Text-based Emotion Detection: A Review

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***Abstract*:**

Textual language is the most natural carrier to express the emotions of human beings. Emotion Recognition and analysis is a major challenging and emerging topic in the research area of Natural Language Processing (NLP) due to its significant academic and commercial potential. Along with the growth of the Internet, people use social media or digital platforms to share their feelings and feedback. Hence, it is important for a machine to understand the emotions, feedback, and textual dialogues to provide emotionally aware responses to users in today's digital world. This survey has been inspired on the well-known fact that, despite there is a lot of work on emotional detection systems, a lot of work is expected to be done yet. The increment of these systems is due to the large amount of emotional data available in Social Web. Detecting emotions from text have attracted the attention of many researchers in computational linguistics because it has a wide range of applications. This paper presents a literature review of existing literature published between 2013 and 2023. This review has meticulously examined the various emotion models, techniques, datasets, research and evaluation metrics in the detection of emotions from the text useful for researchers in carrying out emotion detection activities. We also discussed about the different challenges with their future direction.
Keywords: Deep Learning, Emotion Detection, Machine Learning, Natural Language Processing.

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I. Introduction

Emotions are the psycho-neural processes that are influential in controlling the vigor and patterning of actions in the dynamic flow of intense behavioral interchanges between animals as well as with certain objects that are important for survival [1]. Emotion detection is a means of identifying human emotions such as happiness, sadness, anger, etc. People are using social media to express their feelings by posting, and the user of social media or digital communication is increasing now-a-days. For instance, Facebook has over 2.9 billion active users, YouTube has 2.5 billion active users, whereas Twitter has over 436 million active users [2]. Textual emotion detection is devoted to automatically identifying emotion states in textual expressions, such as Happy, Sad and Angry. People make decisions based on their minds whether they are happy, angry, bored, sad or frustrated etc. In 2021, over 4.26 billion people were using social media worldwide, a number projected to increase to almost six billion in 2027 [3].

The way a person speaks, volume, tone, speed, words, etc., all contribute considerably to emotion detection from speech. However, culture, age, gender, etc., are other factors that may also affect emotion detection from speech. Fortunately, researchers have developed several approaches for emotion detection from speech [4]. The unstructured text makes up the majority of usergenerated content data, which makes the sentiment analysis more challenging. Researchers have been looking into technology since 2005 [5]. They also stated that, as research into sentiment analysis became more and more popular and there was important progress made in the development of deep learning technologies, researchers started to pay more attention to the methods and techniques of sentiment analysis. Deep learning methods have become the focus of discussions among researchers. [6] said that emotions in human and other animals are realized over time and they discussed general principles of emotions in detail, means of expressions of emotions in both human and animals cause and effects of all possible emotions like anxiety, dejection, despair, joy, love, devotion, etc. explanation of emotions with images to show the expressions for particular emotions. Darwin claimed that some emotional expressions are universal for people all over the world. He also claimed that not only humans but also animals of similar species react similarly to a situation. His experiments revealed that for some emotions have similar expressions even in species that are not similar. Based on different emotion theories the emotion models can be divided into two classes that are categorical and Dimensional models [3][7]. Table 1 contains the two examples of emotion models [8].

A. *Organization of the paper*

The rest of the paper is structured as follows. In section 1.2 Research Question and Motivation, 1.3 Objective of this paper, 1.4 and 1.5 Inclusion and Exclusion Criteria respectively are discussed. The quality assessment is discussed in 1.6 section. In Section 2, we discussed a few existing literature reviews of text-based emotion detection with papers and publications. Section 3, discusses the dataset of Text- Based- Emotion-Detection. The different approaches such as Keyword based, Rule based approach, Corpus based approach, Machine Learning based approach, Deep Learning based, and ULM Fit, GPT, etc. are discussed in section 4. In section 5, we have discussed Evaluation metrics, challenges of Emotion detection and the Conclusion of this paper are discussed in section 6 and section 7 respectively.

B. *Research questions and motivation*

Table. 1 Research Question and Motivation

ID	ResearchQuestion	Motivation
RQ1	Whatjournal/conferencepaperabout emotion detection on text?	Identifythemostsignificantjournal/conference paper about emotion detection in text
RQ2	WhataretheEmotionmodelsinemotion detection?	IdentifytheEmotionmodelsinemotiondetection
RQ3	What are the different datasets commonly used in emotion detection in text?	Identify the different datasets commonly used in emotion detection in text
RQ4	Whatarethedifferentapproachesand techniques used in emotion detection?	Identify the different approaches and techniques used in emotion detection
RQ5	What evaluation techniques and the differentchallenges are used in emotion detection in the text?	Identify evaluationtechniquesused in emotion detection in text

C. *Objective*

The main objectives of this study are listed below:

a) We discussed detailed overview of the existing literature on emotion detection with a particular focus on techniques, datasets, applications, and challenges.
b) We discussed and tried to explore the techniques and methods in the research in text-based emotion detection.
c) We also provide an overview of different publicly available datasets that can support emotion detection.
d) We also present the different types of challenges and advantages of our article that are discussed below.

