A Review of Different Approaches for Detecting Emotion from Text

Ashritha R Murthy¹, Anil Kumar K M²
Assistant Professor¹, Department of Computer Science and Engineering, Sri Jayachamarajendra College of Engineering, JSS Science and Technology University. Associate Professor², Department of Computer Science and Engineering, Sri Jayachamarajendra College of Engineering, JSS Science and Technology University.

E-mail id: ashrithar.murthy@sjce.ac.in

Abstract. Emotion detection and analysis is one of the challenging and emerging issues in the field of natural language processing (NLP). Detecting an individual's emotional state from textual data is an active area of study, along with identifying emotions from facial and audio records. The study of emotions can benefit from many applications in various fields, including neuroscience, data mining, psychology, human-computer interaction, e-learning, information filtering systems and cognitive science. The rich source of text available in the Social media, blogs, customer review, news articles can be a useful resource to explore various insights in text mining, including emotions. The purpose of this study is to provide a survey of existing approaches, models, datasets, lexicons, metrics and their limitations in the detection of emotions from the text useful for researchers in carrying out emotion detection activities.

Keywords: Emotion, Lexicon, Machine learning, Psychology, Deep learning

1. Introduction

The emotion is an interdisciplinary field involving psychology, computer science and others. In psychology, emotions are expressed as psychological state differently connected with contemplations, sentiments, behavioural responses, and a level of delight or displeasure [1]. In computer science, emotions can be identified in the form of audio records, video records and text documents. Analysing emotions from the text documents seems to be challenging due to the fact that textual expressions are not always directly use the emotion related words, but often outcome from the understanding of the meaning of concepts and interaction of concepts mentioned in the text document.

Emotion expressions are the crucial form of communication in interpersonal relationship [2]. It can be expressed into positive emotion, negative emotion or neutral [3]. In general the positive emotions are expressed as happy, excited, joy, pride and negative emotions such as sad, disgust, fear, depressed and so on. In such a way, the emotions are expressed in various forms to communicate and the rich source of textual information is obtained from the social networking sites such as YouTube, Twitter, and Facebook etc., where people are spending most of their time in posting and expressing their emotions [4]. By considering the textual data
available on the blogs, it is helpful to identify the intensity of emotion of an individual. For example “Really happy with this purchase” [5] express the positive emotions from a customer about the purchase of product. The term “Really” intensifies the emotion expressed by the customer. In this case it implies it is more positive emotions. Another customer review on the same product [5] expressed negative emotions on the purchase of the product such as “Really disappointed. Alexa has to be plug-in to wall socket all the time. My fault is for not checking”. Here the customer intensifies more negative comment about the purchase. By considering the intensity of emotion through the text, it helps to predict individual emotions. Also, it helps to know the state of emotions of the person that can assist friends and family to take preventive measures against accidents or self harm. The contribution of the paper is to provide the state of the art approaches used in the detection of emotion from text.

In section 2, the relevant emotion models are discussed. In section 3, the existing resources such as the Corpora and lexicon are discussed. In section 4, computational approaches used in literature are discussed. Evaluation metrics used in literature are discussed in section 5. Summary of the existing approaches are discussed in section 6. Finally conclusion is discussed in section 7.

2. Emotion Models

Emotions are recognized by humans and this effect has influenced the way emotions are viewed in scientific terms. Researchers in psychological science believe that individuals have internal mechanisms for a limited collection of responses (usually happy, sad, anger, disgust, and fear) that can be assessed in a simple and objective manner once activated [6]. In order to represent emotions, the three major approaches are used in the psychology research [7] are

1.1 Categorical approach: This approach of emotion involves placing emotions into categories or into distinct classes that are basic and universally recognized [7]. The emotions are independent and also depend on how an experience perceiving the situation which can be categorized into six basic fundamental emotions i.e., (happiness, fear, sadness, surprise, disgust and anger) by Paul Ekman[8].

The model by Robert Plutchik[9] proposed eight fundamental emotions, i.e. acceptance / trust and anticipation. The 8(eight) emotions are expressed in opposite pairs as surprise versus anticipation, joy versus sadness, anger versus fear and trust versus disgust. There are varying degrees of intensity for each emotion, according to Plutchik, which occurred as a result of the perception of events via an experiencer.

The model of Orthony, Clore, and Collins (OCC) [10] differed from the "basic emotions" analogy proposed by Ekman[8] and Plutchik[9]. They accepted, however that emotions emerged as a result of how the events and emotions perceived by an individual differed based on the degree of intensity. Emotions have been categorised into 22, 16 emotions were
added to the basic emotions proposed by Ekman[8] and a much wider representation of emotions as {envy, relief, appreciation, self-reproach, shame, reproach, pity, admiration, disappointment, grief, gratification, fears-confirmed, gloating, hope, like and dislike}.

