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A Survey on Automated Emotion Recognition Using Different Classification Models and Approaches

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Abstract: Automated emotion detection, is a diverse field with a multitude of applications ranging from software engineering to web customization, education, etc. Several methods and approaches have been devised for automatic emotion recognition, which has taken inspiration from human/natural emotion recognition. I have studied and discussed categorical and dimensional models, which can be subdivided into Circumplex, PANA, vector, and Plutchik's models, for defining a myriad of emotions under varied circumstances. I have stratified the approaches used in emotion detection by trifurcating them into lexicon-based, statistical, and hybrid methods. And, I have presented information on different types of classifiers and classes of neural networks that fall under the category of statistical methods, in a systematized way. I have observed that Support Vector Machines provide the most accurate and clear-cut outcome.

Keywords: PANA Model, Emotion Recognition, Circumplex Model, Categorial Models, Vector Model, Dimensional Models, Plutchik's Model

I. INTRODUCTION

Humans vary immensely when it comes to identifying and recognizing emotions. This ability, along with the biological and physiological processes involved, is known as emotional perception. Emotional perception is subjective to environmental influence and is believed to be a crucial component of social interactions. It is because of this ability that we can understand a person's internal state and feelings and communicate efficiently. Though emotions are perceived through many ways -auditory, visual, olfactory, taste, and physiological sensory processes, the primary mode of perception is the visual system. Information about emotions is received by people using emotional cues like facial expressions as well as bodily postures. The face is said to provide cues about one's subjective emotional state. For achieving accurate results, a multitude of different methods, bringing together knowledge and concepts from disciplines such as ML, speech processing, signal processing, etc.

The use of a combination of analysis of human expressions from multimodal forms such as audio, video, and physiology leads to the amelioration of emotion recognition [1]. According to Psychological theory, there are six basic emotions, happiness, sadness, fear, disgust, and anger in addition to the neutral facial expression [2]. Then there are compound emotions that deal with primary and complementary emotions (e.g., happily sad, sadly angry). Classification of facial expressions depends on the algorithms. There are separate algorithms for simple and compound emotions. Knowledge-based techniques, statistical methods, and hybrid approaches are the three main techniques that can be used to classify these emotions [3].

To detect certain emotion types, knowledge or lexicon-based techniques make use of domain knowledge and semantic and syntactic characteristics of a language. These can be further classified into corpus-based and dictionary-based approaches [4]. Then there are statistical approaches in which different supervised and unsupervised machine learning algorithms are implemented. These yield more precise results than the former [3]. Support Vector Machines (SVM), Naïve Bayes, and Maximum Entropy are all examples of machine learning algorithms [5]. Deep Learning is an unsupervised form of ML and is extensively used in emotion recognition [6-8]. Some commonly used deep learning algorithms are- Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Extreme Learning Machine (ELM) which are different architectures of Artificial Neural Networks (ANN) [5]. Next, Hybrid approaches have complementary characteristics from knowledge-based techniques and statistical approaches, being a combination of the two [3].

The main objective of this paper is to present a precise overview of the different models used to define emotions as well as the approaches used to detect emotions- both lexicon-based and machine learning.

The highlights of the paper are as follows:

1) The second section of the paper discusses the different types of emotions and models used to classify them.

2) The third section of the paper encompasses an in-depth analysis of the different approaches that are employed to detect various emotions.

3) The fourth section contains the results and conclusion.

II. CLASSIFICATION

Emotions have been largely defined using two types of models - Categorial and Dimensional. Let us review these quickly.

A. Categorial Models

Categorial models refer to emotions as discrete categories. According to the theory of discrete emotions, every human being has a small number of core emotions, which are the same for everyone regardless of cultural differences or ethnicity. These basic or core emotions are believed to be distinguishable by a person's biological processes and facial expressions, hence called 'discrete' [9]. Most of the basic emotion theories have one theme in common - that there should be functional signatures that will help us distinguish and differentiate between these emotions. That is by looking at a person's brain activity and/or physiology, we should be able to make out the person's feelings [5].