D. *Inclusion criteria*

IC 1: The article is well-researched.
IC 2: The article is scientifically sound.

IC 3: The article is focused on Text based Emotion Detection.

E. *Exclusion Criteria*

EC 1: The article is written in a language other than English.

EC 2: The article evaluates emotion detection but no other research topics.

EC 3: The article already has been listed in another database.

F. *Quality assessment*

QA 1: Are the research objectives well defined?

QA 2: Has the study been cited by other authors?

QA 3: Is the study conclusion believed and backed up by evidence?

II. Related Work

Research on Emotion detection or Emotion Recognition has attracted researchers from different sectors such as computer science, psychology, health care and many more.[3] reviewed sentiment analysis and emotion detection from text streams. The author also discussed the datasets that are used in sentiment analysis and emotion detection. They provided an understanding of the level of sentiment analysis, different emotion models, and the process of sentiment analysis and emotion detection. Recently deep neural networks, have been demonstrated to be the best option when approaching classification tasks of contents in natural language [9]. During theprocess of literature review very small amount of review articles are found and we make an attempt to demonstrate a brief, comprehensive, structured, and critical overview of the field of emotion detection in natural language processing (NLP) [10][11] presents a novel multilabel Hindi text dataset of 58000 text samples with 28 emotion labels and a fine-tuned MultilingualBERT-based transformer model on the fine-grained dataset. The model achieves state-of-the-art performance with an overall ROC-AUC score of 0.92 upon evaluation. In [12], They choose to use fine-tuning instead of pre-training, which requires extensive data and resource. Two pre-trained models were used to determine the effectiveness and performance of the proposed model. Experiments show that the proposed model outperforms all existing base line models, with the highest accuracy of 77%. [13] discussed about the sentiment analysis using product review data and [14] discussed about the Text emotion detection in social networks using a novel ensemble classifier based on Parzen Tree Estimator. [15] discussed the emotion analysis in Arabic Language by applying transfer learning methods.

In [16] a unique AI-based emotion recognition detection mathematical solution system is proposed to analyze the behavior/reaction of people in a group. The proposed solution system will act as a feedback system and was able to amass multiple faces, extract respective emotions and formulate the detected emotions through the proposed solution system to give aggregated behavior/emotion of the group as a whole. [17] innovatively proposed a classification method SVM-NB to obtain more emotional polarities. Finally, the classifier is used to obtain the emotional polarities of the text, including positive and negative categories. The negative emotions were divided into three sub-categories anger,sad, and disgust. The experiments show that the proposed emotion recognition method has better robustness and higher accuracy than the general modal recognition method.[8] reviewed the Emotion detection from both text and speech streams, where they covered the emotion detection research efforts, emotion models, emotion datasets, emotion detection techniques, their features, limitations and some possible future directions. The author investigated different feature sets that have been used in existing methodologies. They also summarized the basic achievements in the field that highlighted possible extensions for better outcomes. [18] proposed a classification approach based on deep neural networks, Bi-LSTM, CNN, and self-attention demonstrating its effectiveness on different datasets. Additionally, they compared three pre-trained word embeddingsfor word encoding. The encouraging results obtained on state-of-the-art datasets allow us to confirm the validity of the model and to discuss what were the best word embeddings to adopt for the task of emotion detection. As a consequence of the great importance of deep learning in the research community, they promote their model as a starting point for further investigations in the domain.

[19] discussed the typical applications of emotion detection, issues relevant to emotion detection, that are text informality, a combination of languages, emotion icons, applicability, etc. emotion recognition from structured and unstructured data, the need to define emotions in different domains, feature selection and extraction methods in emotion detection and also summarize the timelines of emotion detection from ’90s to 1992.[20]discussed the pattern based methods, supervised learning, unsupervised learning, machine learning methods, deep learning methods, and pattern based methods.[21] discussed about the ERIL: an algorithm for emotion recognition from Indian languages using Machine Learning Techniques. The author checked it in Hindi, Gujarati, Marathi, Punjabi, Bangla, Tamil, Oriya, Kannada, Assamese, and Telegu. They got the accuracy of distinct emotions is 95.05 % on average.[22] discussed the lexicon-based approach, and machine learning-based approach. The author concluded their study by saying that as machine learning approaches, the supervised learning approach is more used in emotion detection because it usually leads to better results than unsupervised learning.[23] presented a method for efficiently collecting Japanese emotion tweets carrying the first-person’s emotion using emotional expressions and sentence-final expressions. By exploiting sentence-final expressions, the author identifies the targeted tweets even though the subjects of sentences are often omitted, and first-person pronouns are often not explicitly in Japanese. By applying the method to Japanese tweet data, they constructed a Japanese tweet dataset comprising 2,234 tweets with labels of emotion types and intensities for two types of emotions: joy and sadness. The evaluation results show that the proposed method can improve the collection efficiency of targeted tweets and the reliability of data labels. The author developed classifiers from the dataset that recognize emotion intensities. They also showed that a classifier using a deep learning-based language model outperforms conventional baseline methods using a Bag of Words model and that the Japanese tweet emotion dataset constructed by their method is useful for emotion intensity recognition.[24] reviewed and provided a survey of existing approaches, models, datasets, lexicons, metrics, and their limitations in the detection of emotions from the text useful for researchers and carrying out emotion detection activities. The author also discussed the comparison of various approaches for detecting an individual's emotional state from textual data that has been undertaken. The author said that there are three major approaches to emotion modeling in psychology research that are categorical,

