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Survey of Methods in Sentiment and Emotional Analysis

K. Kesav Raj[1], G. Sujitha[1], R. Karthikaeyan[1] and C. Kishore Kumar[1*]

[1]Department of Computer Science and Engineering, Rajalakshmi Engineering College, Anna University, India.

Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

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Abstract

People tend to convey emotions and show the sentiment either consciously or unconsciously while they speak or write. Many are under the common delusion that both sentiment and emotion are indistinguishable. Sentiment is the mental attitude originating from the feelings whereas emotion is a strong feeling itself. Sentiment analysis is used to identify and extract subjective information about the data. Thus it is also called as Opinion Mining. Emotion analysis gives an idea on people's psychological responses. With the growth of web 2.0 many social media and marketing companies started investing more resources on this field. This helped them to predict several things from computing customer satisfaction metrics to identifying detractors and promoters companies. At present there are several methods and techniques for sentiment and emotion analysis. In this paper we have referred several researches and methods proposed. Finally we have come to a conclusion that combining regression analysis method of sentiment detection and image processing to detect emotion can yield a productive hybrid model for more precise results.

Keywords: Emotional analysis; sentiment analysis; web 2.0; opinion mining; image processing; companies; customer.

**Corresponding author: E-mail: suji.sen2@gmail.com;*

1 Introduction

Sentiment or emotion are key to human actions and influence their behavior. People's perception of reality and the choices they make a considerable degree conditioned upon how others see and evaluate their environment. With development of web 2.0 and boom of internet took the social networking to the next level. The advertising companies and even the government began to invest on sentiment and emotional analysis from the feeds in the social networking. Analysis of sentiment in text became a new rapidly growing field of study and application. The Obama administration used sentiment analysis to gauge public opinion to policy announcements and campaign messages ahead of 2012 presidential election. Several sentiment and emotional analysis tools and applications are being used by some companies and social networking sites. But each was developed with a specific interest for their own companies [1]. Melt water was developed to assess the tone of comments as a proxy to uncover new insights. Google alerts is the most famous of all mainly used to get recent trends and content marketing. Facebook Insights helps if people get more than 30 likes in Facebook Page they can start measuring its performance with Insights. Memotions and Moodies are two stable android apps for emotion deduction. They use voice recognition and predict the emotion through human voice. But has many drawbacks like noise distortion and sore throat.

Many models were proposed but each had their own drawbacks. In this survey paper the most efficient sentiment and emotion analysis method is found so that both can be combined to get a hybrid model which can detect human mind more efficiently [2].

2 Sentiment Analysis

Sentiment analysis is mainly used to identify the attitude of a person with respect to any situation. The attitude here describes about the emotional state of a person. The likes of social media such as twitter and other social networks has stroke up interest in sentiment analysis whose benefits are such as social monitoring for branding marketing etc. It mainly involves the process of determining the contextual polarity of the text i.e., whether a text is positive, negative or neutral. Use of this analysis is to find out how people feel about a particular topic. Categorizing the documents as positive or negative sentiment will be useful for unlabeled documents. We can now see the various methods involved in this process and thereby conclude with the most appropriate and accurate method [3].

2.1 Methods for sentiment analysis

2.1.1 Lexicon based approach

The lexicon-based approach depends on opinion (or sentiment) words, which are words that express positive or negative sentiments. Words that encode a desirable state (e.g., "great" and "good") have a positive polarity, while words that encode an undesirable state have a negative polarity (e.g., "bad" and "awful"). Although opinion polarity normally applies to adjectives and adverbs, there are verb and noun opinion words as well. Researchers have compiled sets of opinion words and phrases for adjectives, adverbs, verbs and nouns respectively [4,5].

In this method of sentiment analysis, the polarity of a review or phrase is adjudged depending on the words used. This analysis runs on the assumption that polarity of whole review or document is based on collective sum of individual polarities. This approach is considered as a simple and basic way to predict sentiments. Anyhow determining the polarity using this approach in microblogs is more difficult. This is mainly because people started using short forms and emoticons to convey their texts. The approach proposed by Chetan Kaushik and Atul Mishra [6] can perform sentiment analysis quicker and vast amount of data can be analyzed. The main component of this approach is the sentiment lexicon or dictionary. Unlike the small sized dictionaries, the dictionary used in the approach contains more than 30 different emoticons along with their polarities. This dictionary is domain specific i.e. the polarities of the words in the dictionary are set according to a specific domain e.g. book reviews, political blogs etc. Same word in different domains can have different meanings, the dictionary used in this approach is made for movie review domain. The dictionary contains all forms of a word i.e. every word is stored along with its various verb forms. Hence eliminating the need for stemming each word which saves more time. Emoticons are generally used by people to depict emotions. Hence it is obvious that they contain very useful sentiment information in them. The Dictionary also contains the strength of the polarity of every word [7].

For example good and great are both positive words but great depicts a much stronger emotion. Negation and blind negation are very important in identifying the sentiments, as their presence can reverse the polarity of the sentence. The dictionary used here also contains various negation and blind negation words so that they can be identified in the sentence.

In this research, twitter data is categorized according to polarity. Detecting the subject towards which the sentiment is directed is a tedious task to perform, but as twitter is used as data source hashtags can be used to easily identify the subject hence eliminating the need for using a complex mechanism for feature detection thereby saving time and effort.