The initial theory that was proposed in [2] concluded six basic emotions, which are - anger, disgust, fear, happiness, sadness, and surprise. Later an expanded list of basic emotions was proposed [10] which are not encoded in facial expressions including a plethora of positive and negative emotions such as - amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, satisfaction, relief, sensory pleasure, and shame.

B. Dimensional Models

Dimensional models are used to define emotions according to where they lie in two or three dimensions. They adopt two dimensions- valence or hedonic tone which is the property that specifies whether affects/feelings are positive, negative, or neutral [11], and arousal - which is the psychological and physiological state of being awoken [12]. The most common dimensional models are the ones reviewed below.

C. Circumplex Model

According to this model, emotions are apportioned in a 2-D space which is circular, as shown in Figure 1 in which arousal and valence represent the vertical and horizontal axes respectively. Neutral valence and a medium level of arousal are shown in the centre of the circle [13]. The developers of this model say that their model represents core/most elementary emotions or feelings. They typically examine emotional facial expressions, emotional words as well as affective states [14].

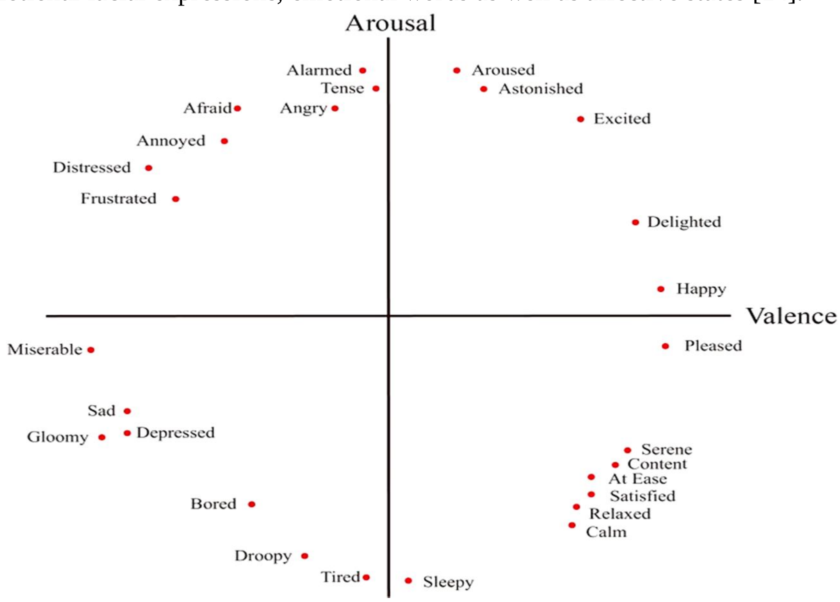

Fig. 1 Circumplex Model

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D. Vector Model

Widely used to test word and picture stimuli [12], this model shown in Figure 2 states that the direction in which a particular emotion lies is determined by the valence. It describes the neutral nature of low arousal states and how they are typified near the meeting point of the vectors; high arousal states are distinguished by their valence. The dimension of each stimulus is scaled individually and directly [14].

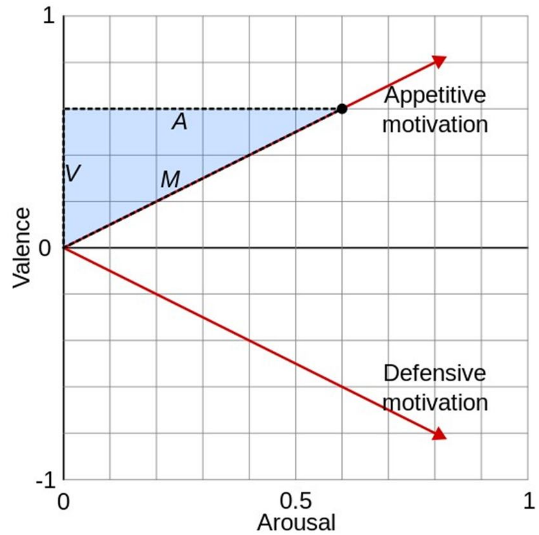

Fig. 2 Vector Model

E. PANA Model

Though this can be explained as a 45-degree rotation of the circumplex model, we consider it to be more like the vector model as shown in Figure 3. It consists of two primary axes - Positive Activation (PA) and Negative Activation (NA) [14]. The PA axis has two ends, one end represents the mood terms like activated, elated, and exited and the other end is denoted by terms like drowsy, dull, and sluggish. The NA axis similarly has two ends - one end represents 'distressed, fearful, and nervous' while the other end is anchored by 'calm, at rest and relaxed' [14].