dimensional, and appraisal based. They also discussed about the different computational approaches proposed for emotion detection from text such as Keyword based, Rule based, Machine Learning based, and Hybrid approaches.

A. Papers and Publications

In between the years 2013 to 2023, we collected some papers that discussed about emotion detection from text. Fig 1 shows the graph of distribution over the past 10 years, and Fig 2 shows the Total no. of publications of Journal and conference proceedings and distribution of selected studies for the last ten years, the graph shows that research on emotion detection is still relevant.

III. DATASET

In the literature, [25][24][3] different existing or customized datasets have been used for emotion detection according to the types of experiments of different researchers. The dataset can be divided into two types, that are public dataset and private dataset. The datasets that are available to the general public through the Google Cloud Public Dataset Program are called public datasets and the customized datasets are called private datasets.

A. ISEAR

The International Survey on Emotion Antecedents and Reactions (ISEAR) database 21 was constructed by the Swiss National Centre of Competence in Research and was created in 1997 by Scherer and Wallbott (1994). This dataset consists of a total of seven emotional labels that are joy, sadness, fear, anger, guilt, disgust and shame. From 37 countries, a total of 3000 people from various cultural backgrounds were asked to complete questionnaires.

B. Cecilia Ovesdotter Alms' Affect data

In 2005, Alm developed a third dataset which includes 185 stories and 15000 sentences labeled with fear, anger, disgust, sad, happiness, and surprise. It also has positively surprised, negatively surprised, or neutral if no emotion is displayed.

C. Emo Bank

Over 10,000 sentences have been dimensionally annotated in accordance with the Valence, Arousal, and Dominance (VAD) criteria in this dataset of the Emotion representation model. News headlines, essays, blogs, newspapers, and other sources were used to create these sentences, where it has been categorically annotated using Ekman's fundamental emotion model, making dual representation possible.

D. Crowd flower

It contains tweets and their labels for the emotional content of texts. It was developed in 2016. It includes labelsfor rage, boredom, anger, empty, fun, enthusiasm, happiness, love, hate, neutral, sadness, relief, worry, and surprise. This dataset has 40,000 tweets.

E. Sem Eval

The database SemEval contains Arabic and English news headlines extracted from news and this dataset has three versions. SemEval 2007 is a collection of news headlines from various publications, including BBC News, The New York Times, CNN, and others. Surprise, anger, fear, sadness, disgust, and joy are all annotated with one or more emotions in each headline. SemEval 2018 is made up entirely of tweets. Anger, fear, disgust, love, joy, optimism, sadness, pessimism, trust, and surprise are among the eleven emotions expressed in each tweet.Distinct test, trial, and training datasets are provided for Spanish, Arabic, and English tweets. SemEval 2019 is made up of textual conversations between two persons.

F. MELD

(Multimodal Multi-party Dataset for Emotion Recognition in Conversation) MELD includes data from textual, audio and video. It has around 1400 conversations and 13,000 statements from the TV series Friends, which are labeled as anger, grief, disgust, surprise, fear, joy, and neutral in dialogues.

G. IMDB

Internet Movie Database (IMDB) was created to help categorize binary sentiment in movie reviews. On IMDB, there are both positive and negative reviews are there, where it has a uniform split. The test and training datasets, each of which received 25,000 reviews in the year of 2011. There are a total of 27,886 unprocessed and unlabeled HTML files in its data.

H. GoEmotions

This dataset consists of 58000 Reddit comments from 2005 to January 2019. This dataset has labeled for one or more of 27 emotions or Neutral as follows: admiration, amusement, approval, annoyance, anger, curiosity, confusion, caring, desire, disgust, disapproval, disappointment, embarrassment, excitement, fear, joy, grief, gratitude, love, sadness, nervousness, optimism, pride, remorse, relief, realization, surprise.

I. Aman

This corpus is made up of blogs that were obtained using Ekman's six fundamental emotions as clue words. It was created by Aman and Szpakowicz in the year of 2007. Here the sentence-level annotations were done and there are a total of eight different emotion classes to choose. It has 1466 sentences labeled with mixed emotion and no emotion, sadness, surprise, happiness, fear, disgust, and anger. Sentences depicting neutral feelings are defined by the word “no emotions”.

