five steps. In the first step text data is converted into tokens, from these tokens emotion words are identified and detected. This technique take text as input and in next step perform tokenization on the input text. Emotional words are identified in the next step, afterwards analysis of the intensity of emotion words is performed. Sentence is checked whether negation is presented in it or not then finally an emotion class will be found as the required output. Table 1 shows that how this technique is applied in real time chat systems.

Table 1 Keyword spotting method in real time chat system

Sr. No	Task Description	Emotion Model	Features	Granularity
1	Emotion detection in chat system and displaying emotion using an	Ekman	WordNet-Affect DB. wordNet1.6 . Emotional weight, OMCS knowledge base	Sentence
2	Laboratory controlled online chat experiment to enact sadness and happiness and reporting strategies that people employ to express emotions in text	Social information processing model, happy and sad	Linguistic Enquiry and word count program, LIWC	Sentence
3	Emotion detection incorporating personality factor in chatting system to improve accuracy results	OCC model, Five-Factor Model (FFM)	Open Mind Common sense knowledge base (OMCS), Concept Net	Sentence

The keyword spotting technique use different methods like Word based Keyword Spotting, Line based Keyword Spotting and Document based Keyword Spotting [7].

3.2 Lexical Affinity Method

Lexical Affinity method is an extension of keyword spotting method. This assigns a probabilistic affinity for a particular emotion to arbitrary words rather than detecting predefined emotional keywords from text. The probabilities which are assigned by this method are part of linguistic corpora. IT has some disadvantages are the assigned probabilities are biased toward corpus specific genre of texts and does not recognize the emotions from the text that not resides at the word-level on which this method operates.

Consider an example,
“I met my old classmate by accident”.

In the above sentence the word “accident” is indicates the high probability which having a negative emotion. But exact situation in this sentence that accident word not showing negative emotional assessment.

3.2.1 Lexicon-Based Approach [8]

Lexicon-based approaches based on an emotion lexicon. They construct a Chinese emotion lexicon from 3 different resources:

1) Use the emotion lexicon from DUTIR1
2) Collect and use a few slang words
3) Collect a list of emoticons from the microblog web site to enhance the lexicon.

This approach use a Chinese segmentation tool to segment a Chinese microblog text into words. Based on the constructed emotion lexicon, count the number of emotion words occurring in a text for each emotion type, and then the emotion label of the text is determined as the emotion type with the number of emotion words appearing in the text. The text is labeled as “none” when a text does not contain any emotion words. The above process also applied on a sentences to get the sentence-level emotion label.

3.3 Learning Based Approach

Learning-based methods try to recognize emotions based on a previous trained classifier/results, which mapped with various machine learning classifiers such as support vector machines , specific statistic learning methods and decision trees, to detect which emotion category/class should the input text belongs.

This approach face difficulties like these methods may classify sentences into only two categories because of insufficient features other than emotion keywords, which are negative and positive. Dung et al. [9] make use the idea that emotions are related to human mental states which are caused by some emotional events. This means that the human mind starts with initial mental state and moves to another state upon the occurrence of a certain event. This idea is implemented using Hidden Markov Model where each sentence consists of many sub-ideas and each idea is treated an event that causes a transition to a certain state. The sequence of events in the sentence is followed by the system and determines the emotion of the text. The system achieved F-score of 35% when tested on the ISEAR (International Survey on Emotion Antecedents and Reactions) dataset [10], where the best precision achieved was 47%.

3.3.1 SVM-Based Approach [8]

SVM based approach is used as the learning model in learning-based approaches. It uses the LIBSVM toolkit 4 for multiclass emotion classification. The following three kinds of text-based features are used at both document-level and sentence-level emotion classification,

1) Word Features: All the Chinese words appearing in a microblog text or sentence are used as features.
2) Punctuation Features: Some punctuation sequences can reflect special kinds of emotions, and collect a list of such punctuation sequences as features.
3) Emotion Lexicon Features: Take the number of words of each emotion type occurring in a text or sentence as feature.

3.4 Hybrid Based Approach

This approach is based on a combination of the keyword based method and learning based method. The main advantages of this approach is that

1) It can give up higher accuracy results from training and adding knowledge-rich linguistic information from dictionaries and thesauri.
2) It will balance the high cost involved for information retrieval tasks and minimize difficulties

Yang et al. [11] presented a hybrid model for emotion classification that includes lexicon-keyword spotting, CRF based emotion cue identification, and machine-learning-based emotion classification using SVM, Naïve Bayesian and Max Entropy. The results which are generated from the above methods are integrated using a vote-based system. The system is on a dataset of suicide notes where it gains an F-score of 61% with precision 58% and recall 64%. This technique achieved relatively good results.