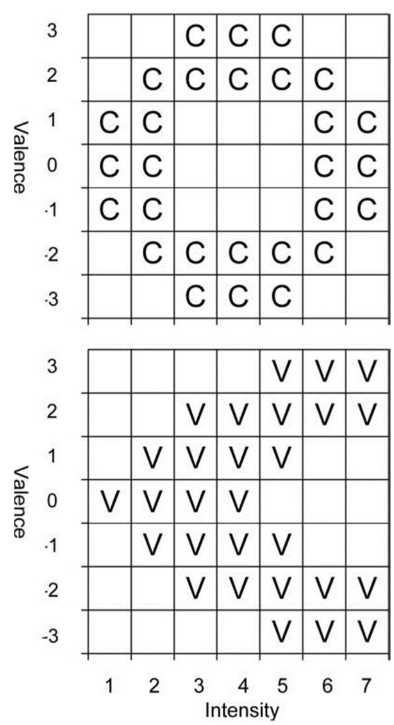

Fig. 3 PANA Model

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F. Plutchik's Model

This is a 3-dimensional hybrid model as shown in Figure 4 of both categorical and dimensional theories [15]. It comprises of concentric circles, with the circle on the interior depicting core/basic emotions; consequently, the one on the exterior depicts more complex emotions. In this theory, he stated 'primary', 'secondary', and 'tertiary' dyads and triads. These dyads and triads are feelings that comprise two and three emotions respectively [15-17].

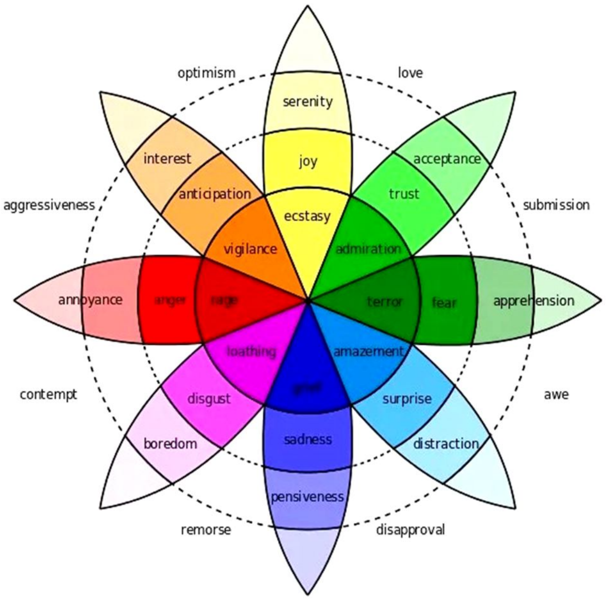

Fig. 4 Plutchik's Model

III. DIFFERENT APPROACHES TO DETECT EMOTIONS

As mentioned earlier, there are several approaches and techniques used for emotion recognition. Figure 5 from [18] correctly describes the general structuring of the algorithms and how the content is presented in the upcoming sections.