J. Smile dataset

This dataset contains discrete emotion annotations of anger, disgust, happiness, surprise, and sad ness for a total of 3085 tweets gathered from 13 Twitter handles affiliated with the British Museum.

K. DailyDailog

This dataset was built by crawling dialogues from regular people conversations. It contains a total of 13118 sentences annotated for neutral, anger, disgust, fear, happiness, sadness, surprise discrete emotion labels.

IV.APPROACHES

The different approaches proposed in the literature for the identification of text-based emotion 8 detection were discussed in the following sections:

A. Keyword-based approach

In this approach, it extracts the key features that are in combination with emotion labels using a lexicon such as Sentiword Net, Wordnet, linguistic rules are applied and sentence structures are exploited. After that, the text preprocessing was done on the given dataset which includes stop word removal, tokenization and lemmatization. In addition, emotion intensity and keyword spotting are evaluated including with Negation checks. Finally, it will determine the emotion label for each sentence.

[26] created 25 emotion classes and proposed a methodology for sentence-level emotion detection which was based on keyword analysis, emoticons, keyword negation, short words, and a set of proverbs etc. They also got an accuracy of 80%.[27] explain the approach based on keyword analysis which contains emotions. For example, we're so happy that he passed" the keyword happy indicatesthe emotion of joy or happiness. But without the word “happy” we can’t detect the emotion of that sentence.[28] created generalized and customized user reviews based on their behaviors on Twitter to use later data. For the text preprocessing step based on the keyword approach, the emotions and sentiments from the Twitter data were used.[29] created method works based on keyword analysis (KA), keyword negation analysis (KNA), a set of proverbs, emoticon, short form of words, exclamatory word and to find emotion they created 25 emotion classes.

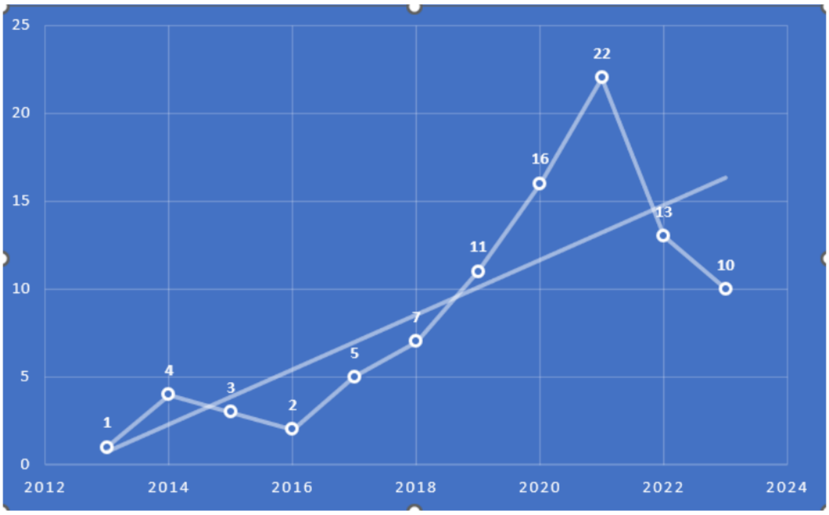

Fig.1 distribution over the past 10 years for selected studies in Emotion detection

