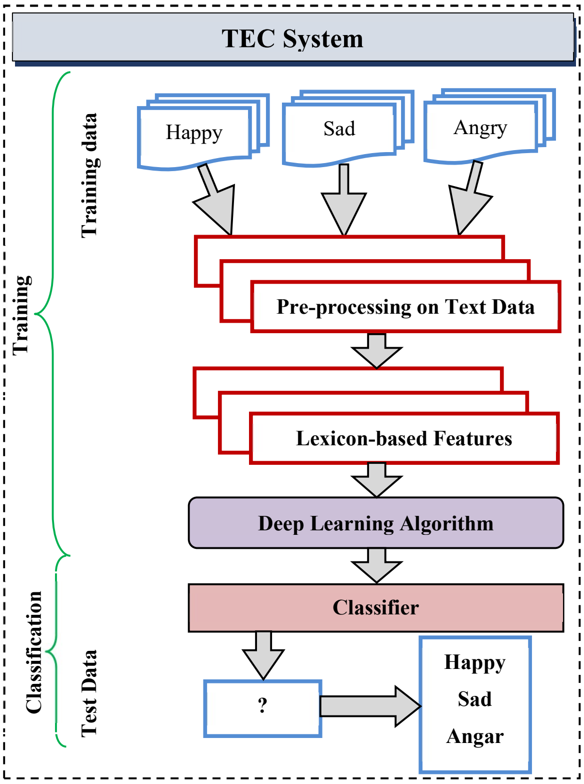

Fig 1: Architecture of TEC System

Classification of the textual emotion deals with the analysis and predicting the hidden information stored in the text sentences [8]. Here, some examples of the textual emotion is given:

Happy: much better day... so far! It's still quite early. Last day of study…………..wow
Sad: Laying n bed with a headache...waiting on your call.
Angry: Why didn't you go to prom? BC my bf didn't like my friends I usually take pictures in the noon.

In this research article, we introducing the concept of emotion recognition from the text data to analyze the types of emotion using the combination of deep learning technique along with optimization or feature selection mechanism. In this TEC system, we use Genetic Algorithm (GA) as a feature selection and feature optimization approaches using the fitness function and Deep Neural Network (DNN) is used as deep learning technique to train and analyze the type of emotion from the text data that is uploaded on the social media platform. The main contributions in this research is listed as:

- We presents a brief survey on existing textual emotion recognition work to analyze the issues faced by the researcher and design text data improved pre-processing techniques.
- We create Lexicon database to find out the text emotion based features.
- We also design an improved objective function for optimization of text features using GA and train the system using DNN as classifier for happy, sad, and angry emotion data.
- To evaluate and validate the performance of proposed TEC system, we calculate the compare with the existing work in terms of Precision, Recall, F-measure, Execution Time, Error Rate and Accuracy.

Basically, in this research, we designed a deep learning technique based TEC system using GA technique and the basic building block of the system is shown in the Fig. 2.

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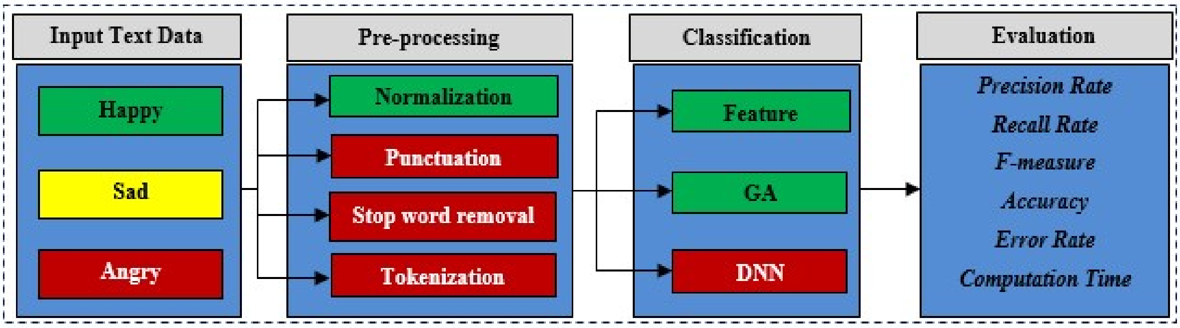

Fig 2: Building Block of TEC System

To design the proposed model, we use MATLAB 2016a with data mining, optimization and neural network toolbox. It is a high performance language for technical analysis and it is mainly used for the research work. In it computation, visualization and programming has done collectively and it easy to understand. The rest of research article is organized as: The brief survey of the existing textual emotion recognition work is given in the Sect. 2 where Sect. 3 describes the material and method of proposed TEC system. The experimental results and comparative analysis is described in Sect. 4 of article. Finally, the conclusion with future scope of TEC system is presented in the Sect. 6.

