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A Survey on Text Based Emotion Detection

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Abstract: Emotion recognition deals with sentiment analysis in Natural Language Processing which mainly focused on extraction and analysis of emotions. Individuals show their emotions through their conversations, emojis, short notes. Various resources like ECG, writings and videos and audios are commonly used to analyze emotions. Nowadays, information from Facebook, Twitters and Instagram etc., are used as a resource for text mining to find hidden emotions. Emotion retrieval behind these posts is a large and complex work. With the assistance of attitude detection, gadgets will create higher choices to assist their users. Hence, attitude detection from text is important in many areas such as decision making, user-robot interaction etc. Work done in this field is very less as compare to other fields. Therefore, it broadens our scope in the field of attitude detection from text. In this paper, we propose a hybrid model which extract phrasal words from the input and calculate the affect vector for the extracted words. Then based on affect vector, the proposed model categorize the sentence into appropriate target class. This survey paper covers the existing emotion detection models, available datasets, their options and their drawbacks. We have a tendency to concentrate on reviewing analysis efforts analyzing emotions supported text and summarize basic achievements within the field and highlight potential extensions for higher outcome.

Index Terms – **Emotion detection, text, emotions, machine learning techniques, Human-robot interaction.**

I. INTRODUCTION

The evolution of AI in 1950 and its emergence within the 20th century, provides effective solution to major social issues underneath varied fields together with natural language process (NLP), that employs process and language-based methods to assist gadgets perceive & typically produce human languages within the type of writings, ECG and specific hand signals. Outstanding contributions within the branch of Natural Language Processing underneath active analysis embrace translation systems, data extraction, queries and respondent systems (Q & A), text account systems, semantic and sentiment analysis and etc. Sub-dividing from the sphere of sentiment analysis whose core intent is to investigate by extracting individual's feelings, attitude, and their reckon through the assignment of polarities like happy, sad or other target classes is that the sub-domain for detecting emotions, that focus on extracting fine-grained emotions like happiness, sadness, boredom, disgust, etc. conversations instead of coarse-grained and general polarity assignments in sentiment analysis.

Detecting emotion from social media data helps to detect the affect writer or reader. Today most of people interact with internet in form of text by writing blog, email, review and comment. Detecting emotion systems were introduced to recommend hints for user-robot communications, so robots may help their users accordingly to their mood and it create good bond between human and technology.[2]. Apart from this, there are few other projects done in the field of audio, eye gazes, gesture and facial expression over the last [3][4]. As internet 2.0 emerges, many individuals write blog to express their feeling with others/ person on internet. As compare to emotion detection in multimodal field, there is more improvement needed in emotion detection from text.

These are some area such as better understanding about newly arrived vocabularies, use of context information; in the real time point of view, the emotion detection system needs more attraction and advancement. This detection system uses the semantic and syntactic analysis to extract the information from the gathered data, then fed into the model which classify the labelled classes.

The area of emotion detection has also applicable in real life situations like detecting emotion from letters, attitude detection in social media hashtags, detection of aggressive statements and negative notes in their posts. However, emotion detection from ECG, emojis and writing blogs, associated alternative ways has a complete mental object, there exists nice scarceness in analysis for texts. This can be as a result of not like multimodal ways, texts may not portray peculiar cues to people's emotion. Also, the emotion detection from text, short notes, emojis, and spelling mistakes can be backtracking including the continual rebirth of recent words as a result. What is more, thanks to the infantile stage of analysis within the branch of NLP, information of applicable detection approaches & also the emotion lexicons are inadequacy out there for the detection purpose. Regardless, the birth of net a pair of Internet 2.0 makes it hectic to work on large amount of data out there in the social media for emotion detection which increased human and robot interactions.

The goal of this survey paper is to help the researchers within the branch of emotion detection. The survey paper discusses the ideas, detection methods, and attitude-labelled knowledge related corpus out there for enterprise text-based impotence research works. It conjointly notifies the progressive improvement in the performance, output, and drawbacks in existing systems.

II. DATASET

Two main emotion models, which are often used in NLP tasks are theory of Ekman (1972), and Plutchik's Wheel of Emotion (1980). In this research we used Plutchik's theory of emotion (Figure 1), due to its notion of emotion polar opposites. For example, joy is opposite of sadness, and anger is opposite of fear.