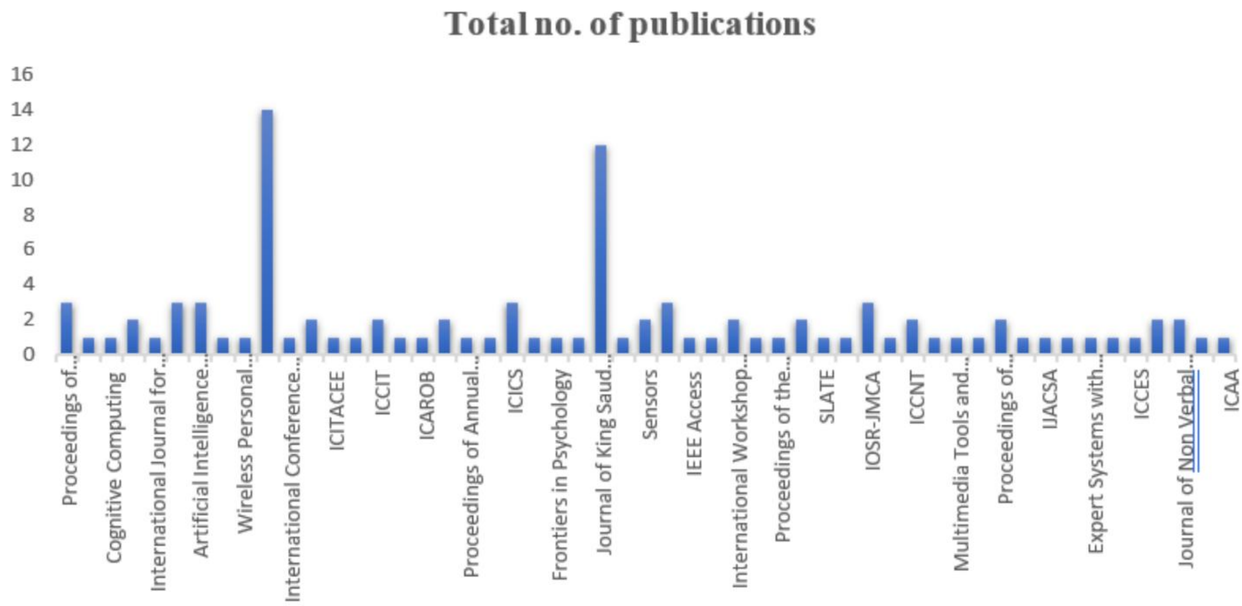

Fig.2 JournalandConference/Proceedingpublicationsanddistributionofselectedstudies

B. Rule-based approach

The rule-based approach is used to manipulate the knowledge in order to view information in an advantageous way. It includes text preprocessing, stop words removal, POS tagging, tokenization, etc. The rules are applied to emotion datasets to determine the emotion labels. After that, the appropriate rules are chosen [24]. [30] proposed efficient emotion detection techniques from text at the sentence level by searching direct emotional words from a predefined emotion keyword database. They also include the negation words and calculate all the evaluation metrics that are Accuracy, Precession, Recall and F1 score, where they obtained the F1 score 66.18%. [31] described the Rule Based approach, which detects the emotion or mood of the tweet and classifies the Twitter message under the appropriate emotional category and obtained an accuracy of 85%. Their proposed system understands the deeper levels of emotions i.e., finer grained instead of sentiment i.e., coarse grained.

C. Corpus-based approach

Corpus-based emotion detection are supervised learning approach where a text corpus with a predefined collection of emotions is extracted from emotion theories. [32] presented different events that took place in April 2019 with a multilingual emotion data set. They collected tweets from the Twitter platform and considering seven emotions, six Ekman's basic emotions plus the "neutral or other emotions", were labeled on each tweet by 3 Amazon MTurkers. There are a total of 8,409 in Spanish and 7,303 in English were labeled. Moreover, in order to validate the effectiveness of the data set, they also proposed a machine learning approach for automatically detecting emotions in tweets for both languages, English and Spanish. [33] used a hybrid approach of Term Frequency Inverse Document Frequency (TFIDF) and deep learning mode and proposed an IoT-based framework for the emotional classification of tweets. Their proposed methodology was analyzed on two different Twitter emotions datasets. The dynamic epoch curves are shown to show the behavior of test and train data points which proved that this methodology outperformed the popular state-of-the-art methods. [34] formed an automatic emotional corpus by merging two computational models which is called Corpus-Based Emotion (CBE). Where the CBE was developed from ANEW and WNA with term similarity measure and distance of node approach. Based on the experiment results, it was known that CBE is able to improve the accuracy in the detection of emotions. The author obtained the F-Measure using WNA+ANEW is 0.50 and F-Measure using CBE with expanding is 0.61. [35] discussed different annotation strategies for these dimensions, based on the event-focused enISEAR. Additionally, they analyzed two manual annotation settings: (1) showing the text to annotate while masking the experienced emotion label; (2) revealing the emotion associated with the text. The author also evaluatesthese strategies in two ways: by measuring inter-annotator agreement and by fine-tuning RoBERTa to predict appraisal variables and their results show that knowledge of the emotion increases annotators' reliability.

D. Machine learning approach

Based on the modeling of the input-output relationship, machine learning techniques are divided into discriminative and generative categories and the most common machine learning techniques for extracting aspects are discriminative neural networks, but they prefer to introduce them separately due to their unique characteristics and recent focus [20].[10] used the machine learning methods in Roman Urdu text-based emotion detection. They collected 18000 labeled sentences from different sources, where the total words are 2,74,708 and the unique words are 39,063. They first preprocessed data to clean and convert it into the correct format so that the classification algorithm can be applied to the processed corpus. The preprocessed text is further processed to extract features that could improve the outcomes. After the completion of the corpus results the author obtained the highest accuracy of 69.54%.

[21] discussed an algorithm for emotion recognition from Indian languages using Machine Learning. The accuracy of their results was 95.5% which was very promising for Indian languages having smaller datasets. [36] proposed a model with communication problems and helped to find and react to the societal situation for children, where they used a total of 1241 sentences of non-insulting and 1255 sentences from insulting sentences as their dataset. After applying the Machine learning algorithm of the SVM method they obtained a recall of 80% which was more than precision i.e. 75%.