1.2 Dimensional approach: In this approach, it considers emotional states to be bound to each other rather than to be independent. Hence, it is represented in dimensional space [7] (uni dimensional and multi-dimensional) describing how emotions are connected based on the event and their degree (low to high) of occurrence. This article explores more on multi-dimensional models for emotional representation.

- Russell’s circumplex model [11] represent the emotions in two dimensional model. As emotions are not independent it distinguished as Arousal (Activation and Deactivation) and Valence (Pleasantness and Unpleasantness) where the dimension Arousal refers to how excited or apathetic an emotion is and the dimension Valence refer to how positive emotion and negative emotion is [7].

  Figure 2.1: Circumplex model by Russell [11].

- In the two-dimensional model, Plutchik’s wheel of emotions [9] represents emotions as a wheel of emotions, as seen in figure 2.2. In the concentric circle, the wheel represents emotions, with the inner core emotions being variants of the eight basic emotions, then the eight basic emotions in the outermost areas of the wheel, and finally combinations of the primary emotions. The wheel shows how the emotions are related, depends on the location on the wheel.

  Figure 2.2: Plutchik’s Wheel of emotions [9]
Russell and Mehrabian [12] represent emotions into three dimension model such as pleasantness (or positiveness), arousal (or responsiveness), and potency (or dominance). In 2D representation the emotions are distinguished as Arousal (Activation and Deactivation) and Valence (Pleasantness and Unpleasantness) and the third dimension as Dominance Power [2]) refers to the degree to which an experienced had been control of their emotions. Figure 2.3 represents 3D emotion space.

![3D Emotion Space Image](image)

**Figure 2.3:** 3D Emotion Space (Valence, Arousal, and Power) Images adapted from [7].

- Parrot [13] organized emotion into three hierarchical structures namely primary, secondary and tertiary emotions with joy, anger, fear, love and surprise as primary set of emotion. Table 1 represents different emotions used in Parrot Emotion Taxonomy.

| Primary emotions | Secondary emotions | Tertiary emotions |
|------------------|--------------------|-------------------|
| Love             | Affection          | Caring, sentimentality, adoration, fondness, compassion, tenderness, love, attraction, affection, liking. |
| Lust             |                    | Desire, arousal, passion, Infatuation, lust. |
| Joy              | Cheerfulness       | Euphoria, satisfaction, gladness, bliss, happiness, Jubilation, delight, elation, enjoyment, joviality, joy, Amusement ecstasy, jolliness, gaiety, glee, cheerfulness. |
| Zest             |                    | Thrill, excitement, enthusiasm, exhilaration, zeal, zest. |
| Contentment      | Pleasure           | Contentment. |
| Pride            |                    | Triumph, Pride. |
| Optimism         |                    | Optimism, hope, Eagerness. |
| Surprise         | Surprise           | Astonishment, surprise, amazement. |
| Irritation       |                    | Agitation, annoyance, irritation, grouchiness aggravation, |
| Sadness          | Sadness            | Gloom, grief, melancholy despair, glumness, misery, unhappiness, hopelessness, sadness, depression, sorrow, woe, |
| Disappointment   | Dismay, displeasure, disappointment |
| Shame            |                    | Regret, shame, remorse, guilt |
| Anger            | Exasperation       | Frustration, exasperation, |
| Rage             | Bitterness, loathing, wrath, dislike, hostility, spite, resentment rage, ferocity, hate, scorn, fury, anger, vengefulness, outrage. |
| Disgust          | Contempt, revulsion, disgust. |
| Suffering        | Hurt, agony, anguish suffering, |
Unclear
| travel guides | Link |
|---------------|------|
| CrowdFlower [24] | Tweets | https://www.crowdflower.com/wp-content/uploads/2016/07/text_emotion.csv |
| WASSA-2017 Emotion Intensities(EmoInt) [25] | Tweets | http://saifmohammad.com/WebPages/EmotionIntensity-SharedTask.html |
| Cecilia Ovesdotter Alm's Affect data [26] | Stories | http://people.rc.rit.edu/~coagla/affectdata/index.html |
| DailyDialog [27] | Dialogues | https://www.aclweb.org/anthology/I17-1099/ |
| Emotion Stimulus[28] | Designed out of FrameNets | http://www.site.uottawa.ca/~diana/resources/emotion_stimulus_data |
| MELD data [29] | Dialogues from Television show | https://github.com/SenticNet/MELD |
| SMILE dataset[30] | Tweets | https://figshare.com/articles/smile_annotations_final_csv/3187909 |
| Dens Dataset[31] | Information obtained from wattpad web histories and project Gutenberg literature | Available on Request |
| The Valence and Arousal dataset[32] | Posts of FB (Facebook) | http://wwbp.org/downloads/public_data/dataset-fb-valence-arousalanon.csv |
| Grounded emotions[33] | Tweets | http://web.eecs.umich.edu/~mihalcea/downloads/groundedemotions.delim | delimiter"005C317$#GroundedEmotions |
| Emotion Lines | FB message chats and Television show {FRIENDS} | https://sites.google.com/view/emotion2019/assets: Available upon registration |
| Amazon Alexa Reviews emotions[5] | Alexa Reviews | https://www.kaggle.com/sid321axn/amazon-alexa-reviews |

3.2 Lexicons

The lexicons used to detect the emotions from the text that are available in literature and are discussed in Table 3.