2. RELATED WORK

The survey of the existing work for the emotion recognition from the textual data is given in this section of research article. Firstly, we analyze our reference paper that inspired me to design a TEC system. In 2019, ***A. Chatterjee et al.*** had conducted a research to design deep learning based model to understand the emotions in text for the big data. They have suggested a novel strategy to detecting feelings such as Happy, Sad and Angry based on Deep Learning in textual data. The core of this strategy lies in mixing depictions based on semantic and sentiment to detect emotions more accurately. In order to train the model, semi-automated methods used to collect large-scale training data with various ways to express feelings. Evaluation of this methodology to real-world dialog datasets shows that it outperforms traditional machine learning baselines as well as other deep learning models off - the-shelf. They have suggested an end-to-end trainable profound learning model called "Sentiment and Semantic Based Emotion Detector (SS-BED)" to detect feelings text based data [9]. ***Wikarsa, & Thahir*** in 2015 developed an application of text mining to detect emotions of twitter users that are categorized into six types of emotions named as sadness, disgust, surprise, happiness, and anger. Three important steps of the text mining consumed here in which pre-processing and validation occurs. Some activities that are performed in the pre-processing were case-folding, cleansing, removal of stop-words, conversion of emoticons and negation, and then tokenization for the training data and the test data on the basis of sentiment analysis have performed morphological analysis to form various models. In the process of measurement of the level of accuracy produced through application by using 10- fold cross validation in the validation phase. It accomplishes 83% accuracy in 105 tweets, through better training of data [10]. ***Bandhakavi et al.*** in 2017 suggest a mixture model to learn a domain-specific word-emotion lexicon, this model assumes that records are a combination of mental and neutral phrases that differ from the supervised LDA (sLDA) generative model that assumes that records are a combination of various mental (subject) phrases. To assessed both GPELs and DSELs for text-based emotion identification. Results from an extensive research of current and suggested lexicons on benchmark-based emotion detection assignments verify that DSELs have important performance gains over GPELs. Showed that both GPELs and DSELs for text-based emotion identification [11]. ***Kakar et al.*** in 2018 have explained that, the ANN is one of the fastest-growing machine learning techniques regarded as non-linear predictive models to execute peak temperature for the entire day (365) of the year classification and forecast weather forecasts. A multi-layered neural network is therefore intended and trained with the current dataset and a connection has been established between the current non-linear climate parameters. Eleven weather characteristics have been used to classify the weather into four kinds. In addition, twenty training examples from 1997-2015 were used to forecast 11 weather characteristics. Because the forecast information is nonlinear and follows some uneven trends and patterns, there are many traditional methods to work on model effectiveness to create prediction better than past models. However, the Artificial Neural Network (ANN) has developed to enhance precision and reliability [12]. ***El Alaoui et al.*** in 2018 present a new

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adaptable strategy aimed at extracting people's opinions on a particular topic by depending on content from social media. The method suggested consists of first constructing a dictionary of the polarity of words based on a very tiny number of positive and negative hash tags linked to a specified topic, then classifying messages into several classes and balancing the weight of the feeling. And through the recent metrics such as upper phrases and repeated more than two successive letters in a single word. To test this model, for the 2016 U.S. presidential election, a case study was performed to go through our model step by step to guess which candidate was the favorite. Compared to this model, the performance findings showed some promising outcomes [13].

Form the survey, we observed that the rapid growth of the internet world has facilitated increased online communication and opened up newer avenues for the general public to post their opinions online. This has led to generation of large amounts of online content rich in user opinions, sentiments, emotions, and evaluations. We need computational approaches to successfully analyze this online content, recognize and aggregate relevant information. Recognizing the emotions like happy, sad and angry conveyed by a text can provide an insight into the author's intent and sentiment, and can lead to better understanding of the text's content. So, according to the above survey of existing research, we design TEC system using the GA along with DNN as a classification technique and the developed TEC system is also known as an essential application of Natural Language Processing (NLP) which aim towards getting the reviewer's feelings expressed in terms of happy, sad and angry by analyzing text data.