Plutchik displayed a 2-D wheel of emotions that indicates positive class on the vertical axis and negative class on the horizontal axis. The figure[1] indicates emotions like calm, sad, depressed, bored, etc. Then those emotions are combined with the fundamental emotions on the outermost layer of the circle. The figure 1.1 states how related emotions are labeled with respect to their positions on the circle.

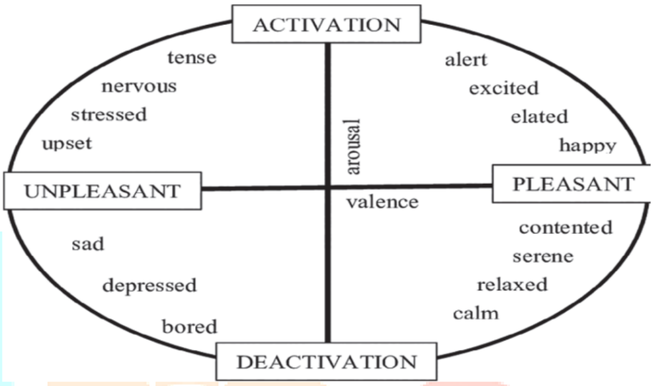

Fig. 1. Russell's circumplex model of affects

Russell and Mehrabian also present a 3-dimensional emotion model made up of Valence/Pleasure, Arousal, and Dominance as the third dimension. The third dimension of Dominance describes the degree to which experiencers had control over their reactions. The 3-dimensional model, however, are highly recommended in projects that represent similarities in emotions.

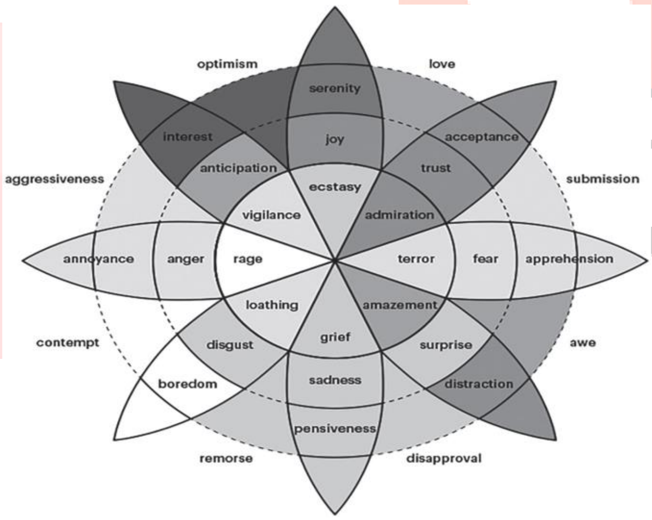

Fig. 2. Plutchik's Wheel of Emotion (1980)

A. Daily Dialog

This dataset contains regular communication speech between humans. It consists of 13,118 sentences annotated for happy, sad, joy, trust, love, rage, etc as emotion labels.

B. CrowdFlower

Supervised data from 29,168 tweets and contains thirteen emotions classes like worry, love, joy, rage, boredom, fear, sad, happy, etc.

C. Smile dataset

Smile dataset consist of 2-D emotion classes like fear, boredom, happy, joy, and sad for a total of 3085 posts gathered from social media about the British Museum.

D. Emobank dataset
The emobank dataset consists of 10,000 sentences which represent the Valence-Arousal- Dominance (VAD) recognization set. These information were extracted from social media posts like twitter, Facebook, etc.

The real-time data can also be used for the text-based emotion detection model, the text data can be directly acquired through tweets and facebook posts, writings and books, shot notes, etc. These real-time data are unstructured, contains grammatical error, spelling mistakes and require more pre-processing, which is quite immense and more time consuming. Sometimes, it's worth going for publicly available dataset.

III. DETECTION APPROACH

This section in the survey paper highlights the rule-based method, machine learning model, and hybrid approaches as a result of the final approaches to police investigation emotions from texts. It additional reveals vital pros and cons associated with each method.