**Table 3: List of lexicons**

| Lexicon | Description | Link |
|---------|-------------|------|
| AFINN [35] | It is manually rated word for valence within an integer between minus five(-5) and plus five(+5). | https://github.com/fnielsen/afinn. |
| Sentiment140 Lexicon [36] | It is automatically generated from tweets that contain emoticons. | http://saifmohammad.com/WebPages/lexicons.html#NRCTwitter |
| NRC Hashtag Emotion Lexicon [37,38] | It is created automatically from tweets that contain hashtags with emotional terms such as #happy. | http://www.saifmohammad.com/WebPages/AffectIntensity.htm. |
#sad. It is primarily associated with words such as anger, fear, anticipation, surprise, happiness and trust.

Bing Liu Lexicon [39] This Lexicon consists of a list of positive and negative opinion words or sentiment words. [https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#lexicon.]

NRC Hashtag Sentiment Lexicon [40] It is automatically generated from tweets that include sentiment-word hashtag such as #amazing. It is associated with positive or negative sentiment. [http://saifmohammad.com/WebPages/Lexicons.html#NRCTwitter.]

WordNet [41] Online English lexical Database. It consists of verbs, nouns, adjectives and adverbs into a set of synonyms called synsets. [https://wordnet.princeton.edu.]

NRC Word-Emotion Association Lexicon [42,43] Use Amazon's Mechanical Truck, Lexicon Annotated Manually. Consist of 8 emotions and two positive and negative sentiments are included [http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm.]

EmoSenticNet [44] Emotions labels to Sentic Concept [https://www.gelbukh.com/emosenticnet/]

| 4. Computational approaches: |
|---|
| The different approaches proposed in the literature for the identification of emotions from the text were discussed in the following sections. |

4.1 **Keyword based approach:**

In this approach, it exploits the knowledge of key features that are combination with emotion labels using a lexicon such as Word-Net Affect and SentiwordNet, linguistic rules are applied and sentence structures are exploited. Further text preprocessing has to be performed on the given dataset which includes stopword removal, tokenization and lemmatization. In addition, keyword spotting and emotion intensity are evaluated including with Negation checks. Finally, it determines the emotion label for each sentence.

CC Liu et al.[14] express this approach is based on the set of keyword which contains emotions. Without a keyword in a sentence means that it doesn’t contain any emotions in them. For example: “Today, I passed my exam with distinction” and the sentence as “Hurray! Today, I passed my exam with distinction” “I passed my examination with distinction today" could indicate the same emotion (joy), but if "hurray" is the only keyword to detect this emotion, the former without "hurray" might remain undetected. They introduced an architecture aimed at providing diverse contexts with a systematic understanding of textual input and better flexibility. That is, with semantic analysis, the extraction of semantic information, the design of ontology based on emotion models and the adoption of new keywords with case-based reasoning.
Sailunaz, Kashfia, and Reda Alhajj [45] used the latter data to create generalized and customized user reviews based on their behaviors on Twitter. For the text preprocessing based on keyword based approach the emotions and sentiments from the twitter data were used. Shivhare et. al [46] developed emotion detector system based on the emotion ontology produced an accuracy more than 75%.

Rahman et. al [47] proposed a methodology for sentence level emotion detection and created 25 emotion classes. It is based on the keyword analysis, emoticons, keyword negation, short word, a set of proverbs etc and achieved an accuracy of 80%.

4.2 Corpus based approach:
Corpus-based emotion detection approaches use supervised learning to induce sources of information such as word-emotion lexicons classified or weakly-labeled from a text corpus with a predefined collection of emotions extracted from emotion theories such as Ekman, Parrot, etc. To model the syntactic and semantic trends of text for emotion detection website such as wikipedia is used and unsupervised learning is also implemented. More works are focused on lexicons, motivated by a considerable amount of study in the area of sentiment analysis.

Anil et al[48] demonstrate how using a generative unigram mixture model (UMM) to jointly model emotionality and neutrality of terms, labelled (blogs, news headlines) and weakly labelled (tweets) emotion text can be used to learn a word-emotion interaction lexicon. UMM generated emotion language models (topics) have significantly lower perplexity compared to those from state-of-the-art generative models such as supervised Latent Dirichlet Allocation (sLDA).

