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Comparative Study on Emotion Detection from Text

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ABSTRACT: Emotion can be expressed in many ways such as facial expression and gestures, speech and by written text. Many of the studies explored emotion analysis from textual data. The task of Emotion detection from text is the advanced version of Sentiment analysis. Emotion through text can be classified as happy, sad, anger, fear, disgust, surprise, etc. In this paper emotion detection based on text and the techniques used in emotion detection are discussed. This review paper provides understanding into various emotion models, and the process of emotion detection from text. Finally, this paper discusses the challenges faced during emotion analysis.

KEYWORDS: Emotion detection, Natural language processing.

I. INTRODUCTION

Human language understanding is the main aspect of natural language processing (NLP). Some of the applications of NLP are speech recognition, document summarization, question answering, speech synthesis, machine translation (Itani et al, 2017). The two critical areas of natural language processing are sentiment analysis and emotion detection. The identification of feelings is one of the core aspects of NLP. Natural Language Processing (NLP) enables us to detect the emotions from written text like reviews, feedbacks, comments, publications, conversations, etc., and take action accordingly.

People express their feelings, arguments, opinions and they give feedbacks and reviews on various products and services on various e-commerce sites. User's ratings and reviews on multiple platforms encourage the service providers to enhance their goods, or services. Today every industry or company is undergoing some digital transition, resulting in huge amounts of structured and unstructured data. The enormous task for companies is to transform unstructured data into meaningful insights units that can help them in decision-making (Ahmad et al. 2020).

Within the business world, vendors use social media platforms like Instagram, YouTube, Twitter, and Facebook to spread the information about their product and efficiently collect customer's comments (Agbehadji and Ijabadeniyi 2021). People's active feedback is valuable not only for business marketers to measure customer satisfaction but also for customers who want to find out more about a product or service before buying it. Emotion Detection assists marketers in understanding their customer's perspectives better so that they may make necessary changes to their products (Jang et al. 2013; Al Ajrawi et al. 2021).

Emotion Detection refers to the accurate identification of emotion from text data. Understanding a person's mood by way of emotion detection can play a significant role in AI systems and applications. Yue et al. (Yue and others 2019). Commercial, Political, and Public security are the three important application areas where emotion detection is used. Commercial applications can provide valuable reaction based feedback to merchants, manufacturers, and consumers about the quality of different products. In politics, emotion data can help inform political strategies for both candidates and officers.

In the healthcare sector, online social media such as Twitter have become essential sources of health-related information provided by healthcare professionals. For example, people share their thoughts, opinions, and feelings on the Covid-19 pandemic (Garcia and Berton 2021). Patients were directed to remain isolated from their loved ones, which harmed their psychological state. To save patients from psychological state issues like depression, health

practitioners must use automated emotion analysis (Singh et al. 2021). People commonly share their feelings on websites through their posts.

II. BACKGROUND

2.1 EMOTION DETECTION:

Emotions are an important component of human life. These emotions influence human decision-making and helps to communicate with the world in a easier way. Emotion detection is the process of identifying a person's state of condition. . Researchers have been working hard since years to detect the emotion for the past few years. . Emotion Detection is the process of identifying human emotion from both facial expressions and the voice. To detect emotion in text NLP techniques, machine learning are used.

However, some physical activities such as heart beat, shivering, sweating, and voice pitch also convey a person's emotional state(Kratzwald et al. 2018). The word 'emotion' was considered a psychological term. Emotion analysis aims to detect and recognize types of feelings through the expression of text documents, such as anger, disgust, fear, happiness, sadness, and surprise. . Emotion Detection is the process of identifying human emotion from both facial expressions and Voice. In English, the word 'emotion' came into use in the seventeenth century, derived from the French word 'emotion, meaning a physical disturbance.

In psychology, complicated states of feeling leads to a change in thoughts, actions, behavior, and personality referred to emotions. Many people in the world are now using blogs, forums, and social media sites such as Twitter and Facebook to share their thoughts with the rest of the world. Social media became one of the important communication media. As a result, a huge amount of data give rise to the word 'big data' and Emotion Detection was introduced to analyze this big data effectively and efficiently (Nagamanjula and Pethalakshmi 2020).

Emotion detection is a means of identifying various human emotions such as enraged, cheerful, or depressed. Emotion analysis has a wide range of applications and can be done using several methodologies. On social media, people freely express their feelings, arguments, opinions in the various topics. Emotion anaysis is the important aspect of human life that conclude a person's state of mind and condition.