3. MATERIAL AND METHOD

This section of article describes the entire working methodology along with the flow diagram which helps to achieve the above mentioned contribution in the TEC system. In this system, there are two phases, first is training and the second is the emotions classification. The design methodology of proposed TEC system is given below in the form of steps and the flowchart of TEC system in shown in the Fig. 3.

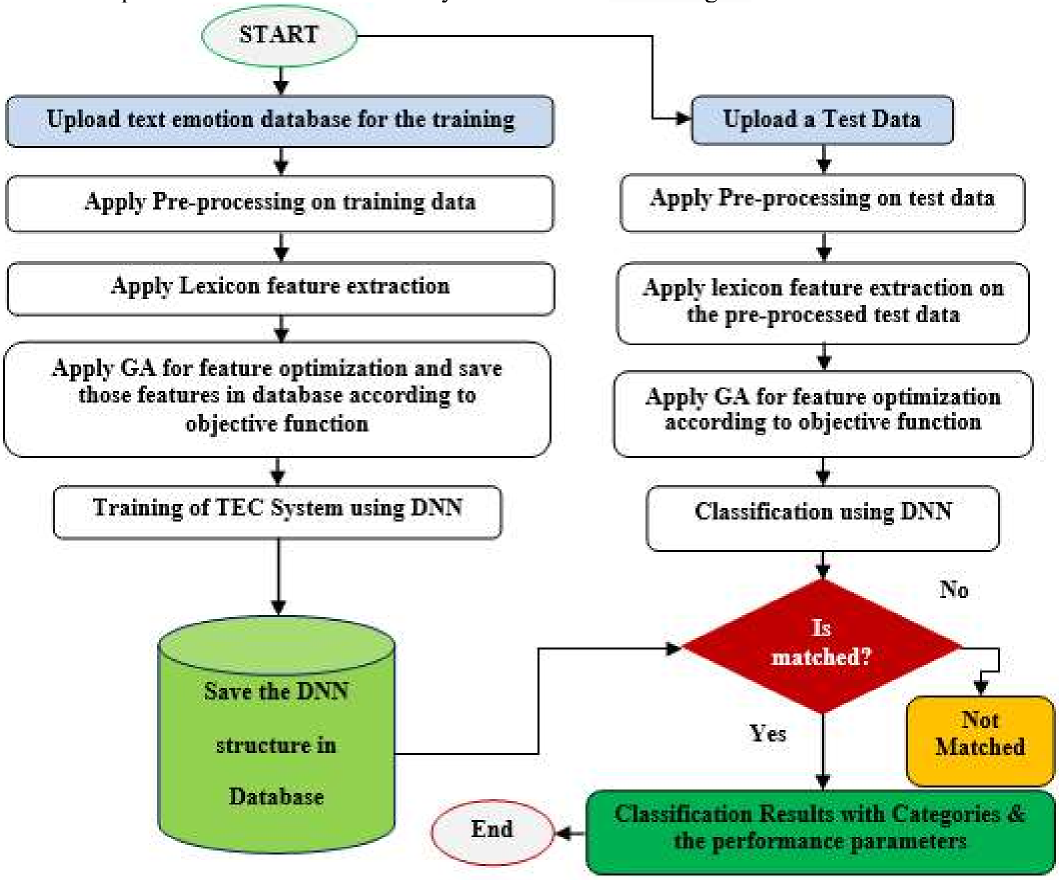

Fig 3: Flowchart of TEC System

Above Fig. 3 shows the flowchart of the TEC system using the concept of GA along with hybridization DNN as deep learning technique. The steps used to classify the emotions form text data in terms of happy, sad and angry using TEC system and the procedural steps are given as:

Step 1: Design a framework of TEC system and upload text data (emotional text file) with different types of emotions like happy, sad and angry for Training and Testing of proposed system.