Flor et al. [49] used multilingual dataset from tweets (English and Spanish). It consists of 8409 Spanish and 7303 English labeled dataset from the tweets. They reported linguistic statistics and applied machine learning to detect emotions. To evaluate the approaches used 10 fold validation and obtained accuracy of 64% for Spanish and 55%. For English. Rachman et al.[50] developed CBE (Corpus Based Emotions) with widely used emotion corpus the Wordnet Affect Emotions (WNA) and the Affective Norms for English Word (ANEW). They showed using the CBE, it improves the performance of detecting emotion with F-Measure using WNA and ANEW obtained is 50% and with the CBE obtained 61%.

Anil et al. [51] proposed the Unigram Mixture Model (UMM) based on the domain specific emotion lexicon. It outperforms the feature derived from supervised Latent Dirichlet (LDA) and Pointwise Mutual information (PMI) and also the combination of n-gram, lexicon and POS. The F score measure for n-gram, PMI+UMM for total emotion intensity and for hybrid approach for the dataset such as SemEval, ISEAR, 10 and 5 cross validation is 38.23%, 39.48%, 6.24% and 52.18% respectively.
A constraint optimization architecture for emotion detection was developed by Yichen Wang and Aditya Pal[52]. To solve the multiple label classification and allow multiple emotions, their proposed model can be used. Their model achieved a precision of 0.43 for the Twitter dataset and a recall of 0.67.

4.3 Rule based Approach

To manipulate knowledge in order to view information in an advantageous way, the rule-based approach is used. It begins with text preprocessing initially, including stop word elimination, POS tagging, tokenization, etc. The rules of emotion are then derived using the concepts of statistics, linguistics, and computation. The best rules are selected later. Finally, the rules are applied to emotion datasets to determine the emotion labels. Subsequently, the appropriate rules are chosen. Additionally, the rules are applied to the emotion dataset for determining the emotion labels.

An alternative approach to improving the sentiment classification of user reviews in online communities is proposed by Asghar, Muhammad Zubair, et al.[53] Lexicon-enhanced sentiment analysis based on a rule-based classification and integrating emoticons, modifiers and domain-specific terms to evaluate the feedback posted in online reviews, in addition to the sentiment terms used in general purpose.

Dibyendu et.al [54] proposed sentence level emotion detection technique by applying semantic rules. It also includes negation words and obtained F1 score of 66.18%. Srinivas Badugu and Matla Suhasini [55] developed a Rule Based Approach that detects the emotions from the tweets and classify into different emotion categories and achieved an accuracy of 85%.

4.4 Machine learning approach

Emotion detection from text is based on classification problem involving different models from the disciplines of Natural Language Processing (NLP), Machine Learning(ML). Machine learning is categorized into unsupervised learning and supervised learning. Naive Bayes (NB), Support vector machine (SVM), conditional random field etc., are the most common traditional unsupervised machine learning.

Hasan et al. [56] in his work of detection of emotion worked on text stream data and use both online and offline messages. Support Vector Machine, Naïve Bayes and Decision Tree (DT) were used to detect emotions and achieved 90% accuracy. For YouTube comments, Tripto and Ali[34] suggested work on machine learning models and obtained classification of 59.2% accuracy and 65.97 % and 54.24% accuracy for Multiclass sentiment labels.

Merav et al.[57] proposed a model for the children with communication problem and help to find how to react to the societal situation. They used dataset which consist of non- insulting sentences (1241) and insulting sentences(1255). Applied ML algorithm
and obtained 80% recall and more than 75% precision for SVM method. And achieved precision and recall is (>75%) for the Tree bagger, Multilayer Neural Network method.

Suhasini and Badugu [58] as implemented the machine learning approaches for the Twitter messages for the detection emotions. They showed efficiency in Naïve Bayes algorithm was more compared to the K Nearest Neighbour (KNN) and obtained an accuracy of 72.60%, 55.50% respectively. Fakhri [59] developed emotion recognition and prediction system for the detection of emotions using text. They used supervised learning algorithm such as Multinominal NB, DT, SVM and KNN for the ISEAR dataset and obtained highest accuracy for the Multinomial Naïve Bayes is 64.08%.

R Jayakrishna et al. [60] used machine learning approach for the Malyalam novel and using the SVM, classified sentences in the novel into happy and obtained precision of 0.94, for sad obtained precision of 0.92, for fear obtained precision of 0.93, for anger obtained precision of 0.90 and lastly for surprise obtained precision of 0.90. Sonia and Kavitha [61] proposed an algorithm to identify the intensity of emotions from the Twitter dataset and identified the intensity of four types of emotions, considering tweets: \{happy, sad, angry and terror\}.

Wikarsa and Thahir [62] implemented machine learning Naïve Bayes algorithm for 105 tweets dataset and applied 10 cross validation to the approach and obtained accuracy of 83%. Forugh and Hooman, [63] in their work vector similarity measure (VSM), keyword base and STASIS approaches are employed to detect emotions in text to find the different categories of emotions and obtained precision of 0.53.

4.4.1 Deep learning approach

Deep learning (DL) is a subset of ML in which programs learn from understanding and experiencing the hierarchy of concepts where each concept is described in terms of its relation to simpler concepts. This methodology helps a program to learn complex ideas by building them on simpler concepts [64].