Some of the recent researches in lexicon based approach is analyzed in Table 1 and the best from lot is taken for final comparison.

2.1.2 Supervised machine learning

This is a machine learning task where a function is derived from a set of training data. This training data is nothing but training examples. These examples consists of set of example inputs with the desired output given by the teacher. The function derived by machine can be used map new inputs to the required output.

The first step in this process is to identify the training sets and gather those sets to represent a real world use. The number of feature should be small and accuracy of the function depends on the representation of input. It is necessary to determine the structure of learned function.

After completing the design the parameters must be found which can be adjusted for optimizing the algorithm. Note that, though there are a wide range of algorithms available, there is no single algorithm which can be supervised for all problems.

Sentiment analysis is conducted at any of the three levels: the document level, sentence level or the attribute level. In this study, we have considered the two largely used models - *Naive Bayes* (NB), and support vector machines (SVM).

In Naïve Bayes technique, the basic idea to find the probabilities of categories given a text document by using the joint probabilities of words and categories. It is based on the assumption of word independence [8]. Most of the algorithms are based on a classifier trained using a collection of annotated text data [9]. It is a collection of words discarding the grammar or order for a subjective purpose. For a document d and class c, Bayes theorem states that:

$$\boldsymbol{P(c|d) = \frac{P(d|c)P(c)}{P(d)}} \tag{1}$$

Naïve Bayes classifier will be:

$$\boldsymbol{c *= \mathbf{arg}\ maxc\ (c|d)} \tag{2}$$

SVMs are a machine learning classification technique which use a function called a kernel .This kernel is used to map a space of data points. Here the data is not linearly separable onto a new space in which it is, with allowances for erroneous classification. This is a highly effective traditional classification technique which outperforms the Naïve Bayes classification.

In the simple case where a linear function divides the two classes, a resulting hyperplane partitions the solution space. This technique gives High Dimension Input Space and Document Vector Space which makes it more trustable [10].

Some of the recent researches in supervised machine learning is analyzed in Table 2 and the best from lot is taken for final comparison.

2.1.3 Regression model

A recently developing model where the global polarity or rating is not the direct result of the words in the review but is drawn from latent aspect ratings. This gave birth to introduction and resolution of the Latent Aspect Ratings analysis problem.

The model is called the Latent Rating Regression (LRR) model and was created by Wang et al. in 2010. It estimates polarity on different aspects in a review but also determines the emphasis of the author on each aspect. It uses a given set of aspects and the overall polarity of the review. It starts with an aspect segmentation step. By recursively associating words with aspects, it can build an aspect dictionary and link each phrase of a review to the corresponding aspect. Then it applies the model based on assumption of reviewer's rating behavior is as follows: to generate an opinionated review, the reviewer first decides the aspects she or he wants to comment on; and then for each aspect, the reviewer carefully chooses the words to express her or his opinions. The reviewer then forms a rating on each aspect based on the sentiments of words she used to discuss that aspect. Finally the reviewer assigns an overall rating depending on a weighted sum of all the aspect ratings, where the weights reflect the relative emphasis she has placed on each aspect." So the overall rating is not directly determined by the words used in the review but rather by latent polarity on different aspects which are determined by the words [11]. This model is the first to give solution to the problem of parts of speech and emoticons in Table 3.

This method gives accurate results but have some issues like - The average performance in simple aspect ratings. But still needs to know the several aspects to be considered as this model is under development. Latent Aspect Rating Analysis is Unified framework for exploring review text data with companion overall ratings. Simultaneously discover latent topical aspects, aspect ratings and weights. It is also a multi-modal opinion analysis and decision support system. Limitation is that it is a Bag-of-words full of assumption. In future it may Incorporate sentence boundary/proximity information or even address aspect sparsity in review content.

2.2 Considerations

After all the analysis of researches stated above in Table 4, the methods for sentiment and emotional analysis can be compared so that a hybrid superefficient model can be found. But the problem is that the comparison cannot be considered genuine unless the parameters are same.

Usually for any analysis the factors in which one type triumphs the other is time, efficiency and accuracy. Since this anatomization is based on sentiment and emotion, the complexity of algorithm with which one finds the result and the percentage of neutrality comes into play as parameters. Hence the legends (parameters) which should be considered for juxta positioning are:

1. Time efficiency
2. Complexity
3. Neutrality rate
4. Accuracy

Table 1. Compilations of researches on lexicon based approach

Year	Authors	Techniques	Parameters	Field	Accuracy
2015	Sara Rosenthal Saif M Mohammad Preslav Nakov Svetlana Kiritchenko Veselin Stoyanov [11]	Sentiment lexicons and a bag-of word/lexiconbased ensemble method	All social media data from 20132015	Twitter	69-72%
2015	Lei Zhang, Riddhiman Ghosh, Mohammed Dekhil, Meichun Hsu, Bing Liu [12]	Augumented lexicon based method & Chi-square test	No. of times the key words are found	Twitter	67-75%
2014	Lukasz Augustyniak, Tomasz Kajdanowicz, Piotr Szymanski, Włodzimierz Tuligłowicz, Przemyslaw Kazienko, Reda Alhajj, Boleslaw Szymanski [13]	A bag-of-word/lexiconbased ensemble method	(25, 95, 487 reviews, longer than 100 characters) 54-97 secs	Epinions.com	80%
2014	Chetan Kaushik and Atul Mishra [6]	Sentiment Lexicon	Data (6, 74, 412) Time taken 14.8 secs	Twitter	73.5%