Step 2: After the uploading the text data, pre-processing is applied in both section. The pre-processing steps of TEC system consist of several phases which are given as:

- ***Text Data Normalization***
- ***Punctuation Removal from Text Data***
- ***Stop words Removal from Text Data***
- ***Tokenization of Text Data***

It is the main and important step regarding to achieve better emotion classification accuracy and we used the given algorithm for the pre-processing:

Algorithm 1: Pre-processing

Input: TD→ Text Data with Emotions
Output: PTD→ Pre-processed of Text Data
Start pre-processing
Calculate, [R, C] = size (TD) // Find out the size of the text data in terms of rows and columns
For m→1 to R
For n→1 to C
If TD (m, n) = Upper Case
Normalized TD (m, n) = TD (m, n)
End – If
If TD (m, n) = {. ? ! , > < etc. = Punctuations}
PTD (m, n) = empty
End – If
If TD (m, n) = {Is am are etc. = Stop words}
SWTD (m, n) = empty
End – If
TTD(m, n)=ASCII (SWTD (m, n))
End – For
End – For
PTD = TTD (m, n)
Return: PTD set Pre-processed Text Data
End – Pre-processing Algorithm

Step 3: Pre-processing have been applied in both section of the proposed TEC system according to the flowchart in training as well as testing section. After pre-processing, we apply the feature extraction on pre-processed data using lexicon-based technique and the algorithm of used Lexicon based feature extraction technique is written as:

Algorithm 2: Lexicon Feature Extraction

Input: PTD→Pre-processed of Emotional Text Data
Output: LFS→ Lexicon Feature set
Start lexicon feature extraction
Load the dictionary of emotional data, L_{DIC}
Calculate, [R, C] = size (PTD) // Find the size of pre-processed data in terms of rows and columns
For m→1 to R
For n→1 to C
If PTD (m, n) = Happy L_{DIC}
Happy Features (m, n) = PTD (m, n)
Else PTD (m, n) = Sad L_{DIC}
Sad Features (m, n) = PTD (m, n)

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Else
Angry Features (m, n) = PTD (m, n)
End – If
End – For
End– For
LFS = [Happy, Sad, Angry Features]
Return: LFS as a Lexicon Feature set
End – Lexicon Feature Extraction Algorithm

Step 4: After the extraction of feature according to their emotion, we need a feature selection approach to achieve better emotion classification accuracy in TEC system, Here, GA is used as a feature selection or optimization approach with a novel fitness criteria which is used to remove the unwanted feature sets from the lexicon features and the algorithm of GA is written as:

Algorithm 3: GA for Feature Selection

Input: LFS→ Lexicon Feature set
F (f) → Fitness function for feature selection criteria
Output: OLFS → Optimized Lexicon Feature Set
Start optimization
To optimized the LFS, GA is used
Set up basic parameters of GA: Population Size (LFS_P) = Number of Element in LFS
Call Fitness function:
$F(f) = \begin{cases} 1; & if\ F_S > F_T \\ 0; & Otherwise \end{cases}$
Calculate, [R, C] = size (LFS)
Set, OLFS = [] // Initiate an empty variable to store selected data by GA
For m = 1→ Row
For n = 1→ Column
F_S = LFS (m, n) // Current feature from LFS_P
$F_T = \frac{\sum_{i=1}^{Row}\sum_{j=1}^{Column} LFS_P(m,n)}{Row \times Column}$ // Mean of all LFS_P
$F(f) = Fit\ Fun\ (F_S, F_T)$
OLFS = GA (F (f), GA Set up, FS (m, n))
End – For
End – For
Returns: OLFS as an Optimized Lexicon Feature Set
End – Feature Selection Algorithm

Step 5: After the GA-based feature selection, we apply DNN as a classifier to train the TEC system based on optimized feature data as an input set and the algorithm of DNN is written as:

Algorithm 4: TEC-Net DNN

Input: OLFS → Optimized Lexicon Feature Set as training data
Class → Happy, Sad and Angry
N → Neurons to carry OLFS
Output: TEC-Net → Trained DNN structure and Classification Results
Start Training
Initialize DNN with OLFS:
Calculate Length, L = Size (OLFS)
For m= 1 → L
If OLFS = Happy List
Group (1) = OLFS (1 → m)
Else if OLFS = Sad List
Group (2) = OLFS (1 → m)
Else
Group (3) = OLFS (1 → m)

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End – If
End – For
TEC-Net = CNN (N)
Train the Model
TEC-Net = Train (TEC-Net, OLFS, Group)
RES = Sim (TEC-Net, Test Text Data Feature)
If RES = 1st Class
Classified Results = Happy Emotion
Else if RES = 2nd Class
Classified Results = SAD Emotion
Else
Classified Results = Angry Emotion
End – If
Return: TEC-Net as a trained DNN structure with Classified Results
End – DNN Algorithm

Step 6: Using DNN, we train the TEC system, and after that we classification of text test data based on their emotion using the TEC-Net.