In many research papers address DL model as long short-term memory (LSTM). LSTM consist of special type of RNN (recurrent neural network) with long-term dependency management capabilities. LSTM overcomes the issue of disappearing or bursting gradient prevalent in RNNs.

Baziotis et al. [65] propose work on SemEval 2018 Task 1 competition using Deep Learning model. Their idea was a two-layer Bidirectional long-term short-term memory (Bi-LSTM) built with a multilayer self-attention system. They used the approach with the tool ekphrasis [66] for pre-processing the text. Because of the limited number of training results, they used a transfer learning approach by pre-training the Bi-LSTMs on the SemEval-2017, Task 4A [67] dataset. A dataset of 550 million English tweets has been collected to be used in text preprocessing, word2vec embedding training [68],
and affective word embedding for calculating the required word statistics. The experimental results revealed that transfer learning did not outperform the random initialization model.

Zishan Ahmad et al. [69] designed a model using the DL classifier for Hindi text emotion detection and also showed that information gathered from resource-rich languages can be extended to other language domains using transfer learning and cross-lingual embedding. They obtained F1 score of 0.53.

Seo-Hui Park et al. [70] developed an emotion detection model using CNN and 144,701 tweets were used and also used a ROC story data. The Joy emotion was found with highest accuracy of 73.3% and Anger results in the lowest accuracy value of 36.7% and the lowest Kappa score is 0.216.

Xiao Zhang et al. [71] introduced the Factor graph model is used to detect multiple emotions or Online Social Network and also proposed multilabel learning algorithm and achieved contextual information and obtained F1 score of 62.7, other categories F1 score for BR is 57.0, F1 score for Back Propagation Neural network is 57.7, F1 score for Probabilistic classifier chain is 54.1, F1 score for Label combination 55.7 and finally F1 score for Machine Learning K Nearest Neighbor is 56.0.

Malte and Ratadiya [72] developed BERT (Bidirectional Transformer). Both for Hindi and English text were tested and attained F1 score of 0.4521 and 0.5520 respectively. Waleed Ragheb et al. [73] developed a model using the SemEval2019 task 3 dataset.

The proposed model use deep transfer learning, self-attention mechanism and turn-based conversational modeling to classify the emotions and 0.7582 F1 score is obtained. Ma et al. [74] used Bi-LSTM to distinguish emotions into good, sad and angry in text and Emoji assertions and noticed that their method’s performance exceeded the baseline models for happy and angry, but not for sad. Bi-LSTMs from documents are capable of extracting contextual knowledge. They obtained Micro F1 score is 0.7557.

Huang et al. [75] proposed Hierarchical LSTMs for the Contextual Emotion Detection (HRLCE) model and with BERT for detection of emotion using SemEval-2019 Task 3 obtained the harmonic means score of 0.779 and ranked 5th among 165 Team. Daniel Haryadi, Gede Putra Kusuma [76] classified seven emotions (anger, fear, joy, love, sadness, surprise, and thankfulness) using LSTM, nested LSTM. And Nested LSTM obtained the best accuracy of 99.167%, LSTM obtained 99.22% average precision, 98.86% of average recall and 99.04% of F1-score.

Mounika Karnaa et al. [77] used LSTM, SVM, NESTED LSTM. Average F1 rank obtained for LSTM is 94.1% and for Nested LSTM 92.2%. And LSTM obtained best average performance. And obtained F1score of 94.1% . Ankush et al. [22] participated in SemEval 2019 in that a training data set consists of 30160 dialogues, and two
evaluation data sets were given as Test1 contains 2755 and Test 2 contains 5509 dialogues were given to the participants. Used Bidirection and Test2, which n LSTM approach and achieved F1 score is 79.59 micro. The best performances obtained for the class “Sad” and for the worst performance obtained for “Happy” emotion.

4.5 Hybrid Approach

In a unified model, the hybrid approach is a combination of different approaches. This approach has a higher likelihood of transcending the other approaches individually, leveraging the strength of the approaches used while trying to conceal their corresponding limitations.

Riahi and safari [79] proposed an approach for emotion detection in implicit texts. Based on three subsystems, they implemented a combinational framework. Every one analyses input information from a different perspective and produces as output an emotion label. A machine learning algorithm is the first subsystem. The second is a vector space model (VSM) based mathematical method, and the third is keyword based submodel with an information fusion component to aggregate the final output of main system. Their conclusions are aggregated and used to annotate the test text if it is otherwise left abandoned and only if all three subsystems agree on the same emotion type. The efficiency of the method proposed is 9.13 % higher than the machine learning subsystem, 16.6 percent better than VSM, and 23% better than the keyword-based method.