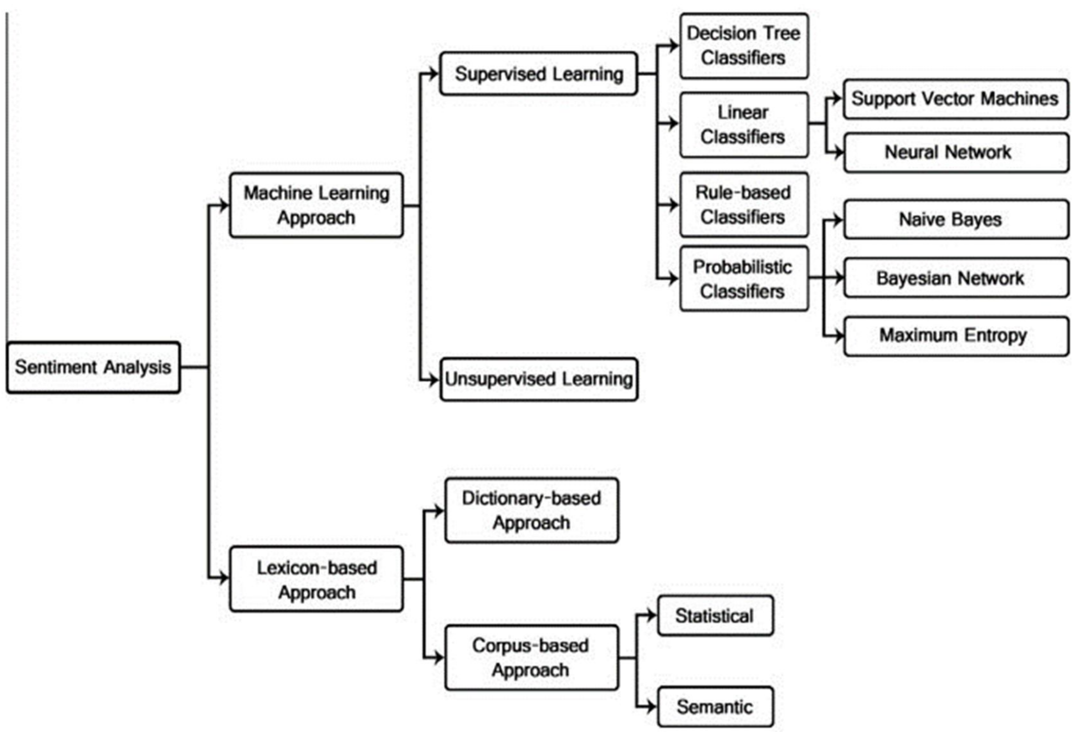

Fig. 5 Sentiment Analysis

These approaches can be chiefly grouped into the following categories:

A. Knowledge-Based Approaches

Also known as lexicon-based approaches, these rely on a sentiment lexicon, which is a collection of precompiled and known terms of sentiment. During the emotion classification process, different knowledge-based resources are put to use like –

1) *Wordnet:* As described in [19], a lexical database of 155,327 words which are organized in 175,979 *synsets* (sets of synonyms), containing nouns, verbs, adjectives, and adverbs. It ignores prepositions, determiners, and other function words. It has diverse applications in artificial intelligence and information systems, like information retrieval, word-sense disambiguation, machine translation, and automatic text classification. It is also frequently used to determine the similarity between words. Currently, there are wordnets in more than 200 languages.
2) *SenticNet 7:* An unsupervised, explainable, reproducible *neurosymbolic* AI system that builds symbolic representations that convert natural language to a kind of protolanguage to better deduce polarity from text using subsymbolic models, and it is primarily used in sentiment analysis [20].
3) *ConceptNet:* Semantic network based on the information in the *Open Mind Common Sense* project based at MIT [21]. The information that it contains can be used as a basis for machine learning algorithms.
4) *EmotiNet:* A knowledge base for capturing, storing, and representing affective reactions to real-life contexts, and predicting the emotional responses triggered by a chain of reactions [18,22].

These knowledge-based resources can further be classified as dictionary-based and corpus-based. Dictionary-based approaches expand the initial list of opinions or emotions by searching for the synonyms and antonyms of an opinion or a seed word in a dictionary. Alternatively, corpus-based approaches expand the initial database by finding other words with context-specific characteristics similar to a given seed list of opinions or emotion words in a large corpus. The corpus-based approach is further classified into statistical and semantic approaches [9].

The statistical approach is used for finding co-occurrence patterns or seed opinion words. This could be done by deriving posterior polarities by using the co-occurrence of adjectives in a corpus [23]. If the corpus is not large enough, it poses the problem of unavailability of root words. This problem is overcome by using the entire set of indexed documents on the web as a corpus for dictionary construction [19].