Step 7: At last of the simulation of the TEC system, we calculate the performance parameters of proposed TEC system like Precision, Recall, F-measure, Execution Time, Error and Accuracy is calculated and compare with existing model based on the Twitter dataset of textual emotions. The sample of used Twitter dataset is given in the Table I with the emotions.

Table I: Twitter Dataset Sample

No.	Twitter Post Data	Emotions
1	mmm much better day... so far! it's still quite early. last day of #uds	Happy
2	Layin n bed with a headache ughhhh...waitin on your call...	Sad
3	why didn't you go to prom? BC my bf didn't like my friends	Angry

Based on the above mentioned Twitter dataset, we simulate the proposed TEC system and calculate the parameters and described in the below section of this research paper.

4. RESULTS AND ANALYSIS

In this section, we describe the simulation results of the proposed TEC system using GA with DNN as deep learning algorithm and compare with existing work by ***A. Chatterjee et al.*** [9]. Here, we described the experimental result of proposed TEC system in which we have to detection emotion from textual data through data mining, by performing some predefined steps on the upload test text data. Below Table II represents the classification performance parameters of the proposed TEC system.

Table II: Performance Parameters of TEC System

Data Sample	Precision	Recall	F-measure	E-Time	Accuracy	Error
1	0.82203	0.757	0.94599	0.14389	99.6842	0.31584
2	0.74589	0.701	0.7001	0.13784	98.8765	0.23567
3	0.83451	0.621	0.89654	0.12768	99.7654	0.32785
4	0.81854	0.673	0.98564	0.15761	97.9889	0.30564

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5	0.83001	0.690	0.95981	0.13981	98.5898	0.31786
6	0.80443	0.689	0.94811	0.14657	99.567	0.40101
7	0.83277	0.709	0.95873	0.14319	98.9816	0.31985
8	0.82579	0.692	0.94091	0.14267	98.9916	0.33012
9	0.82865	0.685	0.94287	0.13914	99.6739	0.32172
10	0.81942	0.693	0.94981	0.13878	98.4675	0.31981
Average	**0.8162**	**0.6901**	**0.9228**	**0.1417**	**98.989**	**0.3195**

The tabular form of parameters of our proposed TEC system have depicted in the Table II, having ten number of text emotion sample and their graphical depiction of parameters of proposed methodology such as Error (%), Precision, Recall, Execution time, F-measure and, Accuracy with respect to the number of text samples. In the Fig. 4, the error in percentage have depicted against the number of text samples it is not necessary the error is increased according to the increasing number of samples. In which maximum and minimum error occurred 0.4010 and 0.23567.

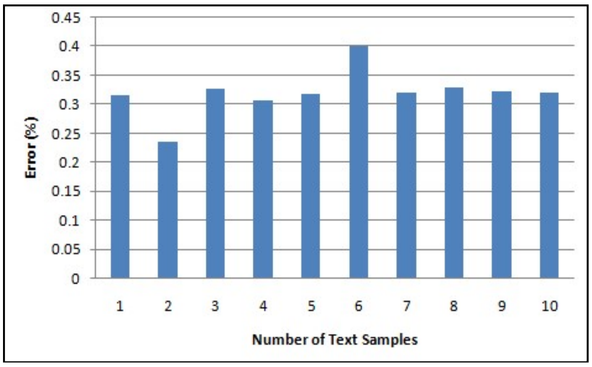

Fig 4. Error Rate of TEC System

The execution has been defined as the time consumed by the TEC system classify the emotion is known as execution time. In the Fig. 5 shows the execution time against the number of text samples maximum and minimum obtained execution time to perform the task have 0.15761 and 0.012678.

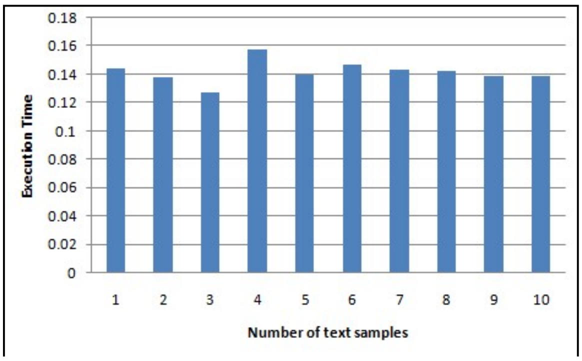

Fig 5. Execution Time of TEC System

The word accuracy implies that two or more measurement values are closed to each other. The accuracy value varies due to the observational error. As explained in the Fig. 5, the maximum and minimum precision obtained from the given graphically representation have 0.83451 and 0.74589.