This section outlined the major approaches for text based emotion detection and shown how syntactic and semantic information can be beneficial for emotion detection. Current methods are lacking in in-depth semantic analysis for detecting hidden phrase patterns and more investigations need to be done to identify, build and incorporate knowledge rich linguistic resources that have a focus on detecting emotions.

4. Limitations

There are few limitations in the above methods [12]

4.1 Ambiguity in Keyword Definitions

Using emotion keywords is a straightforward way to detect associated emotions, the meanings of keywords could be multiple and vague, as most words could change their meanings according to different usages and contexts. Even the minimum set of emotion labels could have different emotions in some extreme cases such as ironic or cynical sentences.

4.2 Incapability of Recognizing Sentences without Emotional Keywords

Keyword-based approach is totally based on the set of emotion keywords. Therefore, sentences without any emotional keyword would imply that they do not contain any emotion at all, which is obviously wrong.

For example,
"I passed the GATE exam today" and "Hooray! I passed the GATE exam today"

Should denote the same emotion (joy), but the former without "hooray" could remain undetected if "hooray" is the only keyword to detect this emotion.

4.3 Lack of Linguistic Information

Syntax structures and semantics even have influences on expressed emotions.
For example,
"I laughed at him" and "He laughed at me"

Would signifies different emotions from the first person's perspective. Ignoring linguistic information also poses a problem to keyword-based methods.

4.4 Difficulties in Determining Emotion Indicators [13]

Learning-based methods can automatically determine the probabilities between features and emotions but the methods still need keywords, but in the form of features. The most intuitive features could also be emoticons which can be seen as author's emotion annotations within the texts. The cascading problems would be the similar as those in keyword-based approaches.

5. Text Normalization Techniques for Resolving Short Messaging Language

5.1 Dictionary Substitution Approach

Normalization of short messaging language words can be considered as a general area where our matter belongs to. There are different sub areas like sense disambiguation, text to speech synthesis and spell correction under the concern of normalizing short messaging language words. This is the traditional approach for short messaging language mapping.

There were some popular web sites such as translate [14] which facilitates a service to translate short messaging language to plain text and vice versa. In this approach for text normalization [15], the solution is based on a corpus with 3000 short messaging language words. Firstly, each tweet preprocessed and then built a native dictionary by referring the corpus and filtering preprocessing words from it. If there are two or more mappings for a word, then random mapping is used (The random word gets selected from the list of mapping words). Dictionary substitution approach is poor approach because an incorrect word substitution may change the meaning of the sentence. In the approach described in [16], collection of short messaging language candidates was formed by using a twitter corpus and compared twitter corpus against English Wikipedia corpus to filter out of vocabulary terms. Manually categorization of those terms using crowdsourcing [17] as abbreviations, short messaging language words, proper names, interjections and other. For automatic categorization, machine learning algorithm are trained with these manually classified vocabulary terms. It gains a fair amount of accuracy for classification task with high probabilistic scores by using MaxEnt Classifier with context tweets.

5.2 Spell Checker Approach

This spell checker approach focuses on resolving short messaging language words to plaint text words not only by looking at just the characters, but considering contexts of that words also [18]. This approach uses edit distance to find out words confusions. For checking how suitable a particular word is for replacing, it uses context based spell checker approach. Minimum edit distance is a method used in identifying the difference between two words. For transforming one string to another string minimum number of edit operations are required.

Basically Deletion, Insertion and Substitution are the edit operations. While determining the value this approach uses marking schema for each edit operation. For an example, the cost for both insertion and deletion edit operations is 1 and the cost for substitution is 2. Similarly determine a value for converting each word to another word. This value is important in spell correction applications. In spell checking application the minimum edit distance of short messaging language word is calculated and using those values predict the exact word of short messaging language word as the word with minimum edit distance value [18].

In this approach use the minimum edit distance to determine wrongly interpreted short messaging language words. Text contains plain text words and short messaging language words. Consider an example the word 'tomorrow', the most frequently used short messaging language word of it is 'tmrw', but there are many versions of word 'tmrw' such as 'tmrrw', 'tmow'. Thus, for these a words, predict the most possible correct word of it using minimum edit distance.

In this approach an experiment is performed to find the accuracy. For that Peter Norvig simple spell correction algorithm [19] is used. This algorithm is modified to do for testing the accuracy of this. 76 different derivations of various short messaging language terms and tagged them with their short messaging language word. After that passed those items to our spell checker and compared the results. Out of 76 words 47 words get correctly tagged with their short messaging language text, which leads 62% accuracy.