Table 2. Compilation of researches on supervised machine learning

Year	Authors	Techniques	Parameters	Field	Accuracy
2015	Aamera Z. H. Khan Dr. Mohammad Atique Dr. V. M. Thakare [14]	Feature extraction	Positive and negative	twitter	80%
2014	Duyu Tang, Furu Wei, Nan Yang, Ming Zhou, Ting Liu, Bing Qin [15]	Word embedding	Unigrams, bigrams and trigrams	twitter	70-78%
2014	Tomas Mikolov, Quoc Le [16]	Paragraph vector	Fixed length	Socher et al., 2013b & IMDB	50%
2014	Ms. Gaurangi Patil, Ms. Varsha Galande, Mr. Vedant Kekan, Ms. Kalpana Dange [9]	Natural Language Processing and Information Extraction	3FOLD AND 10 FOLD Kernel parameters	Computer and Communication Engineering	85%

Table 3. Different polarities in regression model

Polarity	Emoticons
Neutral	:|
Negative	:(, :-(, =(, :/
Positive	:) , :-), =), =D, :D

Table 4. Compilation of researches on regression model

Year	Authors	Techniques	Parameters	Field	Accuracy
2015	Ramon F. Astudillo, Silvio Amir, Wang Ling, Bruno Martins† , Mario Silva, Isabel Trancoso [17]	Serendio lexicon	• *p* parameter of the underlying system (Bernoulli distribution) • α and β parameters of the prior distribution (beta distribution)	Twitter data	60%
2014	Onal Itir, Ali Mert Ertugrul, and Ruken Cakici. [18]	Support Vector Regression (SVR)	No of tweets	Kaggle	20-50%
2014	Lorenzo Coviello, Yunkyu Sohn, Adam D. I. Kramer, Cameron Marlow, Massimo Franceschetti, Nicholas A. Christakis, James H. Fowler [19]	Instrumental variable regression	Emotional expression (*yjt*), individual-specific factor (*fj*), time-specific factor (*ht*).	Social networks and meteorology	80%

2.2.1 Time efficiency (t)

Efficiency is a measurable concept that can be determined by the ratio of useful output to total input. Time efficient is the state or quality of being **efficient**, or able to accomplish something with the least waste of time.

There are several algorithms and designs to detect the sentiment or emotion. But one such algorithm or model can be efficient only when it takes less time to analyze considerable number of data sets in least available time.

Time efficiency can be defined as the time taken to analyze ‘n’ data from the data sets. For better understanding we have here selected the number of datasets to be thousand.

Here n=1000,

i.e. $$\boldsymbol{t} = \frac{\textit{time taken to analyse n data}}{\textit{n data from data sets}} * \mathbf{1000} \tag{3}$$

2.2.2 Complexity

Generally to characterize something with many parts that interact within themselves in many ways, an Appropriate parameter used is Complexity. Since there is no exact definition about the term complexity, the consensus among researchers is that there is no agreement about how complexity can be defined. In our survey, we consider this parameter to check the complexity of an algorithm.

Usually it is very convenient to classify algorithms based on the relative amount of time or relative amount of space they require and specify the growth of time /space requirements as a function of the input size. Complexity of an algorithm is a measure of the amount of time and/or space required by an algorithm for an input of a given size (n). In analyzing an algorithm, rather than a piece of code, we will try and predict the number of times "the principle activity" of that algorithm is performed. For example, if we are analyzing a sorting algorithm we might count the number of comparisons performed, and if it is an algorithm to find some optimal solution, the number of times it evaluates a solution. If it is a graph coloring algorithm we might count the number of times we check that a colored node is compatible with its neighbors.

2.2.3 Neutrality rate

The word neutral may sometime seem to be positive but it is nothing but having no strongly marked or positive characteristics or features. A sentiment or emotional detector can be better only when the neutrality rate is low. It is not supporting or helping either side of the polarity which is a way of telling that “i can't decide”. Neutral sentiment includes a click or a scroll but has not follow through for a consumption. Ie someone just checked out the image. Learning from negative and positive examples alone will not permit accurate classification of neutral examples. Moreover, the use of neutral training examples in learning facilitates better distinction between positive and negative examples. In Sentiment analysis, the neutrality is handled in various ways, depending on the technique that is being used. In lexicon-based techniques the neutrality score of the words is taken into account in order to either detect neutral opinions or filter them out and enable algorithms to focus on words with positive and negative sentiment.

On the other hand when statistical techniques are used, the way that neutrals are handled differs significantly. Some researchers consider that the objective (neutral) sentences of the text are less informative and thus they filter them out and focus only on the subjective statements in order to improve the binary classification .In other cases they use hierarchical classification where the neutrality is determined first and sentiment polarity is determined second.

Finally in most academic papers of sentiment analysis that use statistical approaches, researchers tend to ignore the neutral category under the assumption that neutral texts lie near the boundary of the binary classifier. Moreover it is assumed that there is less to learn from neutral texts comparing to the ones with clear positive or negative sentiment. Koppel and Schler (2006) showed in their research both of the above assumptions are false. They suggested that as in every polarity problem three categories must be identified (positive, negative and neutral) and that the introduction of the neutral category can even improve the overall accuracy. Their work was primarily focused on SVM and they used geometric properties in order to improve the accuracy of their three binary classifiers.