A. Rule based approach
The rule-based approach mainly focus on the grammar error, spelling mistakes and abbrevation, thus on notice attitudes from documents. Constraints for few documents is additionally merely created; however, with huge volume of data can be easily handled with this method, but the accuracy is very low when compared with other detection approaches.

Keyword-based emotion detection approach contains the below 5 process, where a file or word document is provided as training data and at end, an emotion class is generated as output. At the very first step data tokenize and stop word are remove then tagged the data with different label such as verb, noun, adjective and adverb, etc. From these NAVA words, emotion word is identified. Now respective emotion for this emotion word will be identified in next step and intensity of this word is calculated. Now checked the negation in sentence and finally extract the emotion class present in the sentence. The flow diagram of keyword spotting technique is as below.

Fig. 3. Keyword primarily based model

B. The machine learning approach

The machine learning approach give solution to the function downside by classifying data into varied classes and it evaluates the performance of the machine learning model. This method is usually distributed using a supervised or associate unattended machine learning technique. The add supervised machine learning algorithms are wide enforced in text-based dysfunction issues and have offered comparatively higher solution for detection rates than in problems where unattended machine learning algorithms were enforced.

In the machine learning technique of emotion detection, the classifier automatically learns from its previous training set. This machine learning based categorization is called as supervised learning because this is guided by pre-classified training set. Supervised and unsupervised technique has been used for automatically detect the affect from input text such as anger, joy, disgust and fear etc. this section gives the basic knowledge of supervised and unsupervised learning.

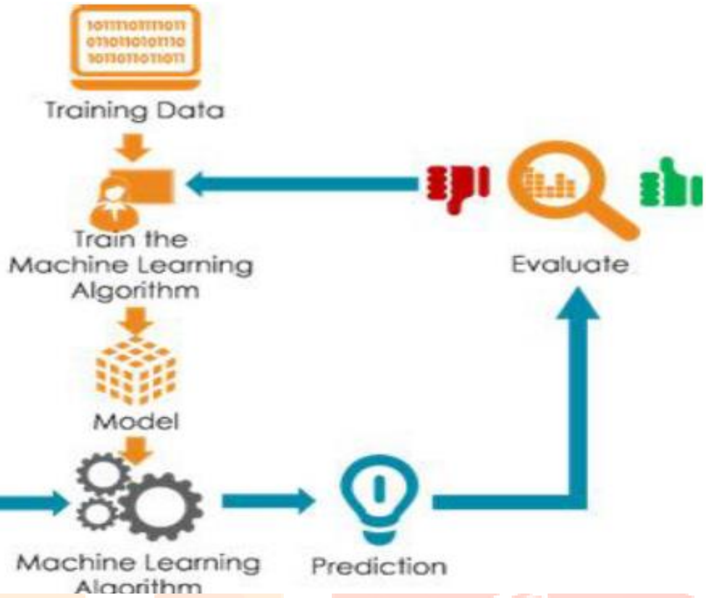

Fig. 4. Machine learning model

C. Hybrid approach

The hybrid approach combines the rule-construction and therefore the machine learning approaches into a single model. Both learning based and keyword-based approach have some limitation and could not give satisfactory result. The hybrid system uses the basic rule-based algorithm to retrieve the semantics and syntactic analysis, and use the default or existing dictionaries to extract the features from the input data. These semantics and attributes are then associated with affects in the form of affect association rules. As a result, once the search keywords match the words in the emotion list, it creates the vector affects from each token and the model fit the sentences into its respective target classes.

Table 1: Comparison of Precision, Recall, F-Measure and Accuracy:

	Precision	Recall	Accuracy
Rule based	59.98	62.66	57.50
Machine Learning	64.89	65.97	63.68
Hybrid	75.90	68.39	65.23