Ramalingam et al. [80] developed a hybrid model combined with the keyword and learning based method and obtained high accuracy result for detection of emotions from the text. Angelina et al [81] used twitter dataset with NRC emotion lexicon. And used SVM for multiclass classification and implemented on the software WEKA obtained accuracy of 84.92%, Spark obtained accuracy of 88.01%.

Hamed Khanpour, Cornelia Caragea [82] proposed system explains with or without lexicon system to develop health domain is often expensive. It also combines with CNN and LSTM model to capture the Hidden semantics in online health model. And also used ConvexLex LSTM and obtain high performance. There dataset contain 1066 sentences Cancer Survivors’ Network (CSN) so it is represented as B-DS. And another set on the lung cancer discussion contains 1041 sentences and represent as L-DS found Joy and Sad sentence more compare to other emotions. And the highest F1 score of ConvLex LSTM for joy is 93.2 and 89.8 and for sad 92.3 and 89.4

Perikos and Hatzilygeroudis [83] developed model which classify emotions and found the performance was satisfactory. Used Naïve Bayes, maximum entropy, knowledge based tool, and Ensemble classifier used and obtained an accuracy of 77%, 85%, 80%, and 87% respectively
5. Evaluation Metrics:
Evaluation metrics are used to measure the statistics between the good models that can be fit. The most common metrics used to measure the models are Kappa Coefficient, multi label accuracy (Jaccard accuracy), F-Score, Precision and Recall, Accuracy, Pearson Correlation, 10 fold cross validation, Chi Square.

5.1 Kappa Coefficient: [70]
It is a statistical measure of an inter-annotator reliability or agreement. Kappa coefficient is used to assess qualitative documents and determine the agreement between two annotators. The equation (1) used to calculate kappa is:

\[ K = \frac{p_0 - p_e}{1 - p_e} = 1 - \frac{1 - p_0}{1 - p_e} \]  
Eq. (1)

Where \( p_0 \) is an annotator's relative observable agreement and \( p_e \) is the hypothetical probability of chance agreement. Using the observed data, \( p_0 \) and \( p_e \) are calculated to determine the probability of each observer randomly informing each group. It ranges from 0 to 1.

5.2 Jaccard Accuracy: [86]
It defined as the size of the intersection divided by the size of the union of two label sets and is used to compare set of predicted labels for a sample to the corresponding set of labels in original. It ranges from 0 to 1. The following equation (2) is used to calculate Jaccard Accuracy is:

\[ J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \]  
Eq. (2)

5.3 Precision, Recall, F-Score, Accuracy:
The Precision (P) defined as the number of true positives (TP) over the number of true positives plus the number of false positives (FP). [52], [57], [60], [63]. The following equation (3) is used to calculate the Precision:

\[ P = \frac{TP}{TP + FP} \]  
Eq. (3)

The Recall defines as the number of true positives over the number of true positives plus the number of false negatives [52],[57]. The following equation (4) is used to calculate Recall is:

\[ R = \frac{TP}{TP + FN} \]  
Eq. (4)

where \( R \) represents Recall, \( TP \) is True positive and \( FN \) is False negative.

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 best value =1 and worst value as 0. [22], [50], [51],
The following equation (5) is used to calculate the F1 score is:

$$F1 = 2 \frac{P \times R}{P + R}$$  \hspace{1cm} \text{Eq. (5)}$$

Where P denotes as Precision and R denoted as Recall.

Accuracy metric is to measure the classification models. [46], [47], [49], [55], [56], [59], [61], [62], [81], and is calculated using the equation (6, 7):

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$  \hspace{1cm} \text{Eq. (6)}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$  \hspace{1cm} \text{Eq. (7)}$$

Where TP represent True positive, TN represents True negative, FP represents False positive, FN represents False Negative

### 5.4 Pearson Correlation [85]

It is the statistics that measure the statistical relationship or is the best method for an association, between the two variables that are continuous because it is based on the covariance of the two variables, and then it is divided by the product of their standard deviations. The following equation (8) is used to calculate Pearson Correlation is:

$$r = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma(x_i - \bar{x})^2(y_i - \bar{y})^2}}$$  \hspace{1cm} \text{Eq. 8}$$

Where r is a correlation coefficient, $x_i$ is values of the x-variable in a sample, $\bar{x}$ is mean of the values of the x-variable, $y_i$ is values of the y-variable in a sample and $\bar{y}$ is mean of the values of the y-variable

### 5.5 10-fold cross validation: [49],[51],[62]

The cross-validation technique is used to partitioning the original sample into a training set to train the model and a test set to validate it and to evaluate predictive models in machine learning. This procedure is named as k fold cross validation where the original data splits into k subsample. If a specific value is chosen for k, it can be used in the model reference instead of k, such as k=10 becomes a 10-fold cross-validation.