2.2.4 Accuracy

Accuracy is a level of measurement that yields true (no systematic errors) and consistent (no random errors) results. Freedom from error (correctness), or closeness to truth or fact, resulting from exercise of painstaking care or due diligence. Accuracy depends on how the data is collected, and is usually judged by comparing several measurements from the same or different sources.

2.3 Comparison and inference

Considering the above explained parameters, we compare and apply it on each method in, Table 5 to get their respective parametric value and conclude i.e. suggest the most efficient method.

From Table 5 and Fig. 1, it can be clearly inferred that the regression method of sentimental analysis is comparatively better than the other two methods. Even though the machine learning method has more accuracy, the regression model surpasses it with less time and neutrality factor. Hence we can conclude that the regression model is the most efficient and productive method for sentimental analysis.

Table 5. Comparison of parameters in sentiment analysis

Method	Time efficiency	Complexity	Neutrality rate	Accuracy
Lexicon based approach	0.0219	o(n)	Medium	73.5%
supervised machine learning	25	o(n)	Low	85%
Regression model	7.2	$o(n^{k+1}\log(n))$	very low	80%

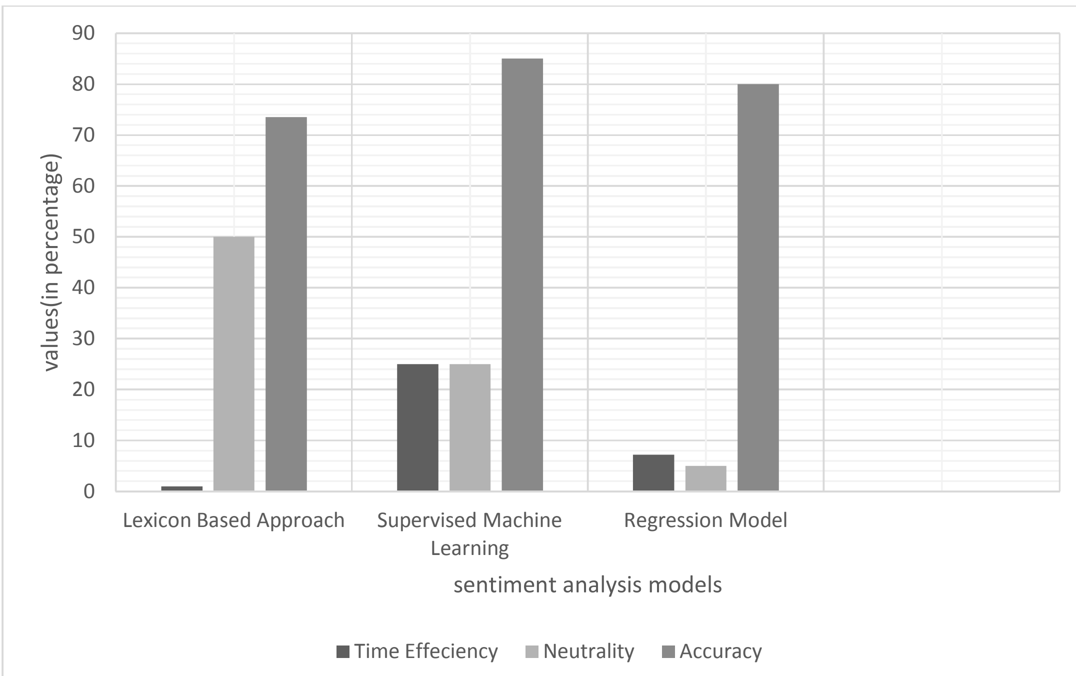

Fig. 1. Comparisons of methods in sentimental analysis

3 Emotion Detection

The task of recognizing a person's emotional state, for example- anger, confusion or deceit across both voice and non-voice channels is termed as Emotion detection. The most common technique is to analyze the characteristics of the voice signal, with word used as an additional input and their facial expressions through the camera display. Recent technological advancements have enabled human users to interact with computer in many ways. Beyond the confines of the keyboard and mouse, new modalities for human computer interaction such as voice, gesture, and force-feedback have emerged. Despite important advances, one necessary ingredient for natural interaction is still missing which is *emotion*. Emotions play an important role in human-to-human communication and interaction, allowing people to express themselves beyond their verbal domain. The ability to understand human emotions is desirable for the computer in several applications.