6. Conclusion

In this paper, the survey on existing emotion recognition approaches is done and observed that existing system make use of plain text only. This paper describes the different text based emotion recognition methods and their limitations. The problems are faced by the emotion recognition system while processing raw text which contain both plain text and short messaging language. This paper addresses the existing different approaches for resolving processing of raw textual data which contain combination of both plain text and short messaging language. These types of system are applicable for different e-contents like chat, blogs, e-learning systems etc.

References

[1] Pilar Rodriguez, Alvaro Ortigosa, Rosa M. Carro, "Extracting Emotions from Texts in E-learning Environments," Sixth International Conference on Complex, Intelligent, and Software Intensive Systems 2012.

[2] Sivaraman Sriram, Xiaobu YuanAn, "Enhanced Approach for Classifying Emotions using Customized Decision Tree Algorithm," IEEE, 2012.

[3] Sidney K. D'Mello and Art Graesser. "Language and Discourse Are Powerful Signals of Student Emotions during Tutoring," IEEE Transactions On Learning Technologies, VOL. 5, NO. 4, 2012

[4] Carlo Strapparava, Rada Mihalcea, "Learning to Identify Emotions in Text," SAC'08 proceedings of the 2008 ACM symposium on applied computing pages 1556-1560.

[5] Haji Binali, Chen Wu,Vidyasagar Potdar, " Computational Approaches for Emotion Detection in Text," IEEE DEST 2010.

[6] Chun-Chieh Liu, Ting-Hao Yang, Chang-Tai Hsieh, Von-Wun Soo, "Towards Text-based Emotion Detection: A Survey and Possible Improvements," in International Conference on Information Management and Engineering,2009.

[7] Frinken, V.; Fischer, A.; Manmatha, R.; Bunke, H. "A Novel Word Spotting Method Based on Recurrent Neural Networks" Pattern Analysis and Machine Intelligence, IEEE Transactions on Year: 2012, Volume: 34, Issue: 2 Pages: 211 – 224

[8] Wen, Shiyang, and Xiaojun Wan. "Emotion Classification in Microblog Texts Using Class Sequential Rules." Twenty-Eighth AAAI Conference on Artificial Intelligence. 2014.

[9] Dung T. Ho, and Tru H. Cao. "A high-order hidden Markov model for emotion detection from textual data." Knowledge Management and Acquisition for Intelligent Systems. Springer Berlin Heidelberg 2012. 94-105.

[10] Klaus R. Scherer, and Harald G. Wallbott. "Evidence for universality and cultural variation of differential emotion response patterning." Journal of personality and social psychology 66.2 (1994): 310

[11] Hui Yang, et al. "A hybrid model for automatic emotion recognition in suicide notes." Biomedical informatics insights 5.Suppl 1 (2012): 17.

[12] C.-H. Wu, Z.-J. Chuang, and Y.-C. Lin, "Emotion Recognition from Text Using Semantic Labels and Separable Mixture Models," ACM Transactions on Asian Language Information Processing (TALIP), vol. 5, issue 2, Jun. 2006, pp. 165-183, doi:10.1145/1165255.1165259.

[13] C. M. Lee, S. S. Narayanan, and R. Pieraccini, "Combining Acoustic and Language Information for Emotion Recognition," Proc. 7th International Conference on Spoken Language Processing (ICSLP02), 2002, pp.873-876.

[14] (2013) Translate. [Online]. http://transl8it.com/

[15] Karthik Raghunathan and Stefan Krawczyk. (2009) Investigating SMS Text Normalization using Statistical Machine Translation. English. [Online]. http://nlp.stanford.edu/courses/cs224n/2009/fp/27.pdf

[16] Benjamin Milde. Crowdsourcing slang identification and transcription in twitter language. English. [Online]. http://www.ukp.tudarmstadt.de/fileadmin/user_upload/Group_UKP/teaching/TA2012/BM_twitter_slang.pdf

[17] Wikipedia contributors. (2013, June) Crowdsourcing. [Online]. http://en.wikipedia.org/wiki/Crowdsourcing

[18] Damerau, F.J.: A techniqu for computer detection and correction of spelling errors. Common. ACM (7) (1964)
[19] Peter Norvig. Norvig. [Online]. http://norvig.com/spell-correct.html

Author Profile

Chetan Chopade received the B.E. in Computer Technology, in 2013 from YCCE, Nagpur affiliated to RTMNU University. Perusing M.E. degree in Computer Engineering from Pune Institute of Computer Technology, Pune affiliated to Savitribai Phule Pune University.