[37] proposed an algorithm and identified the intensity of four types of emotions that are happy, sad, angry and terror in which datasets are collected from the Twitter dataset.[38] developed and evaluated a supervised learning system that can automatically classify emotion in text stream messages, offline training tasks, and online classification tasks. The first task created models to classify emotion in text messages. For the second task, they developed a two-stage framework called EmotexStream to classify live streams of text messages for real-time emotion tracking. [24] [31] developed an emotion recognition and prediction system for text-based emotion recognition in the text stream. They used supervised learning methods such as Multinominal NB, DT, SVM and KNN for the ISEAR dataset and obtained the highest accuracy of 64.08% by using Multinominal NB. [34] used vector similarity measure (VSM), keyword base and STASIS approaches are employed to detect emotions in text and find the different categories of emotions and achieved a precision of 0.53. [31] The authors as implemented the machine learning 10 approaches for the Twitter messages for the detection of emotions. They showed efficiency in the Naïve Bayes algorithm was more relevant compared to the K Nearest Neighbour (KNN) and obtained an accuracy of 72.60%, and 55.50% respectively.[38][39] implemented machine learning Naïve Bayes algorithm for 105 tweets dataset and applied 10 cross-validationsto the approach and obtained an accuracy of 83%.

E. Deep Learning Approach

Deep learning approaches are dominating than other traditional approaches for sentiment analysis where the programs learn from experience and understand the world in terms of a hierarchy of concepts. This approach allows a program to learn complicated concepts by building them based on simpler ones. The most used deep learning model here is long-short-term memory (LSTM). LSTM is a special form of recurrent neural network (RNN) with the capability of handling long-term dependencies. LSTM overcomesthe vanishing or exploding gradient problem common in RNNs[41] [11]. Convolution Neural Networks works well for those tasks where feature detection in the text is important. The resulting abstract features were used effectively for sentiment analysis, question-answering, and machine translation. CNN is used as a feature learner for input text in our approach [42].[28] extracted a sample word-emotion lexicon from that corpus and their experiment demonstrates that this sample word-emotion lexicon enhances the emotion detection results by 22.27% compared to the SMO classification using the train/test option.

A Neural Network, where the output from the previous step is used as input to the current step for sequence classification – sentiment classification video classification. Long-Short Term Memory (LSTM), a special type of recurrent neural network with the capability of handling longterm dependencies. The LSTM overcomes the vanishing or exploding gradient problem common in RNNs. [17] aimed to find the correlation between the sentiments and emotions of the people from within neighboring countries amidst the coronavirus (COVID-19) outbreak from their tweets. The study also utilized the publicly available Kaggle tweet dataset for March - April 2020. Tweets from six neighboring countries are analyzed, employing NLP-based sentiment analysis techniques. The author used 16,784 tweets as test data to access model accuracy. The model achieved an accuracy of 76% and an F1 score of 78%. The author said that the reason for the good accuracy achieved in the validation phase is that their process of validation is indeed the same as the process used in preparing the Sentiment140 dataset – the dataset on which their model is based upon for sentiment polarity assessment.

[43] proposed a novel deep dual recurrent encoder model that utilizes text data and audio signals simultaneously to obtain a better understanding of speech data. Their model encodes the information from audio and text sequences using dual recurrent neural networks (RNNs) and then combines the information from these sources to predict the emotion class. Their proposed model outperforms previous state-of-the-art methods in assigning data to one of four emotion categories(angry, happy, sad and neutral) when the model was applied to the IEMOCAP dataset, as reflected by accuracies ranging from 68.8% to 71.8%.

F. Transformer model

- UMLFit

ULMFit was developed at the beginning of 2018 which was the first 'pure' transfer learning application. It employs AWD-LSTMs, an LSTM version that employs Drop Connect for improved regularization and improves using averaged stochastic gradient descent (ASGD). The ULMFit 11 has three LSTM layers and 400 dimensions in the embedding layer, with 1150 hidden units in each of them [25]. Fig. 3 shows that the different papers that were discussed about the Transformer models.

- GPT
  Open AI GPT [44][25] design is purely attention-based, with no recurrent layers. By combining learned position embeddings with byte-pair encoded token embeddings and incorporating these embeddings into a cross-layer transformer decoder framework with the purpose of standard language modeling, pre-training is achieved. The model performs at each step by utilizing a decoder architecture. The GPT, primarily used for text representation, is formed by the trans former decoder with 12 attention heads and 12 transformer layers. XLNet [45] [46] [25] Transformer-XL and Permutation Language (PLM) models are employed.
- XLNet
  XLNet is a language model that is both auto-regressive and auto-encoding. BERT masks the data and uses a bi-directional context to try to predict the masked data, whereas XLNet uses the permutation objective. RoBERTa [2] [47] [25] [48].
- RoBERTa
  RoBERTa (short for Robustly optimized BERT technique) is a precise architectural clone of BERT with a larger dataset and tuned hyperparameters for pretraining that was introduced. The pre-training masking approach has been changed from static to dynamic. Static masking was performed just once during pre-processing, whereas dynamic masking is performed many times during pre-processing, i.e., every sequence is masked just before feeding it to the model.
- DistilBERT
  DistilBERT [49] [25] proposed distillation in neural networks, which tries to increase the speed of models. It was accomplished by using a simplified version of the BERT architecture with few parameters. It takes the original BERT's design, decreases the layersto half of the original BERT, and eliminates poolers and token embeddings to create a faster and smaller BERT for common applications.