### 5.6 Chi Square [84]

To test the independence of two cases, a chi-square test is used in statistics. We can get observed count O and predicted count E given the data of two variables. Chi-Square tests how the predicted number E and the measured number O deviate from each other. The following equation (9) is used to calculate ChiSquare is:

$$x_i^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$  \hspace{1cm} \text{Eq. (9)}$$
Where \( c \) = degree of freedom, Observed value(s) and \( E \)=expected value(s)

6 Summary of existing approach

Table 4 discuss about the summary of the existing approaches, contribution and limitations.

Table 4: Summary of the recent existing approaches in text-based emotion detection

| Proposed Work (Author, Year) | Approaches Used | Contribution | Limitations |
|------------------------------|-----------------|--------------|-------------|
| Suhasini and Badugu, 2020 [58] | Machine Learning(ML) | Demonstrated the efficiency of the Naive Bayes(NB) in correlation with the K Nearest Neighbor (KNN). The accuracy obtained for NB is 72.06% and KNN 55.50%. | Low extraction of relevant data in sentences. |
| Ahmad Fakhri Ab. Nasir et.al 2020 [59] | Machine Learning(ML) | Comparisons of Four machine learning algorithm and developed graphical UI | Worked for Basic Model. Mixed emotions are not included |
| Seo-Hui Park et.al 2020 [70] | Deep Learning(DL) | Created an embedding emotion model using CNN, highest accuracy for joy of 73.3%, lowest accuracy value of 36.7% and the lowest Kappa score of 0.216 | Negate sentence were not achieved. |
| Dibyendu et al, 2020 [54] | Rule Based | Used ISEAR dataset with specific regard to phrasal verbs to identify emotions. | Lack of contextual meaning. Insufficient words in vocabulary for the lexicon. |
| Mounika Karnaa et al. 2020 [77] | Deep Learning(DL) | Using LSTM, SVM, Nested LSTM identified Multiclass labels for emotion and achieved the accuracy F1=94.1, 92.9, 92.2 respectively | Recommended to use for complex dataset. |
| Flor Miriam Plaza-del-Arco et al. 2020 [49] | Corpus Based | Used Multilingual dataset and applied machine learning approach for detection of emotions from dataset and obtained accuracy for Spanish 0.64 and accuracy for English 0.55 | Anger, disgust, fear, sad emotions are not able to be identified by the proposed system. |
| Xiao Zhang et.al 2020 [71] | Deep Learning(DL) | Factor graph model is used to detect multiple emotions or Online Social Network and also proposed multilabel learning algorithm and achieved contextual information. F1 score of 62.7 | Limited annotated text is been used. |
| Author(s) | Method | Description | Result | Note |
|-----------|--------|-------------|--------|------|
| Daniel Haryadi, Gede Putra Kusuma 2020 [76] | Deep Learning (DL) | Classified emotions into seven they are: (fear, anger, love, joy, surprise, thankfulness and sadness) using LSTM AND nested LSTM. Obtained best accuracy for Nested LSTM is 99.167% and average precision and recall for LSTM is 99.22%, 98.86%, respectively and Obtained F1-score 99.04%. | Recommended to use more sophisticated Deep learning for the challenging dataset. |
| Hasan et al, 2019 [56] | Hybrid | Developed Emotex for online stream data and obtained accuracy of 90% | Semantic featured extraction should be improved. |
| Malte and Ratadiya 2019 [72] | Deep Learning (DL) | Constructed BERT (Bidirectional Transformer). Both for Hindi and English text were tested and attained F1 score for Hindi is 0.4521 and for English is 0.5520. | Hindered in performance due to presence of slang in Non English. |
| Waleed et al., 2019 [73] | Deep Learning (DL) | SemEval2019 dataset were used. The proposed model use deep transfer learning, self attention mechanism and turn-based conversational modeling to classify the emotions. Obtained F1 of 0.7582. | Failed to find the emotion –“happy” |
| Luyao et al, 2019 [74] | Deep Learning (DL) | Bidirectional LSTM was used to distinguish emotion oriented text into good, sad and angry and emoji’s. Showed that the output of their method surpassed the baseline models {happy, angry} but failed for the sad. Micro F1 score of 0.7557 | Limited types or classes of emotions |
| Ankush et al, 2019 [22] | Deep Learning (DL) | Developed Bidirectional LSTM and obtained a highest micro F score of 79.59 | Not suitable for generalisation due to number of categories are finite. |
| Zishan Ahmad et al, 2019 [69] | Deep Learning (DL) | The information collected from resource-rich languages can be extended to other language domains by transfer learning and from the cross-lingual embedding. Obtained F1 of 0.53 | Contextual meanings of word are disregarded. |
| Huang et al, 2019 [75] | Deep learning | Proposed Hierarchical LSTMs for the Contextual Emotion | Misclassification were high |
|                  | Model/Approach               | Method/Details                                                                                                                                  | Issues/Improvements                                                                 |
|-----------------|-----------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Forough and     | Detection (HRLCE) model      | Forough and Hooman, 2019 [63] employed the Harmonic Mean score of 0.779 with BERT.                                                            | Weak qualitative extraction of information                                           |
| Hooman, 2019    | and with BERT obtained the  |                                                                                                                                                |                                                                                      |
|                 | harmonic mean score of 0.779|                                                                                                                                                |                                                                                      |
|                 |                             | Vector similarity measure (VSM), keyword base and STASIS approaches are employed to detect emotions in text to find the different categories of emotions and obtained precision of 0.53. |                                                                                      |
| Angelina et al., 2019 [81] | Hybrid                  | To derive actionable emotion patterns in Tweets, the NRC emotion lexicon and SVM were used against WEKA, Spark software 84.92%, 88.01% accuracy were obtained. | Not suitable for generalisation due to the finite number of classes of emotions     |
| R Jayakrishnan et al, 2018 [60] | Machine Learning(ML) | Using the SVM, classified sentences in the novel into happy and obtained precision of 0.94, for sad obtained precision of 0.92, for fear obtained precision of 0.93, for anger obtained precision of 0.90 and lastly for surprise obtained precision of 0.90 | Disintegration of semantic information in texts document and Fail to understand the context of a word in the sentence. |
| Hamed Khanpour, | Hybrid                      | The proposed system explains with or without lexicon system to develop health domain is often expensive. It also combines with CNN and LSTM model to capture the Hidden semantics in online health model. F1 score of ConvLex LSTM (B-DS and L-DS cancer data) for joy 93.2 and 89.8 and for sad 92.3 and 89.4 | Limited emotions are identified                                                      |
| Cornelia Caragea 2018 [82] | Hybrid                  |                                                                                                                                                |                                                                                      |
| Ramalingam et al, 2018 [80] | Hybrid                  | Developed model combined with keyword-based and learning-based and obtained satisfactory results.                                              | Better classification techniques should be applied to improve performance.           |
| Merav et al, 2018 [57] | Machine Learning[ML]     | Developed automated model for communication problem with children and others for the better society assistance and to develop the mode applied machine learning algorithm and | Lack of semantic information                                                          |
| Methodology | Type | Evaluation | Description |
|-------------|------|------------|-------------|
| SVM method | Machine Learning | 80% recall and precision obtained more than 75%, and t Multi-Layer Neural Network and the Tree Bagger: precision and recall obtained more than 75% |