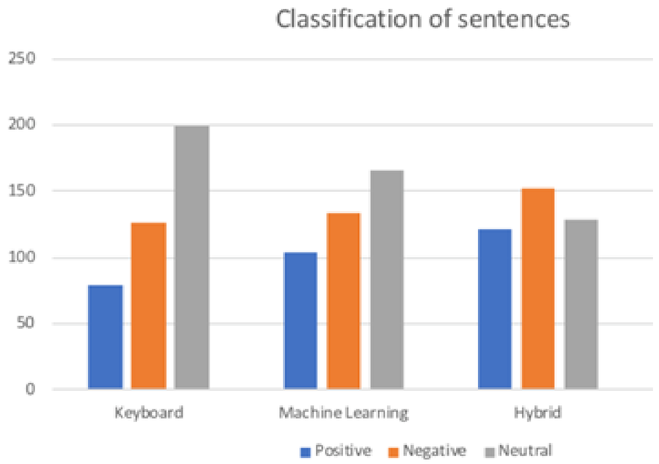

Fig. 5. Comparison of all major Emotion detection techniques

IV. EXISTING WORK

Emotion classification in sentiment and emotion analysis is an important and challenging task due to the ambiguous nature of emotions. Researchers utilize the explicit indications of emotions, such as emoji, in order to obtain the sentiment and emotions contained in social media text and improve the accuracy of the classification. Understanding emojis is significantly useful in as emojis are often used to complement text and carry semantical and sentimental information [4]. Several approaches have already been proposed to interpret and utilize emojis in emotion classification. In this section, overview of the related work performed is presented and discussed.

The earlier researches in Natural Language Processing, often used stickers as a kind of distant supervision to generate huge volume of annotated text, in which the emojis that express happiness or joy such as positive polarity, and sadness or anger such as negative polarity. However, stickers are used as an assistant way, and research work for stickers itself is really lack [4]. In these researches, emojis are often clustered in one emotional class, though while emojis can be considered as multi-label classification problem. These researches often manually specified which emotional category each emoji belong to (Wood and Ruder, 2016; Asghar et al, 2017). Such manual categorization requires an understanding of the emotional content of emoji, which is immense, complicated task and time-consuming. Besides, the availability of large number of emojis, and the frequent addition of new emojis in social media platforms, makes it more hectic and difficult task to manually update and categorize emojis. Moreover, any manual selection and categorization is prone to misinterpretations and may omit important details regarding usage.

In the paper [1] the research worker studied the accuracy of K-Nearest Neighbour and Navie Bayes, a machine learning inside the emotion detection victimization tweets inside the Sentiment analysis and 40 corpus. Their model identified that underneath stable constraints, Navie Bayes is compared with the K-Nearest Neighbour and the performance 72% as compared to 50%.

In the paper [2] work supported the attitude detection by semantic and syntactical conditions and tokens with specific attention to expression NAVA words. The author accumulated information from the ISEAR info, pre-processed the knowledge, and pre-processed it to seek out expression NAVA words. The author identified few expression NAVA words that may be listed to emotion tokens but weren't. Therefore, they introduced a list of words with expression and created an information consist of emotion keywords with their meaning. Victimization the WordNet feeling corpus, the ability reference book, & the created list info, where found to be familiar with the tokens and expression words consequently. The performance of their model was good, but it also stated that their approach did not find the solution for the flaws bestowed in existing models just like the existing attitude dictionaries and disrespect with linguistics supported information.

The work by Singh [3] contributed to resolution the linguistics extraction disadvantage linked with the text-based disfunction by passing through a 2-stage feature extracting approaches, linguistics & math steps. The linguistics method included the feature extraction process from gathered data victimization the part of speech tags and used the smoothing methodology in getting eliminate the weak linguistics choices inside the math level. The used the same on the other available texts and posts, victimization the Support Vector Machine classifier categorized the target classes like happy, boredom, happiness, rage, sad. Their model gives a good result in accuracy when compared to other alternate ways. However, was the particular undeniable fact that their methodology did not take into thought the affiliation between choices.

In the paper [5] the research worker introduced an emotion classifier from twitter data victimization three feeling lexicon. They retrieved the options from these databases one by one and used the nltk dictionaries to have an impression on feeling lexicon to induce synonyms of feeling verbs in the dictionaries. The researcher then identified the dependencies in data additionally as a result of the contextual information of feeling verbs. The researcher trained their model victimization the Support Vector Machine classifier and predicted the feelings into one in each of the half-dozen Ekman's categories of target classes. The performance of their model ranges from 68%, 53% and 81% on the three feeling corpora used, severally.