V.EVALUATION METRICS

To measure the statistics between the good models that can be fit or not different evaluation metrics are used. Fig. 4 shows that the distribution of Evaluation Methods used in Text-Based Emotion Detection.

A. Accuracy

The accuracy metric is to measure the classification models. [50] [51] [27] [24] [41] [32] [53] [54] are calculated using the equation:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad \text{(Eq.1)}$$

B. Precision

The Precision (P) is defined as the number of true positives (Tp) over the number of true positives plus the number of false positives. [43] [21] [24] [55] [30].

$$P=\frac{Tp}{Tp+Fp} \quad \text{(Eq.2)}$$

C. Recall

The Recall is defined as the number of true positives over the number of true positives plus the number of false negatives [30] [43] [24].

$$R=\frac{Tp}{Tp+Fn} \quad \text{(Eq.3)}$$

D. F-Score

F-Score measure is used to provide a score that balances both the concerns of precision and recall in one number and macro F1 score is used to measure when multiple classes are declared. MacroF1 score has a best value =1 and a worst value as 0. [31] [9] [51] [23] [24] [63] [64].

$$F1=2 *\frac{PxR}{P+R} \quad \text{(Eq.4)}$$

Based on literature studies, the most widely used methods in text-based emotion detection are Jaccard Accuracy and Precision, Recall and F-score over the past 10 years. Some other common metrics used to measure the models are Kappa Coefficient, multi-label accuracy (Jaccard accuracy), Accuracy, Pearson Correlation, 10-fold cross-validation, Chi Square.

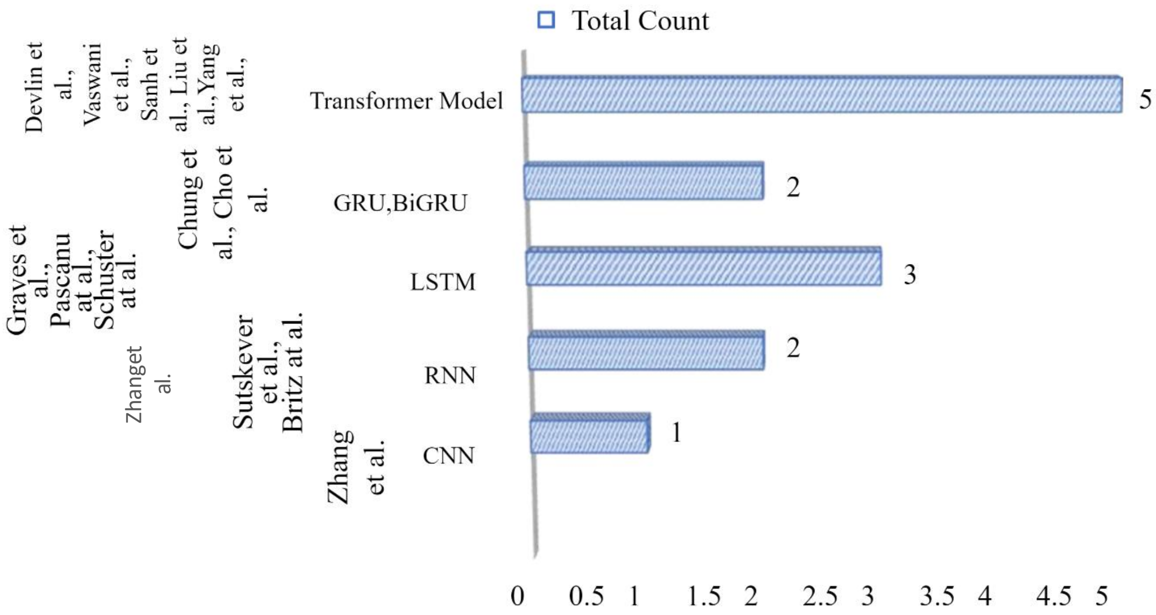

Fig.3 Papers that were discussed about the different approach in TBED [26] [48] [49] [56] [57] [58] [59] [60] [61] [62]

Table. 2 Emotion models

Reference	Emotion	Approach	Structure
OCC [39]	Admiration, anger, appreciation, disappointment, disliking, fear, fears confirmed,gloating, gratification,gratitude, happy-for, hope, liking, pity, pride, sorry- for, relief, remorse, reproach, resentment, self-reproach, shame	Dimensional	Tree
Ekman[12]	Anger,disgust,fear,joy,sadness,surprise	Categorical	-