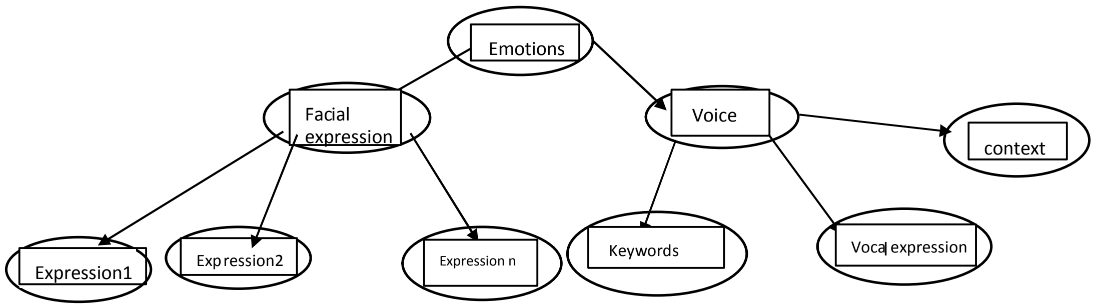

Fig. 2. Classifications of emotional analysis

Happiness is a positive emotion and everyone wants to experience it. It generally used as a synonym of pleasure and excitement. Fear, anger, disgust and sadness are negative emotions and most people do not enjoy them. Sadness can be described simply as the emotion of losing a goal or social role. It can be described as distraught, disappointed, dejected, blue, depressed, despairing, grieved, helpless, miserable, and sorrowful. Fear is a negative emotion of foreseen danger, psychological or physical harm. Anger is the most dangerous emotion for everyone. During this emotion, they hurt other people purposefully. Although anger is commonly described as a negative emotion, some people often report feeling good about their anger but it can have harmful social or physiological consequences, especially when it is not managed .Surprise is neither positive nor negative. It is the briefest emotion triggered by unexpected events. Disgust is a feeling of disliking and is the emotion of avoidance of anything that makes one sick. Disgust usually involves getting rid of and getting-away from responses.

3.1 Methods in emotion detection

At present there are only two techniques used in emotional analysis. They are voice recognition and image recognition. In voice recognition, we use K-Means and Support Vector Machines (SVMs) to classify opposing emotions.

3.1.1 Image processing

Generally, there are two typical models to represent emotions: categorical emotion states (CES) and dimensional emotion space (DES). CES methods consider emotions to be one of a few basic categories, such as fear, contentment, sadness, etc. The categorical perspective is useful to thin about emotions as distinct categories rather than dimensions. For example, the emotions of anger and anxiety, although similar in terms of being high-arousal emotions, are nevertheless associated with different facial expressions, feelings, and action tendencies. The DES methods mostly employ the 3-D valence-arousal-control emotion space, 3-D natural-temporal energetic connotative space, 3-D activity-weight-heat emotion factors, and 2D valence-arousal emotion space for affective representation and modeling.

CES in the classification task is easier for users to understand and label, while DES in the regression task is more flexible and richer in the descriptive power. The dimensional view of emotion is based on research studies in which subjects rate their emotional experiences. Emotions that occur together, which are experienced as similar to each other, are understood as defining a common dimension. For exam plea, the emotions of distress, anxiety, annoyance, and hostility are very similar in terms of experience and, thus, seem to anchor one end of a dimension of negative affect. The dimensional approach to emotion, thus, refers more to how people experience their emotions than to how they think about their emotions. In contrast, the categorical approach relies more on conceptual distinctions between emotions: the primary emotions are those that have distinct facial expressions or distinct motivational properties. The dimensional approach, on the other hand, suggests that what we experience are various degrees of pleasantness and arousal and that every emotion we are capable of experiencing can be described as a combination of pleasantness and arousal (Larsen & Fredrickson, 1999; Larsen & Prizmic, in press).

The categorical perspective is useful to thin about emotions as distinct categories rather than dimensions. For example, the emotions of anger and anxiety, although similar in terms of being high-arousal negative emotions, are nevertheless associated with different facial expressions, feelings, and action tendencies.
Table 6 gives the comparison of two recent researches on image processing.

Table 6. References in image processing

Year	Authors	Techniques	Parameters	Accuracy
2015	Samiksha Agrawal, Pallavi Khatri [20]	Viola and Jones algorithm	Facial actions	99.8%
2014	Sicheng Zhao, Yue Gao, Xiaolei Jiang, Hongxun Yao, Tat-Seng Chua, Xiaoshuai Sun [21]	Principles-of art-based emotion features (PAEF)	Symmetry, emphasis, movement, harmony, variety, gradation	85%

3.1.2 Voice recognition

Voice recognition is the ability of a program to receive, interpret or to understand and carry out spoken commands.

COVAREP is one of the algorithm used in voice recognition which allows more reproducible research by strengthening complex implementation through shared contributions and openly available code which can be discussed, commented on and corrected by the community. The content comparative method is a method for analyzing data .It involves identifying a phenomenon, object, event or setting of interest, few local concepts, principles, structural or process features of the experience or phenomenon of interest [19].

Table 7. References in voice recognition

Year	Authors	Techniques	Parameters	Field	Accuracy
2014	Gilles Degottex, John Kane, Thomas Drugman, Tuomo Raitio, Stefan Scherer [22]	COVAREP	Glottal flow	Open source	58%
2015	Arti Rawat Pawan Kumar Mishra [23]	Voice recognition through neural network	Framing, windowing, Fast fourier Transform, Mel scale filter bank, Log energy computation	Neural networks.	93.38%

Table 7 gives a clear observation of two research based on voice recognition.

3.2 Considerations

As given earlier for sentiment analysis it is necessary to consider certain common parameters for comparison purpose. In case of emotion analysis the parameters that can be used are very limited. Firstly we should look into number of categories of emotion being considered for a particular research. Most of them follow Ekman emotion classification – sad, happy excited tender scared angry. Next one can look into number of test subject. Test subjects can vary in age, color and even race. Finally the accuracy obtained using a particular method. Below is a comparison table of best of the research from both emotion analysis method.

3.3 Comparison and inference

As we did for sentiment analysis, we follow the same procedure to find the best method for the process of emotional analysis. We have filled in the Table 8 with best research found from Tables 6 and 7 so that values of the parameters are considered and compared to come out with an appropriate conclusion.