Almanie [6] developed a web-based software that displays the emotions expressed by individuals in land through the analysis of their twitter data. The author handly created a knowledge set with 4000 Arabic words in conjunction with stickers by combining information from three sources in conjunction with emotional survey queries and responses from individuals in land with utterly completely different culture. The knowledge is pre-processed and classified into one in each of happiness, sadness, fear, joy, fear, and disappointment cases where words contained less express. Thus, implementation is done, the feelings are being classified were hold on throughout a information beside their location and sets of queries running at identical time. With connection supervised techniques, support vector machines, K-NN, most Entropy are variety of the foremostly used approaches in this field.

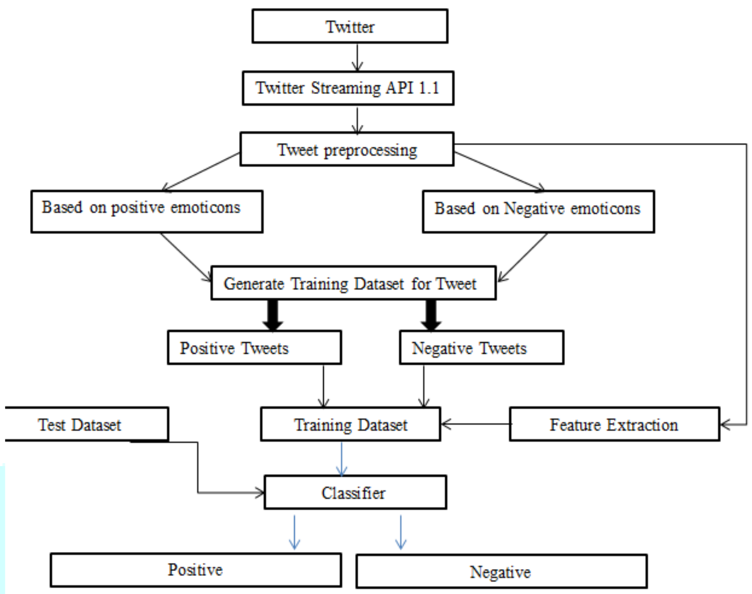

Fig. 6. Architecture diagram

In the paper [7] author proposed an emotion estimation net (ESiN), which is a combination of both contextual information and tokenized vector affects of the input data to find or classify the output target classes. Here the author used the affect state define Paul Ekman: joy sadness anger surprise hate and fear. Limitation of this model depends on the input data and the lexicon used for feature learning. And this approach is better in sentence level but not efficiently work in documents.

In [8], author proposed a novel unsupervised approach for emotion recognization at sentence level. These frameworks are including four main components such as pre-processing, semantic, syntactic and sentence analysis. This approach is applied on three standard datasets. And 3 lexicons which has data from wiki., electronic books, kindle and Wiki-Guten corpora, created by merging the two aforementioned data sets. Their model retrieves meaning and steam words of the unknown words from various lexicons or dictionaries. The main drawback of this model is that, it is highly dependent on the attached lexicons.

In the paper [9] the researcher developed an algorithm which retrieve the writer's attitude from their post or letters. In that algorithm they classify words [11] in: Direct Affective Word (DAW) which directly showcase the affects of the user's emotion and Indirect Affective Word (IAW) other words are belongs to IAW group. And they collect the data (customer review) from different site such as planetfeedback.com, ciao.it, cnet.com, complaint.com, ecomplaint.com [10]. In this paper they consider the six-emotion class of Ekman. In their experiment consider the training set in which 50% of DAW words are manually tagged. And other half (50 %) which is used in the testing phase. The author manually assign value to the value calculated by software.

LeCompte and Chen[10] studied the implications of emojis and stickers in emotion detection from social media posts. The author's research used the pattern match technique and so the Support Vector Machine and K-NN to categorize labels into happiness, sadness, boredom, disgust, etc. Their model performed well with very good accuracy. They jointly indicated that below equal conditions, Multinomial Naïve mathematician performed higher than Support Vector Machine.

Jian [11] bestowed a hybrid approach for the machine-driven detection system for multilinguists data info. Their model used information science approach to find the keywords from the collected data and then classify them as per the construct of feeling framework presented by Vagn Walfrid Ekman victimization the Support Vector Machine initial then Navie mathematician. They'd said that their technique provided higher ends up with alternative routes achieving accuracy of 82%.