The semantic approach makes use of different principles to compute the similarity between words and gives sentiment values directly. It gives similar sentiment values to semantically close words, for example, wordnet [9].

B. Statistical Approaches

As illustrated in [9], statistical methods involve the use of numerous supervised and unsupervised models. Examples of supervised machine learning algorithms include decision-tree classifiers, rule-based classifiers, probabilistic classifiers (like Naïve Bayes, Bayesian Networks, Maximum Entropy) as well as Linear classifiers (like Support Vector Machines (SVM) and neural networks).

1) Decision-Tree Classifiers

This is a supervised learning approach that is employed regularly in data mining, statistics, and machine learning. The training data space is decomposed hierarchically, in which a condition or predicate on the attribute value is used to divide the data. This predicate is the absence or presence of one or more words. There are other kinds of predicates that depend on the similarity of documents to correlate sets of terms [9]. This may be used for further division of documents. There are several kinds of splits like- the Single Attribute split, Similarity-based multi-attribute split, Discriminant-based multi-attribute split, etc. [9].

There are two types of decision trees- classification and regression tree models [9].

a) Classification tree models: Classification trees are those tree models where the variable can take a discrete set of values, i.e., Classification analysis is done when the predicted outcome to which the data belongs is discrete.
b) Regression tree models: In regression tree models, the target variable can take continuous values, which means that this type of analysis is done when the predicted outcome can be considered as a real number.

One of the biggest advantages of this method is that it is highly intelligible and simple to understand and interpret. It performs well with large datasets and provides accurate results with flexible modelling. It has built-in feature selection [9].

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2) Rule-based Classifiers

As described in [9], Rule-based classifiers are those that identify, evolve, or learn rules to store manipulate, or apply. In these classifiers, the data space is modelled with a set of rules. Rule-based approaches include artificial immune systems, linear classifier systems, association rule learning, or any other method which covers contextual knowledge, and relies on a set of rules. Although these rules can be generated using several criteria, two of the most recurrently used criteria are confidence and support. The former refers to the number of instances in the training dataset, pertinent to the rule. The latter refers to the conditional probability that the right-hand side of the rule is satisfied only if the left-hand side is satisfied.

The fundamental difference between decision-tree and rule-based classifiers is that decision-tree is a strict hierarchical partitioning of the data space, whereas overlaps in the decision space are allowed in the rule-based classifiers [9].

3) Probabilistic Classifiers

Probabilistic classifiers involve the usage of mixture models, wherein the mixture model assumes that each class forms a component of the mixture, with each mixture model being a generative model. Hence, they are also called generative classifiers [9].

a) Bayesian Network

It is a probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph. It is also known as Bayes Net, Bayes Network, Belief Network, or Decision Network. These networks are ideal for taking an already occurred event and predicting the likelihood that the event occurred due to any of the several possible known causes [24,25]. They perform three main inference tasks as outlined below –

Inferring unobserved variables and answering probabilistic queries about them.

1. Parameter learning
2. Structured learning

b) Naïve Bayes

These are simple but highly scalable probabilistic classifiers. It evaluates the posterior probability of a class, based on the word distribution in the document. In this classifier, we assume that features are independent. It makes use of the Bayes theorem to predict whether a given feature belongs to a particular label or not [9].

These are used for -

- To better understand and quantify opinions and attitudes around specific products and brands, sentiment analysis (a form of text classification) is commonly leveraged within marketing.
- This method has also been leveraged to predict different cognitive states among humans using fMRI data.

c) Multinomial Logistic Regression (Maximum Entropy)

This is known by a diverse set of names including multiclass LR, polytomous LR multinomial logit (mlogit), as well as maximum entropy (MaxEnt). This type of model is used when the dependent variable has 3 or more possible outcomes [9].