Table 8. Comparison of emotional analysis methods

Author	Method	No. of categories	Test subjects	Accuracy
Samiksha Agrawal Pallavi Khartri [20]	Image Processing	3 (sad happy and neutral)	6 random people	99.84%
Arti Rawat Pawan Kumar Mishra [23]	Voice recognition through neural network	5 (happy, sad, neutral, disgust and anger)	10 samples of 5 random people	93.38%

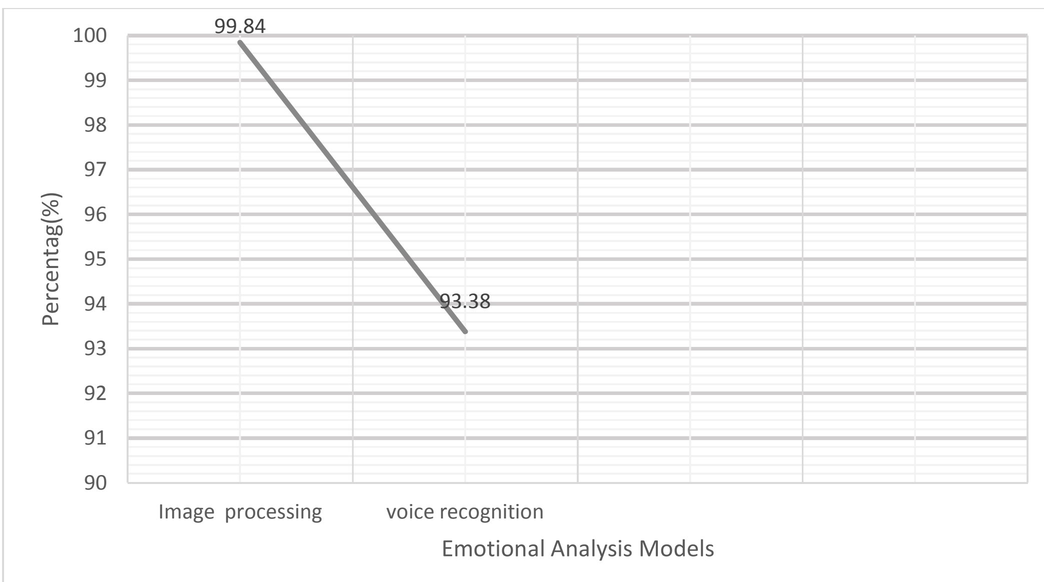

Fig. 3. Comparison of accuracy rates

Fig. 3 gives the comparison graph of each model and those accuracy is calculated with help of following parameters,

Accuracy for Image processing suggested in [21] is found using following formulae:

Euclidean Distance from neutral in an image is measured using:

$$Euclidean\ Distance(x, y) = \sqrt{(x1 - y1)^2 + (x2 - y2)^2 + \cdots (xn - yn)^2} \quad (4)$$

Calculation of accuracy rate id then done on the basis of Euclidean distance and mean error using:

$$accuracy = \left(\left(Dist_{frmNeutral} - error\right) * Dist_{frmNeutral}\right) * 100 \quad (5)$$

$\boldsymbol{Dist_{frmNeutral}}$ = Distance from neutral which is found using Euclidean distance formula.
Error=mean error

In voice recognition method suggested in [23], accuracy is found using following parameters:

Performance (mse): It measures the network performance according to the mean square error (mse).

Epoch: Epochs are directly related to the iterations in which the network is trained.

Time: Time function is related to training time. The training time shows how time is taken by the network to be trained and give the simulated output.

Accuracy of each expression is found using these parameters and average accuracy is given as accuracy of model as whole in our comparison.