2.2 EMOTION MODELS/THEORIES:

In english, the word 'emotion' came in to existance from French in the seventeenth century meaning a physical disturbance(Dixon 2012). Before the nineteenth century feelings, craving, and fondness were categorized as mental states. In psychology, complicated states of feeling lead to a change in thoughts, actions, behavior, and personality referred as emotions. Widely, emotion models are categorized into two categories: dimensional and categorical. Text-based emotion recognition using artificial intelligence engage Natural Language Processing (NLP) which combines techniques in linguistics and computations to help computers understand and produce texts and verbal in the form of human languages.

Dimensional Emotion model This model represents emotions focusing on three parameters: valence, arousal, and power. Valence means polarity, and arousal means excited feeling (Bakker et al. 2014). For example, Furious expresses more extreme anger. Power or dominance indicate restriction over emotion.



Fig 1 Dimensional model of Emotions

Categorical Emotion model In the categorical model, emotions are defined distinct, such as angry, joyful, sadness, and fear. Depending upon the particular categorical model, emotions are classified into four, six, or eight categories. Various emotion models that are dimensional and categorical.

The emotional states defined by the models makes the set of labels used to write the sentences or documents. Batbaatar et al. (2019), Becker et al. (2017), Jain et al. (2017). . Sailunaz and Alhajj (2019) used Ekman models for commenting tweets. Some researchers used customized emotion methods by extending the model with one or two additional states. Roberts et al. (2012) used the Ekman model to annotate the tweets with the 'love' label. Laubert and Parlamis (2012) referred to the Shaver model because of its three-level hierarchy arrangement of emotions. Polarity is explained at the first stage, followed by the second stage consisting of five emotions, and the third stage shows various 24 emotion states. Some researchers did not refer to any method and they divided the dataset into three basic feelings: happy, sad, or angry.

III. PROCESS OF EMOTION DETECTION

Process of emotion detection comes across various stages like collecting dataset, pre-processing, feature extraction, model development, and evaluation.

3.1 DATASETS FOR EMOTION DETECTION:

The most common datasets used for Emotion Detection are SemEval, Stanford sentiment treebank (SST), international survey of emotional antecedents and reactions (ISEAR) in the field of emotion analysis. SemEval and SST datasets have various variants which differ in terms of domain, size. English datasets include mainly the tweets, reviews, feedbacks, stories from various social media like Youtube, Instagram, Tweeter, etc . A dimensional model named valence arousal dominance model (VAD) is employed in the EmoBank dataset collected from news, blogs, letters, etc. Many studies have acquired data from social media sites like Twitter, YouTube, and Facebook and had it labeled by language and psychology experts within the literature. Data crawled from various social media platform's posts, blogs, e-commerce sites are usually unstructured and thus have to be processed to make it structured to reduce some additional computations.

3.2 PRE-PROCESSING OF TEXT:

People usually communicate their feelings and emotions in simple way on social media. As a result, the data obtained from the social media platform's posts, comments, remarks are highly unstructured, making emotion analysis difficult for machines. As a result, pre-processing is an important task in data cleaning since the data quality significantly impacts many approaches that follow pre-processing. The organization of a dataset necessitates pre-processing, including tokenization, stop word removal, POS tagging, etc. (Abdi et al. 2019; Bhaskar et al. 2015).

Tokenization can be defined as the process of converting a sequence of strings into pieces such as words, keywords, phrases, symbols and other elements called tokens. Tokens are individual words, phrases or even whole sentences. with the method of tokenization, some characters like punctuation marks are discarded. (Nagarajan and Gandhi 2019). For example, consider the sentence: "Never give up". The most common way to form the tokens is based on space. Assuming space as a delimiter, the tokenization of the sentence results in three tokens – Never-give-up. It's essential to normalize the text to achieve uniformity in data by converting the text into its standard form. (Ahuja et al. 2019).

Unnecessary words like articles and some of the prepositions which do not contribute towards emotion detection must be removed. For example, stop words like "is," "at," "an," "the" have nothing to do, so these need to be removed to avoid unnecessary computations (Bhaskar et al. 2015; Abdi et al. 2019). POS tagging is the way to identify different parts of speech in a given sentence. This step is useful in finding various aspects from a sentence that are generally described by nouns while emotions are conveyed by adjectives (Sun et al. 2017).