Highlights of this technique are -

- It needs a small amount of training data to detect parallel sentences between any pair of language.
- Studies have shown that these classifiers can produce useful and accurate results for any language pair.

d) Linear classifiers

As elaborated in [26,27], Linear classifiers achieve the goal of statistical classification by making a classification decision based on the linear combination of the characteristics. These classifiers take less time to train and use while maintaining accuracy levels comparable to non-linear classifiers. There is linear predictor p which is a separating hyperplane. Let us consider a linear predictor p. Its output is the output of the linear classifier. Linear classifiers are frequently used where there is an issue with the speed of classification since it is often the fastest classifier.

e) Support Vector Machines

As illustrated in [5,9], its job is to maximize the margin between the decision hyperplane and the examples in the training set.

The main purpose of Support Vector Machines is to determine the linear separators in search space that can best separate the varied classes. SVMs are supervised learning models that can be used in both -

- Text and hypertext categorization- in both inductive and transudatory settings, they significantly reduce the need for labelled instances.
- Image classification- After just 3-4 rounds of relevance feedback, we can achieve significantly higher search accuracy than traditional query refinement schemes using SVM.

4) Neural Networks

Next, Artificial Neural Networks (ANN), namely, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Extreme Learning Machines (ELM), which are all widely used, fall under the category of deep learning algorithms. Deep Learning comes under the unsupervised family of machine learning and deep learning approaches are very popular in the domain of emotion recognition [5,9].

a) Artificial Neural Networks

Artificial Neural Networks (ANNs) are composed of artificial neurons, each with inputs and a single output that can be sent to multiple other neurons. These artificial neurons are conceptually derived from biological neurons. ANNs are known for their ability to reproduce and model non-linear processes, which is why they are extensively employed in emotion recognition [5,9]. Some of the architectures of ANN:

- *Convolutional Neural Networks (CNN)*

Inspired by biological processes [9], these are among the most popular deep learning models, specifically designed to process pixel data and have applications in image and video recognition, image classification, etc. With CNNs, convolution layers filter the image to produce a feature map. Next, this map is input to layers that are fully connected and according to the output of the FE classifier, the facial expression is recognized as belonging to a particular class.

- *Long Short-Term Memory (LSTM)*

This is an architecture of another class of ANN called the Recurrent Neural Network (RNN) [5,9]. A common Long Short-Term Memory (LSTM) unit is composed of a cell and three gates- input gate, output gate, and forget gate. Unlike standard feedforward neural networks, it has feedback connections and can process not only single data points but also entire data sequences. This is what makes LSTM ideal for processing and predicting data, speech recognition, speech activity detection, human activity detection, etc.

- *Extreme Learning Machines (ELM)*

Extreme Learning Machines or ELMs [5] are feedforward artificial neural networks used often for classification, feature learning, etc. They can have single or multiple layers of hidden nodes. The parameters of the hidden nodes need to be tuned. Some studies have shown that these can outperform support vector machines in both classification and regression applications.

C. Hybrid Approaches

As stated in [3,9,18,28], these bring together characteristics from both techniques and are very common with sentiment lexicons. They are computationally complex, but they are known to have superior classification performance contrary to situations wherein we employ knowledge-based and statistical approaches independently. They play a crucial role in the majority of methods. The role played by knowledge-based resources like SenticNet, which combines both linguistic and statistical elements like Sentic computing and iFeel, is indispensable in the emotion classification process.

IV. RESULTS AND DISCUSSION

In the first instance, the basic 6-emotions theory put forth in [29], proposed that human beings show 6 basic emotions which can be linked to facial expressions. This list was further expanded to 15 emotions ranging from envy and pride to nostalgia. Next, researchers at the University of California, Berkley identified many more emotions - 27 to be precise, which were, in turn, modelled into a 'map' [2,10,29,30].

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Then comes the category of dimensional approaches - a concept that contrasts the former. Contrary to what the theory of basic emotions says (that different emotions arise from separate neural systems), these theories opine that there's a common and interconnected neurophysiological system that's responsible for all affective states [31].

We have discussed 4 of the most used classification models - the circumplex model, the vector model, the PANA model, and Plutchik's model [3,31].

We have already discussed the lexicon-based, statistical-based, and hybrid approaches in detail in the above sections, now let us have a look at the situations in which they prove to be most useful and their accuracy levels.