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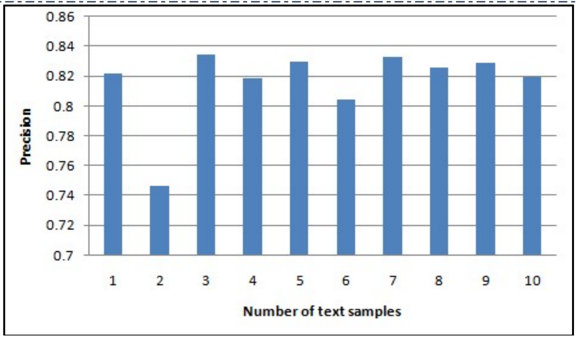

Fig 5. Precision of TEC System

The parameter, Recall is defined as the **how many of the** *true* **positives have been obtained found** as described in the Fig. 6. The average recall found from the graph have 0.6901 that means near to 69%.

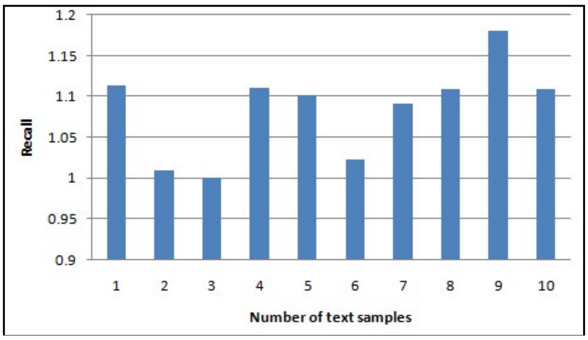

Fig 6. Recall of TEC System

The term F-measure defined as a harmonic mean of the precision and recall of the TEC system and it has been explained graphically in the Fig. 7, from this the maximum and minimum obtained f-measure has 0.757 and 0.621. The average f-measure is near to the 0.9228 that it is the more than 92% and it is a good achievement by utilizing the DNN as a classifier.

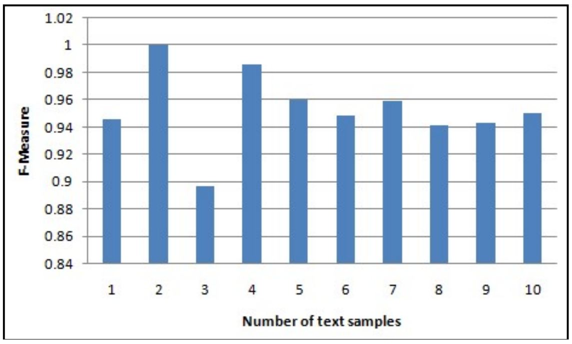

Fig 7. F-Measure of TEC System

Accuracy of the proposed work is the capacity of machine to measure the precise value. In other words, the measured value's closeness to a normal or true value. By taking the reduced measurements, it can be achieved. It represent graphically in the Fig. 8.

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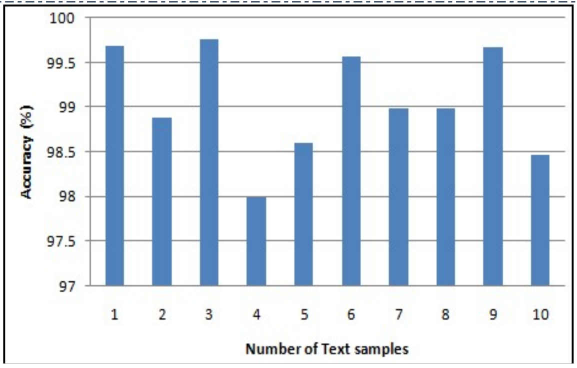

Fig 8. Accuracy of TEC System

The comparison of base and proposed work explain in the tabular form in Table III in which we can analyse the some parameters such as precision, recall and F-measure to measure the efficiency of the proposed and base work.