Stemming and lemmatization are two crucial steps of preprocessing. In case of stemming, words will be converted to their root form by truncating suffixes. This process reduces the unwanted computation for the sentences (Kratzwalld et al. 2018; Akilandeswari and Jothi 2018). Lemmatization involves morphological analysis to get rid of inflectional endings from token to show it into the base word lemma (Ghanbari-Adivi and Mosleh 2019). for example , the term "caught" is converted into "catch" (Ahuja et al. 2019)

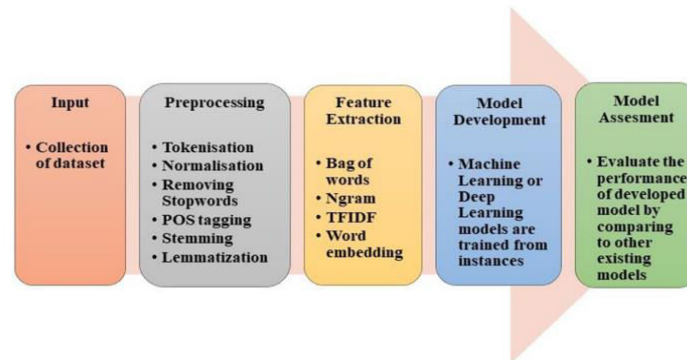


Fig 2 Pre-processing of text

3.3 FEATURE EXTRACTION:

The computer understands text in terms of numbers. The process of converting the text or words into realvalued vectors is called word vectorization or word embedding. It is a feature extraction technique where a document is broken down into sentences that are further broken into words; after that, the feature map or matrix is built. In the resulting matrix, each row represents a sentence while each feature column represents a word in the dictionary, and the values present in the cells of the feature map generally denote the count of the word in the sentence or document. For carrying out the feature extraction, one of the most straightforward methods 'Bag of Words' (BOW) are used, in which a fixed-length of vector count is defined where each entry corresponds to a word in a pre-defined set of words.

The count of word in a sentence is assigned to 0 if it is not present in the pre-defined dictionary, or else a count is greater than or equal to 1 based on the number of times it appears in the sentence. Hence, the length of the vector is equal to the words present in the dictionary. The advantage of this technique is easy to implement but has significant drawbacks, it loses the order of words in the sentence, and does not capture the definition of a sentence (Bandhakavi et al. 2017; Abdi et al. 2019). For example, to represent the text “are you enjoying playing” from the pre-defined dictionary I, Hope, you, are, enjoying, playing would be (0,0,1,1,1,1). However, those representations can be improved by text pre-processing.

The N-gram method is an excellent way to solve the order of words in sentence representation. In an n-gram representation of vector, the text is represented as a combination of unique n-gram means group of n adjustment terms. TFIDF is abbreviated as Term frequency-inverse document frequency, another method usually used for feature extraction. This method represents text in matrix form, where each number contains how much information these terms in a given document. It is built on the assumption that rare terms have more information in the text document (Liu et al. 2019). Number count of a word w appears in a document divided by the total number of words W in the document is called Term Frequency, and IDF is log is defined as total number of documents (N) divided by the total number count of documents in which word w appears (n). (Songbo and Jin 2008). Ahuja et al. (2019) practiced on six pre-processing techniques and compared two techniques of feature extraction to identify the best approach. They used six machine learning algorithms and applied n-grams with $n = 3$ and TF-IDF for feature extraction and concluded TF-IDF gives better performance over n-gram. The availability of large volumes of data allows a deep learning network to find good vector representations. Feature extraction for word embedding based on neural networks is more important. In the word embedding with neural network-based, the same semantics words or words those related to each other are represented by common vectors.

3.4 TECHNIQUES FOR EMOTION DETECTION:

Figure 3 presents various techniques for emotion detection which are broadly classified into lexicon-based approach, machine learning-based approach, deep learning-based approach and Transfer learning approach.

Lexicon-based Approach:

Lexicon-based approach is a keyword-based search approach that searches for emotion keywords assigned to some psychological states (Rabeya et al. 2017). The popular lexicons for emotion detection are WordNet-Affect (Strapparava et al. 2004) and NRC word-emotion lexicon (Mohammad and Turney 2013). WordNet-Affect is an extended form of WordNet which consists of affective words annotated with emotion labels. NRC lexicon consists of 14,182 words, each assigned to at least one particular emotion. The authors concluded that features derived from their proposed lexicon

outperformed the opposite baseline features. Braun et al. (2021) constructed a multilingual corpus called Multilingual Emotional Football Corpus, consisting of football reports from English, Dutch and German internet sites and match statistics crawled from Goal.com. The corpus was created by creating two metadata tables: one explaining details of a match sort of a date, place, participation teams, etc., and therefore the second table consisted of abbreviations of football clubs. Authors demonstrated the corpus with various approaches to understand the influence of the reports on game outcomes.