1) Lexicon-based approach: It is highly dependable when it comes to analysing simple sentences wherein the emotions are clearly expressed [32].
2) Statistical approaches: Also called learning-based approaches, these are first trained from a training set then the classifier will detect the emotion directly for a word or a more complex structure of classifiers [32].
3) Hybrid: Detection of keywords, learning of patterns, and plenty of other information from dictionaries and thesauri [32].

A. *Accuracy Levels*

Let us now review the accuracy results for these three categories as observed through various experiments –

1) *SVM*

TABLE I

A COMPARISON OF THE ACCURACY LEVELS OF DIFFERENT APPROACHES (IN DESCENDING ORDER)

Sr. No.	Support Vector Machines (SVM)		
	Algorithm	Accuracy (in %)	Year
1	SVM with information gain feature extraction [33]	91.15	2009
2	SVM with features based on unigram [34]	82.9	2002
3	SVM with a linear kernel [35]	80.29	2011
4	Speaker-dependent SVM with thresholding fusion [36]	75.67	2015
5	SVM which has features like WordNet affect, General Inquirer, etc. [37]	73.89	2007

As can be seen from the Table I the information gain feature extraction method gives the most precise results.

2) *ZBC*

Let us now review the accuracy levels of the Naïve Bayes Classifier through Table II.

TABLE III

A COMPARISON OF THE ACCURACY LEVELS OF DIFFERENT ALGORITHMS OF THE NAÏVE BAYES CLASSIFIER

Sr. No.	Naïve Bayes Classifier (NBC)		
	Algorithm	Accuracy (in %)	Year
1	NBC and Naïve search [38]	~85	2012
2	NBC with features based on unigram [34]	78.7	2002
3	Facebook query, language query, etc. [39]	NA	2013
4	ERR-based NBC [40]	NA	2014
5	Multinomial NBC with features [41]	NA	2014

Here we can see that Naïve Bayes Classifier (NBC) and Naïve Search algorithm provide accurate results with an accuracy percentage being ~85\%.

3) *Hybrid*

Let us review the accuracy levels for Hybrid approaches in the descending order of accuracy outlined in Table III below.

TABLE IIIII

A COMPARISON OF DIFFERENT HYBRID ALGORITHMS

Sr.	Hybrid Approaches		
No.	Algorithm	Accuracy (in %)	Year
1	SVM and CRF with applied rules [42]	91	2015
2	Hybrid SVM, 100 folds [43]	89	2004
3	Multinomial NBC with greedy search [44]	85	2013
4	NBC and SVM using information gain and Chi-square methods [45]	71	2014
5	Keyword-spotting and rule-based methods [46]	NA	2013

It is evident from the above table that SVM and CRF applied rules work best with 91\% accuracy. CRF, also known as Conditional Random Fields, is a class of statistical modelling methods frequently used for structured prediction.

V. CONCLUSION

When it comes to dimensional models, I believe, the least effective model is Plutchik's wheel of emotions, the reason being, it is too simplistic and may fail to incorporate other, bigger emotional nuances within it. Moreover, the vector and PANA models work better, if the stimuli we use are similar to events, autobiographical memories, etc.

The keyword-based or lexicon-based approach is the most used one and precisely detects emotions at the basic word level.

The statistical methods require the use of a training set to detect emotions. One of these approaches is the SVM which is a binary classification technique. It uses several algorithms which were developed over time like the SVM with linear kernel, speaker-dependent SVM with thresholding fusion, SVM with features based on unigrams, etc. but the most accurate results are provided by SVM with information gain feature extraction. Then we have the Naïve Bayes classifier. If we vary the representation of the input text, we get different types of NBCs, the most accurate algorithm being NBC and Naïve Search. Finally, we have the hybrid approach wherein we combine different approaches; and if we look at the data, the most accurate algorithm is the one that combines SVM and CRF with applied rules. Hence, we can see that different approaches and algorithms work best under different circumstances and conditions. However, as is evident from Table I Support Vector Machines seem to perform best among the studied approaches.

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