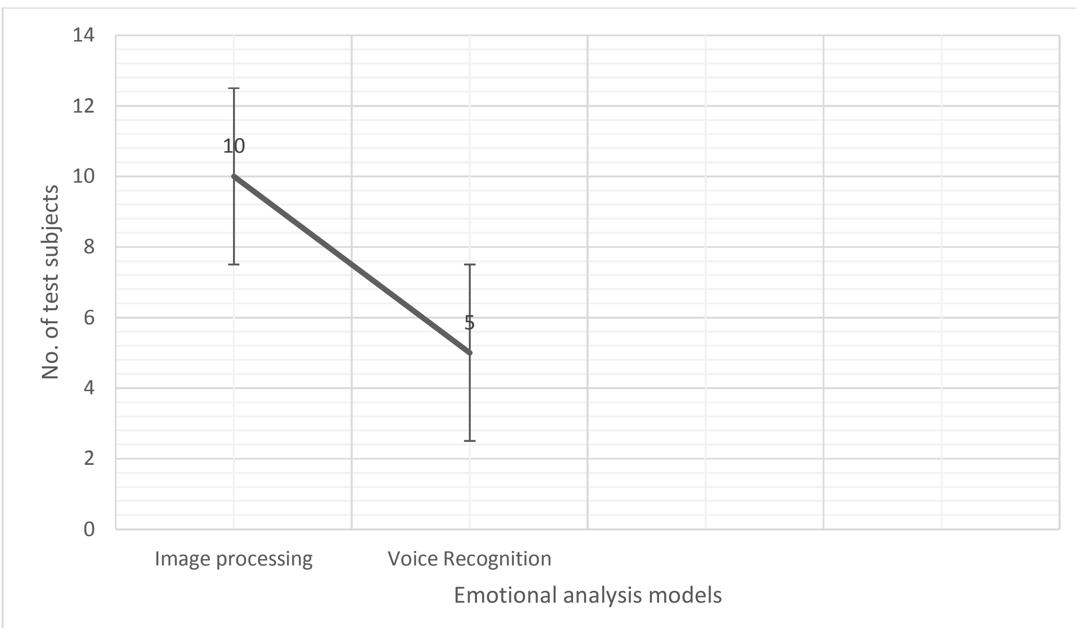

Fig. 4. Comparison of test subjects

Fig. 4 shows the comparison of number of test subjects used for each method where test subject's face is detected and the results are stored. These test results show happy, sad and neutral expressions so that these test results can be compared with that of the experimental subject's (random) face detected, to find the accuracy of the model with their respective distance from neutral value for method proposed in [21].

In [21], various samples had been tested for the recognition of emotion with help of 10 samples of 5 different emotions of 5 person's recorded voice and accuracy is found with help of parameters described above.

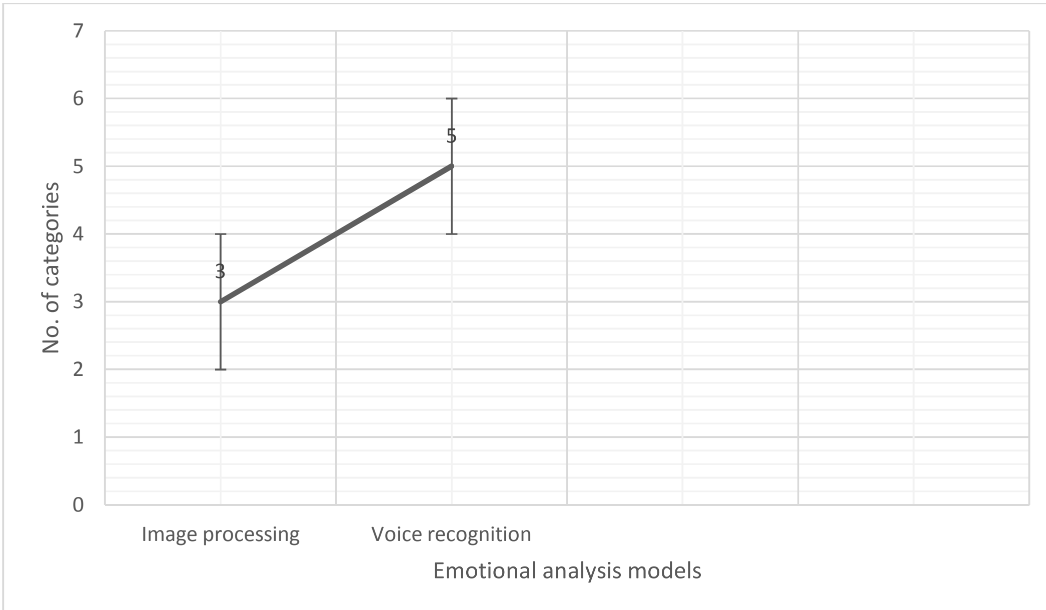

Fig. 5. Comparison of categories used

In Fig. 5, the category refers to the types of emotions that has been considered for each model eg: happy or sad. In case of image processing method [21] three emotions are considered- happy, sad and neutral. Whereas in case of voice recognition model proposed in [23] five emotions are recorded- happy, sad, neutral, disgust and anger.

From the above three graphs it is clearly inferred that the process of image processing yields you more accurate and better output than the voice recognition process. One may think that voice recognition model has considered more categories but when the number of categories is increased the accuracy of voice recognition model decreases. Since image processing is an upcoming technology, its advancements may yield us with more accurate answers.

4 Conclusion

The presented survey paper enhanced the recent updates and researches in Sentiment and Emotional analysis. About twenty of the recently published and well cited papers were analyzed and categorized. After all the analyzation made, it is clear that enhancements in this field are wide open. The data taken from microblogs and other forums in mostly used in these methods. These information plays a great role in expressing people's feelings, or opinions about a certain topic or product. Using social networking sites and micro-blogging sites as a source of data, deeper analysis and advancement may result better product. There are some benchmark data sets, like IMDB which are used for frame the core algorithm. However in many applications, it is important to consider the context of the text and the user preferences. In future, analysis of languages other than English is highly expected. From Fig. 1 of sentiment analysis and Figs. 3, 4, 5 of emotional analysis it is clear that combining the Regression method and the image processing method can result you in a hybrid model of highly productive and accurate results in this field.

Competing Interests

Authors have declared that no competing interests exist.

References

[1] Jyoti Rani, Kanwal Garg. Emotion detection using facial expressions -A review. IJARCSSE; 2014.

[2] Sicheng Zhaoy, Yue Gaoz, Xiaolei Jiangy, Hongxun Yaoy, Tat-Seng Chuaz, Xiaoshuai Suny. Exploring principles-of-art features for image emotion recognition. National University of Singapore, Singapore; 2014.

[3] Eric Marchi, Bj¨orn Schuller, Simon Baron-Cohen, Amandine Lassalle, Helen O'Reilly, Delia Pigat Autism Ofer Golan, Shimrit Fridenson-Hayo, Shahar Tal. The state of play of ASC-inclusion: An integrated internet based environment for social inclusion of children with autism spectrum conditions. arXiv:1403.5912v1 [cs.HC] 24 Mar; 2014.