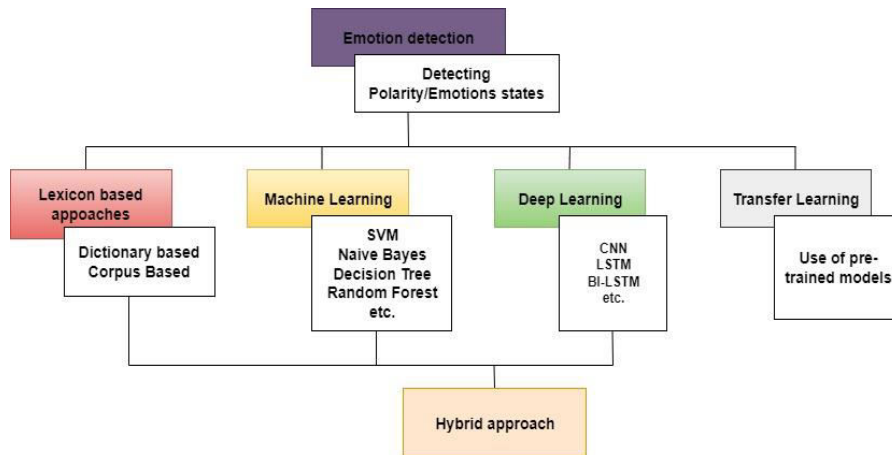


Fig 3 Techniques for emotion detection

Machine learning approach:

There is another approach for Emotion detection called the machine learning approach. The whole dataset is divided into two parts i.e., a training dataset and a testing dataset. The training dataset contains the information used to train the model by supplying the various characteristics of different instances for an item. The testing dataset is used to see how successfully the model has been trained from the training dataset. Emotion detection or classification requires different types of machine learning models like Naïve Bayes, support vector machine, decision trees, etc. Hasan et al. (2019) evaluated the machine learning algorithms such as Naïve Bayes, Support Vector Machine, and decision trees to identify emotions in text messages. Jain et al. (2017) extracted the emotions from multilingual texts collected from youtube comments, posts, blogs, etc. The authors used a novel approach for data collection and applied SVM and Naïve Bayes machine learning algorithms for emotion classification of twitter text. Results revealed that an accuracy of 71.4% was achieved while using Naïve Bayes algorithm. Asghar et al. (2019) has applied multiple machine learning models on the ISEAR dataset to find out the best classifier. They found that the logistic regression model performed well when compared to other classifiers with a recall value of 83%.

Deep learning approach:

Deep Learning and Hybrid Technique Deep learning area is component of machine learning that processes information or signals within the same way as the human brain does. Deep learning model has multiple layers of neurons. Thousands of neurons are interconnected to every other, which accelerates the processing in a parallel fashion. Chatterjee et al (2019) developed a model called Sentiment and Semantic Emotion Detection by feeding sentiment and semantic representations to 2 LSTM layers, respectively. These representation are then concatenated and then passed to a mesh network for classification. The novel approach is based on the probability of multiple emotions present within the sentence and utilized both semantic and sentiment representation for better emotion classification. Results are calculated over their own constructed dataset with tweet conversation pairs, and their model is compared with other baseline models. Xu et al. (2020) extracted features emotions using two-hybrid models named 3D convolutional-long STM (3DCLS) and CNNRNN from video and text, respectively. At the same time, the author's implemented SVM for audio-based emotion classification. Author's decided the results by fusing audio and video features at feature level with MKL fusion technique and further combining its results with text-based emotion classification results. It provides better accuracy than every other multimodal fusion technique, intending to analyse the sentiments of drug reviews written by patients on social media platforms.