In paper [12], the author refers to extract data/emotion from Czech newspaper headline and categorize it into various affect classes. The Czech language is considered as more complex language and the main problem is that verbs and noun can have different forms for same meaning. Here, for the identification and classified the emotion state and the overfitting issue is resolved. The cross-validation is based on the learning phase and the input is split into ten disjunctive subsets. In which 3/4th part of the dataset is used in the training phase and the remaining for testing by using different algorithm each time. So, they used the splits to train the model and to evaluate its performance and accuracy.

Tzacheva [13] used 3-D feeling corpus to tokenize gathered information from social media into feeling categories. Then categorized attitudes victimisation Support Vector Machine. Ten, they found pattern matches the keyword and use the hand written constraints to remodel anger or boredom feeling to joy & recognized. Improved the performance of the model.

LIMITATION:

Below are some best-known limitations from the approaches used in the existing papers:

1. Word ambiguity
2. Incapability to recognize emotion in absence of emotion keyword
3. Lack of linguistic information
4. Out of word vocabulary

V. PROPOSED WORK

It was realized that analysis within the field is preponderantly categorized into 2 main phases. The phases are extracting the discourse information from text and find the similarities between them. The introduction of transformers-based embeddings has shown a big increase within the quality of discourse info extraction. However, the utilization of transformers is limited by some limitations, viz., out of vocabulary (OOV) limitation, inflated complexness, and significantly the tactic overfitting in little networks.

Due to the highlighted drawbacks of transformers, associate degree ensemble of attention and neuro-fuzzy networks would facilitate cut back the limiting effects, so increasing classification performance. The networks area unit expected to specialize in the extraction of relevant options whereas the neuro-fuzzy networks provide clearer quality and classification of the extracted feature before classification.

Proposed design is simple to know and implementation. This model is part learning primarily based and keyword based. During this model used perspective keywords to sight the have an effect on from input text, and at the same time update the dictionary in step with input text. So, rule can provide a lot of correct result for next coming back input. the subsequent rule is planned to calculated have an effect on category of sentence and update worth of likelihood of word for any processing.

ALGORITHM:

Calculate the affect class of Sentence
Input-> Feed the input sentences
Step1- Input unannotated text
Step2- Pre-processing the given data
Step3- Extract emotion keywords from the list
Step4- Check for the words if they are noun or adjective or adverb or verb
Step5- Check for the relavent word in the dictionary.
Step6- If word found in dictionary return affect vector of word.
Step7- If words were mismatch then calculate similarity between words and affect class.
Step8- Calculate the affect of the sentence and output the highest score
Step9- Update the dictionary simultaneously
Output-> Target class

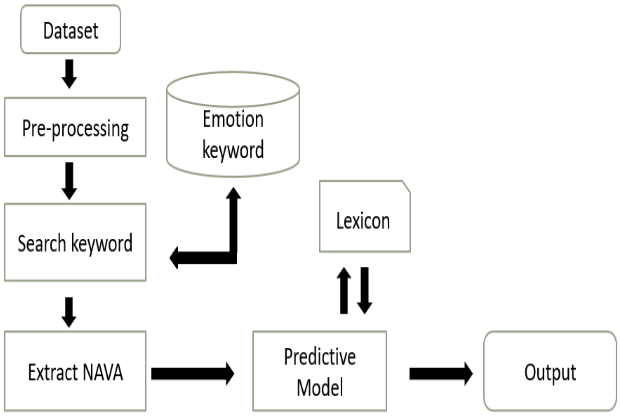

Fig. 7. Architecture diagram

VI. CONCLUSION

This model is partially machine learning based and keyword based. This model used attitude keywords to detect the affect from input text, and simultaneously update the dictionary according to input text. So, algorithm will give more accurate result for next coming input. The following algorithm is proposed to calculated affect class of sentence and update value of probability of word for further processing.

VII. FUTURE SCOPE

The cultural affiliations of a private greatly influence their expressed emotions toward things. However, there exist few emotion labeled resources for languages apart from a people Language. The supply of wealthy resources in different languages like French, Spanish, Hindi, so on will greatly modification the narrative and encourage analysis within the field so as to balance work tired totally different languages.

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