[4] Lei Zhang, Riddhiman Ghosh, Mohammed Dekhil, Meichun Hsu, Bing Liu. Facial expression recognition using facial movement features. IEEE Transaction on Affective Computing; 2011.

[5] Maite Taboada, Julian Brooke, Milan Tofiloski, Kimberly Voll, Manfred Stede. 311. Lexicon based methods for sentiment analysis. Computational linguistics. 2011;37(2):267–307. MIT Press.

[6] Chetan Kaushik, Atul Mishra. A scalable, lexicon based technique for sentiment analysis. Computer Engg. Department, YMCA University of Science & Technology, Faridabad.

[7] Donato G, Bartlett MS, Hager JC, Ekman P, Sejnowski TJ. Classifying facial actions. IEEE Trans. Pattern Anal. Mach. Intell. 1999;21(10):974–989.

[8] Pablo Gamallo, Pablo Gamallo. TweetNorm_es: An annotated corpus for Spanish microtext normalization- Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14)" ELRA, Reykjavik-Paris; 2014-15.

[9] Gaurangi Patil, Varsha Galande, Vedant Kekan, Kalpana Dange. Sentiment analysis using support vector machine. UG Students, Dept of Computer, VIIT Engineering College, Pune, India.

[10] Hongning Wang, Yue Lu, Chengxiang Zhai. Latent aspect rating analysis on review text data: A rating regression approach. In Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD' 10, New York, NY, USA. ACM. 2010;783–792.

[11] Sara Rosenthal, Saif M. Mohammad, Preslav Nakov, Svetlana Kiritchenko Veselin Stoyanov – SemEval 2015 Task 10: Sentiment Analysis in Twitter- Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015), Denver, Colorado, June 4-5, c 2015 Association for Computational Linguistics. 2015;451–463.

[12] Lei Zhang, Riddhiman Ghosh, Mohamed Dekhil, Meichun Hsu, Bing Liu. Combining lexicon-based and learning-based methods for twitter sentiment analysis. Technical Report, Hewlett-Packard Development Company, L.P.; 2011.

[13] Lukasz Augustyniak, Tomasz Kajdanowicz, Piotr Szymanski, Włodzimierz Tuligłowicz, Przemyslaw Kazienko, Reda Alhajj, Boleslaw Szymanski. Simpler is better? Lexicon-based ensemble sentiment classification beats supervised methods. International Workshop on Curbing Collusive Cyber-gossips in Social Networks (C3-2014), August 17, 2014 Proc. IEEE/ACM Int. Conf. Advances in Social Network Analysis and Mining, ASONAM, Beijing, China; 2014.

[14] Aamera Z. H. Khan, Mohammad Atique, Thakare VM. Combining lexicon-based and learning-based methods for twitter sentiment analysis. National Conference on "Advanced Technologies in Computing and Networking"-ATCON-2015 Special Issue of International Journal of Electronics, Communication & Soft Computing Science and Engineering; 2015.
ISSN: 2277-9477.

[15] Duyu Tang, Furu Wei, Nan Yang, Ming Zhou, Ting Liu, Bing Qin- Learning Sentiment-Specific Word Embedding for Twitter Sentiment Classification- Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics, Baltimore, Maryland, USA, June 22-25. 2014c;1555–1565.

[16] Quoc Le, Tomas Mikolov. Distributed representations of sentences and documents. Proceedings of the 31st International Conference on Machine Learning, Beijing, China, JMLR: W&CP; 2014.

[17] Ramon F. Astudillo, Silvio Amir, Wang Ling, Bruno Martins†, Mario Silva, Isabel Trancoso. Detecting emotional contagion in massive social networks. PLOS ONE. 2014;9:3.

[18] Itir Onal, Ali Mert Ertugrul, Ruken Cakici. Effect of using regression on class confidence scores in sentiment analysis of twitter data. Proceedings in Computational Approaches to Subjectivity, Sentiment & Social Media Analysis ACL; 2014.

[19] Lorenzo Coviello, Yunkyu Sohn, Adam D. I. Kramer, Cameron Marlow, Massimo Franceschetti, Nicholas A. Christakis, James H. Fowler. Detecting emotional contagion in massive social networks. PLOS ONE. 2014;9:3.

[20] Samiksha Agarwal, Pallavi Khatri. Facial expression detection techniques: Based on Viola and Jones algorithm and principal component analysis. Fifth International Conference on Advanced Computing & Communication Technologies; 2015.

[21] Sicheng Zhao, Yue Gao, Xiaolei Jiang, Hongxun Yao, Tat-Seng Chua, Stefan Scherer, Xiaoshuai Sun-Exploring Principles-of-Art features for image emotion recognition-school of computer science and technology, proceeding 22nd ACM Multimedia Conference. Harbin Institute of Technology, China.

[22] Gilles Degottex, John Kane, Thomas Drugman, Tuomo Raitio, Stefan Scherer COVAREP—A collaborative voice analysis repository for speech technologies IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 2014;960-964.

[23] Arti Rawat, Pawan Kumar Mishra. Emotion recognition through speech using neural network. International Journal of Advanced Research in Computer Science and Software Engineering. 2015;5:5.

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