Table III: Comparison of Proposed with Existing

Parameters	Proposed	Chatterjee et al. (2019)
Precision	81.62	80.87
Recall	69	64.09
F-Measure	95.31	71.34

The representation of comparison among our proposed work and base work in tabular form in Table III, the accuracy of proposed work on the basis of given parameters such as Precision, Recall and F-measure have increased from the base work. So, achieve the better performance in our methodology from existing work.

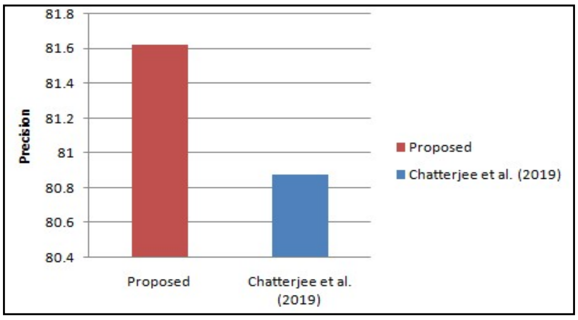

Fig 10. Precision Comparison

The graphical representation of precision of proposed and ***Chatterjee et al.*** in Fig. 10, in which precision of proposed work has increased.

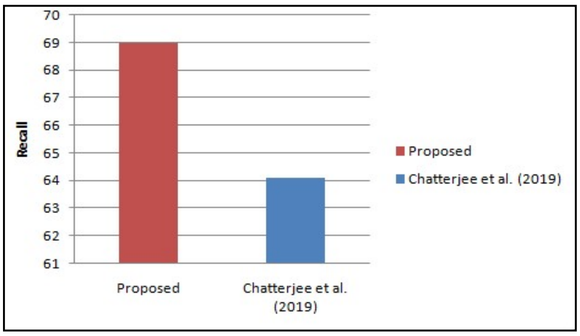

Fig 11. Recall Comparison

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The Recall of proposed and Chatterjee et al. (2019) has described in Fig. 11 and it is far better than the existing work.

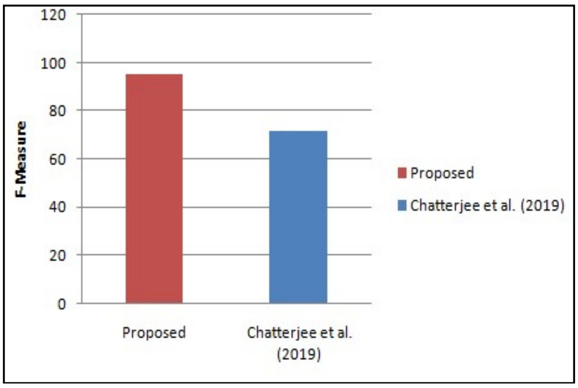

Fig 12. F-Measure

The parameter F-measure of proposed and ***Chatterjee et al.*** have shown in Fig. 12, it has been increased in proposed work.

So, we can say that the utilization of GA based DNN is very helpful for the detection or classification of emotions from the textual data.

5. CONCLUSION AND FUTURE WORK

In this paper, a TEC system using the lexicon feature based textual emotion classification with GA and DNN as a deep learning technique is proposed for analysis of social media data. Lexicon based emotion classification using the concept of data mining is a process of analyzing the written text by user in order to find out the emotions in text data on the social media platform. In this research work, we try to focus on the text based emotion detection by the data mining technique. For Emotion Detection, distinct parameters should be considered from an artificial intelligence. Different kinds of methods are used to identify human feelings such as facial expressions, body motions, blood pressure, heart beat and textual data. Text based emotion recognition performed through various techniques named as keyword spotting method (word, line and document based), lexical affinity method (lexicon based), learning based approach and hybrid based approach. There are many application area of detection of emotion from text on social media. In the task of detection of emotion, feature extraction is essential task which is performed through the pre-processing technique. So GA is used to select the best feature set form the lexicon features and then, we train the TEC system using DNN as a classifier. Here the performance has measured on the basis of Error (%), Precision, Recall, Execution time, F-measure, Accuracy (%) on the ten number of text samples. Our proposed work obtained improved precision (0.92%) recall (7.66%) and f-measure (33.59%) parameters as compare to Chatterjee et al. There is a number of possible instructional equipment for future study in this particular area of research work. In data mining phase, perform text based detection through implementing other types of algorithm and techniques and it also makes possible to detect emotions from audio and video files, in which input is first converted into the text using some processing tools and then algorithm is applied to get the emotions.

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