Matla, Suhasini, 2017 [55] Rule Based Four emotions with 85% accuracy were identified by the process. Because of limited categories, the proposed methodology has stronger generalisation potential and low contextual information extraction.

Sonia and Kavitha, 2017 [61] Machine Learning(ML) The intensity of four categories of emotions: happy, sad, angry and fear were identified. A comparatively limited number of data. Limited number of categories of emotions. Disregarded for adjective strength.

Anil Bandhakavia et. al. 2017 [51] Lexicon Based Developed UMM Model based on the DSEL and outperforms the PMI and sLDA methods. Only high quality lexicon can capture the context.

Rahman et al. 2017 [47] Keyword based Developed the method which solves the problem in sentence level emotion detection and emoticons and achieved 80% of accuracy with 25 emotion classes, keyword analysis, short form of words, keyword negation analysis, emoticons set of proverbs and so on. Need to work future for paragraph sentences.

Perikos and Hatzilygeroudis, 2016 [83] Hybrid The performance of classifying emotions was satisfactory. Used NB, maximum entropy, knowledge based tool, and Ensemble classifier used. Obtained Accuracy of 77%, 85%, 80%, 87% respectively. Better classification techniques can be applied to improve the execution process.

Fika Hastarita Rachman et al. 2016 [50] Corpus Based Developed Corpus Based Emotion (CBE) with Wordnet Affect Emotion (WNA) and ANEW (Affective Norms for English Words improved performance with F score of 0.61. The label was seen only with highest frequency scattered.

Wikarsa and Thahir, 2015 [62] Machine Learning(ML) Five categories with 83 percent precision obtained. A better ML algorithm can enhance performance. And also considered small number of Tweets.
Shiv Naresh Shivhare et al. 2015 [46]  
**Keyword based**  
Keyword based technique is used and ontology approach helped to overcome semantic features. Proposed system achieved accuracy more than 75%

Yichen Wang, Aditya Pal 2015 [52]  
**Lexicon based**  
Developed optimized framework suitable for large dataset and multi label emotions are also identified. F measure of 0.63 for SemEval and ISEAR of 0.74

### 7 Conclusion

In this paper, a comparison of various approaches for detecting an individual’s emotional state from textual data has been undertaken. The three major approaches of the emotion modeling in the psychology research such as Categorical approach, Dimensional approach and Appraisal based approaches was discussed. Further, different computational approaches proposed for emotion detection from text such as Keyword based approach, Rule based approach, Machine learning-based approaches and Hybrid approaches was discussed. It further explores existing state-of-the-art with focus on their approaches applied, evaluation measures, datasets used, signification contributions and limitations useful for budding researchers.

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