Transfer Learning and Hybrid Approaches :

Transfer learning is a part of machine learning. The model was trained on the large datasets to solve one problem can lead to other related issues. Re-using a pre-trained model on related domains as a start point can save the time and results in a efficient way. Zhang et al. (2012) proposed a paper instance learning method by directly modeling the domains of different distributions. Authors categorized the dataset: Amazon product reviews and Twitter dataset into positive and negative emotions. Tao and Fang (2020) proposed extension of recent classification models in aspect-based emotion analysis to multi-label classification. The authors also extended transfer learning models called XLNet and Bert and they evaluated the proposed approach on different datasets. Deep learning and machine learning approaches gives good results, but the hybrid approach can give better results than deep learning and machine learning since it overcomes the limitations of each traditional model. Mladenović et al. (2016) proposed the feature reduction technique, a hybrid framework made of emotion lexicon and Serbian wordnet. The authors expanded both lexicons by adding some morphological emotional words to avoid loss of critical information while process of stemming. Al Amrani et al. (2018) compared their hybrid model made of random forest model and SVM, i.e., RFSVM, on amazon's product reviews. The accuracy level of the RFSVM by the authors conclusion is 83.4%, whereas the accuracy of SVM and random forest are 82.4% and 81% respectively over the 1000 reviews of dataset. Alqaryouti et al. (2020) proposed the hybrid rule-based approach and domain lexicon to the aspect-level emotion detection to understand people's opinions regarding smart applications of the government. The authors concluded that the proposed technique exceed other lexicon-based baseline models by 5%. Ray and Chakrabarti (2020) combined the rule-based approach to extract the aspects with a CNN model with 7-layer deep learning to tag every aspect. The accuracy of the hybrid model was 87%, whereas the accuracy of individual models is 75% with rule-based and CNN model achieves the accuracy of 80%. Many researchers implemented the proposed methods on their datasets collected from social networking sites like twitter, facebook.

3.5 MODEL ASSESSMENT:

Finally, the best performing model is compared with other baseline models based on different parameters. A confusion matrix which is used to measure recall, precision, accuracy is acquired and provides the count of correct and incorrect predictions based on known actual values. Confusion matrix displays true positive (TP), false negative (FN), false positive (FP), true negative (TN) values for data fitting based on positive and negative classes.

IV. CHALLENGES IN EMOTION ANALYSIS:

In the Internet world, people are generating huge data in the form of informal text. Social networking sites facing various challenges like spelling mistakes, new slang, and improper grammar. Due to these challenges, machines find difficult to perform emotion analysis. Sometimes people do not express their emotions and feelings clearly. For example, in the sentence "Are you feeling too hungry?", 'Are' is misspelled as 'r,' 'you' is misspelled as 'u,' and 'too' is used to show more impact. Moreover, this sentence does not express the emotion of the person. Therefore, emotion detection from real-world data will face many challenges and sometimes cannot be solved due to many reasons (Batbaatar et al. 2019). One of the major challenges faced during emotion recognition is the lack of resources. For example, statistical algorithms needs a large amount of annotated dataset. Anyways, gathering data is not much difficult, but manual labeling of the large dataset is hard, time-consuming and less reliable (Balahur and Turchi 2014). The other major issue regarding resources is the various types of resources are available in the English language. Therefore, emotion detection in the regional language rather than the english face huge challenge.

Furthermore, the corpora and lexicons are domain specific, which have limitation on re-use in other domain. People usually express their sadness or disappointment in sarcastic and using harsh words, which is hard to detect (Ghanbari-Adivi and Mosleh 2019). For instance, in the sentence, "This story is excellent to make us sleep," the excellent word indicates positive sentiment, but in actual the user felt it quite dull. Therefore, sarcasm detection has become a huge task in the field of emotion detection. The other major challenge is that people express multiple emotions in a single sentence. It is difficult to determine several aspects and their corresponding emotions from the multi-opinion sentence. It is difficult to determine several aspects and their corresponding emotions. To find the emotion of multi-opinionated sentences look harder and creates problem. Another challenge is that it is hard to detect valence or polarity from comparative sentences. For example, consider two sentences 'laptop A is worse than laptop B' and 'laptop B is worse than laptop A.' The word 'worse' in both sentences will mention negative polarity, but they oppose each other (Shelke 2014).

V. CONCLUSION

In this paper, existing techniques for emotion detection are presented. As per the paper's review, it can be concluded that the lexicon-based technique performs well for emotion analysis. The performance of machine learning algorithms and deep learning algorithms depends on the pre-processing of the data and size of the dataset. Recurrent neural networks, especially the LSTM model, are prevalent in emotion analysis, as they can extract features very well. But Recurrent Neural Networks with attention networks performs very well. At the same time, it is important that the lexicon-based approach and machine learning approach are also evolving and have obtained better outcomes. Also, preprocessing and feature extraction techniques have a significant impact on the performance of various approaches of emotion analysis.

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