V.CHALLENGES

Table 3. Challenges of Emotion detection in existing studies

Problem Identification	ChallengesinEmotionDetection	FutureDirection
Datasets	Annotated datasets, Imbalanced datasets, Domain dependent datasets, Language dependent datasets, Mislabeled emotions	Domain Adaptation, Transfer Learning,GAN, Multi-modalityin text and data sources
Accuracy	Several techniques arenot robust Accuratenessofcurrentsystems	Auto-encodersEnsemblemethods
Qualityoftext	Incomplete information, typing mistakes Slang words,shorttexts, emojis, Detection of sarcasm, irony, harmony	Multitask Learning System Transfer learning Pattern-basedapproach
Semantics	Inabilitytorecognizeimplicitemotions	Pre-trainedwordembeddings Best–Worst Scaling (BWS) Annotation Scheme Deep Learning algorithms

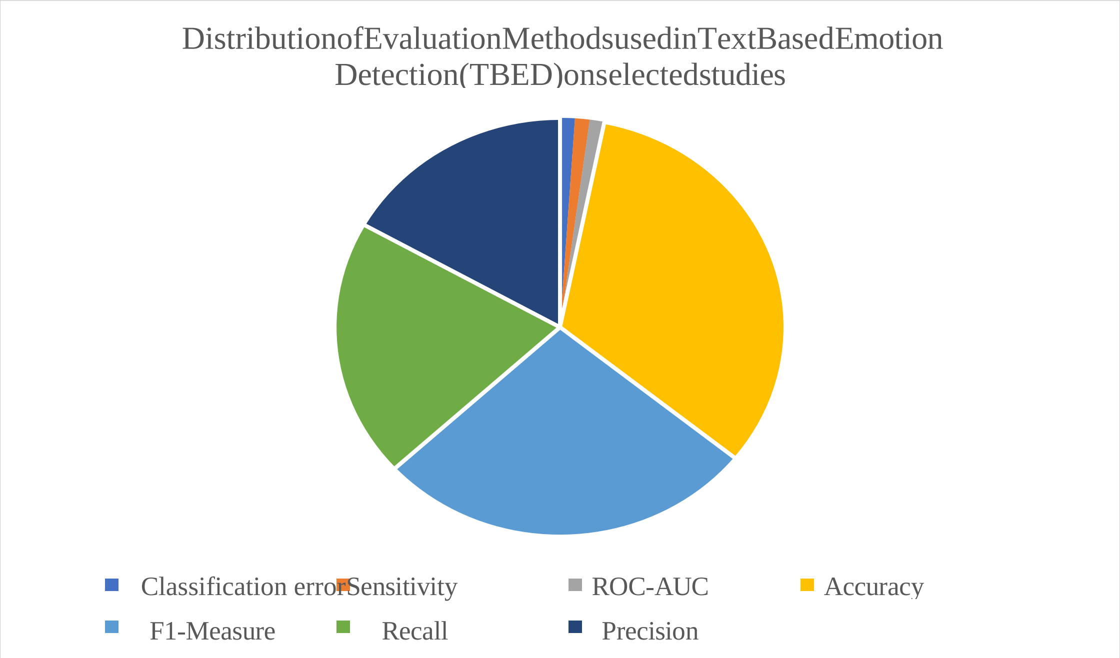

Fig.4 Distribution of Evaluation methods in TBED

VI. CONCLUSION

As per the paper's review, we analyzed the different approaches such that keyword based approach, Rule-based approach, Machine learning-basedapproach, Deep learningapproach, *etc*. areusedintext-basedemotiondetection.Wefurtherexplorethedatasetsused,evaluation metrics, significance,limitationsand contributionsof text-based emotion detection for future researchers. Boththe Deep Learning and MachineLearning approach are dominatingand favoritetechniques because of their automatic learning performance.

Somekeyadvantagesofourarticleare:

- This review paper will provide a comprehensiveoverview of the current state-of-art emotion detection in text streams. Since, we summarize the key research findings, trends in the field, making it easier for readers to follow the track.
- Our review paper evaluates the different evaluation metrics and approaches used in text-basedemotion detection. We also discuss the list of benchmark datasetsthat are essential for comparing new models used in text-based emotion detection.
- By discussing the challenges and future directions, this paper can inspire new researchers towards important issues.

However, a few limitations of our work are:

- This article is deprived of the possibility of theoretic concepts, and in the literature, one can find articles in abundance, where possibilistic concepts bring interesting implications. Despite the author's efforts, it may not be possible to include every relevant study, potentially omitting important research from the review.
- Also, this review paper has a cutoff point for the inclusion of studies, which means that recent advances in the field may not be adequately covered.

This review paper may overlook interdisciplinary insights that could be valuable for understanding text-based emotion detection from multiple perspectives.We hope that through this review paper, the reader will have a better understanding of the research done on this topic, the features extracted, the methodologies used, and the results reported by various researchers.

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