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# Emotion Detection from Text

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**Abstract**:- Detecting emotion from text is a relatively new classification task and advancements in textual analysis have allowed the area of emotion detection to become a recent interest in the field of natural language processing. There is still a question on how to detect emotion from a text input. To solve this problem, this project generates an Emotion Detection Model to extract emotion from text at the sentence level. The proposed methodology does not depend on any existing affect lexicons such as WordNet Affect. Our method detects emotion from a text-input by searching direct emotional key words from that input. To make the detection more accurate, emotion-affect-bearing words and phrases were also analyzed. The experiments show that the method could generate a good result for emotion detection from text input. To detect emotion from text we have considered Ekman's six emotions class (joy, sadness, anger, disgust, fear, surprise). Our approach showed above 77% accuracy in detecting emotion from text input.

**Keyword:-** Language Processing, EmotionEstimation, Methodologies, Experiment, Result &Discussion, Futer Network.

## I. INTRODUCTION

Emotion is one type of affect, other type of being mood, temperament and sensation. Emotions have been widely studied in psychology and in behavior sciences, as they are an important element of human nature. Nowadays they have also attracted the attention of researchers of computer science, especially in the field of human computer interactions. Advancement in textual analysis have allowed the area of emotion detection to become a recent interest in computational linguistic. Emotion detection is the newer area of textual analysis and therefore, has weaker standard methods.

Emotion can be expressed as happiness, sadness, anger, disgust, fear, surprise and so forth. While board topic of emotion has been studied in psychology for decades, very little effort has been spent on attempting to detect emotion from text. In this work, we assume that emotion reaction of an input sentence is essentially represented by its word appearance.

1.1: RELATED WORK: The concept of affective computing in 1997 by Since Picard proposed that the role of emotion in human computer interaction. This domain attracted many researchers from computer science, biotechnology, psychology, and cognitive science and so on.

This sub-section outlines some lexical resources that researchers have compiled over the years to support affective computing and a verity of recently proposed methodologies.

Lexical resources: One of the first such resources was a list of 1,336 adjectives manually labeled in "Predicting the semantic orientation of adjectives" in the year 1997. WordNet-Affect was introduced hierarchy of affective domain labels in "Wordnet-affect: an affective extension of wordnet" in the year 2004. The subjectivity lexicon developed by is comprised of 8,000 words. Motivated by the assumption that different senses of the same term may have different opinion-related properties developed SentiWordNet, a lexicon based on wordnetin the year 2006. An automatically generated lexicon called SentiFul database was introduced in "Sentiful Generating a reliable lexicon for sentinel analysis" in the year 2009.

Emotion Detection Approaches: Emotion detection approaches can be broadly classified into keyword-based, linguistic rules-based and machine learning technique.

Keyword-based Approaches using Affect Lexicon: Keyword based approaches are applied at the basic word level. Such a simple model cannot cope with cases where affect is expressed by interrelated words.

Linguistic Rules-based Approaches: The ESNA system was developed to classify emotions in news headlines. Chaumartin manually added seed words to emotion lists and created a few rules in their system UPAR7, which identifies what is being said about the main subject and boosts its emotion rating by exploiting dependency graph.

Machine Learning Approaches: To overcome the limitations faced by rule-based methods, researches devised some statistical machine learning technique which can be sub-divided into supervised and unsupervised techniques.

Supervised machine learning with affect lexicons: One of the earliest supervised machine learning methods was employed by Alm, where they used a hierarchical sequential model along with SentiWordNet list for fine-grained emotion classification. Blog sentences have been classified using Support Vector Machine (SVM).
Unsupervised machine learning with affect lexicons: An evaluation of two unsupervised techniques using WordNet-Affect exploited a vector space model and a number of dimensionality reduction methods. News headlines have been classified using simple heuristics and more refined algorithms.

1.2: Difficulties: Many current approaches to emotion detection are based on supervised learning methods, in which large set of annotated data (where text has been labeled with emotions) is needed to train the model. Although the supervised learning methods can achieve good results, the availability of large annotated data set is very low and a model trained on one domain does not translate well to another.
Some methods do not use supervised learning, but most of these methods use manually designed dictionaries of emotion keywords. A problem with such an affect lexicon-based method is that the number of emotion categories is fixed and limited in the dictionary. Another problem is that ifa sentence expresses emotion using words that do not appear in the dictionary, then it would be considered to be unemotional.
There are also methods that rely on linguistic rules, but designing such rules is not a trivial task. In addition, most of the current emotion detection methods look at individual words without considering the context a word is in. However, a word can invoke different emotions in different context.
The work is organized as following:
Language Processingentitled ‘Language Processing’ describes about the Natural Language Processing (NLP) and the basics of different type of English sentences.
Emotion Estimationentitled ‘Methodologies’ describes about different emotion detection’s approaches.
Methodologiesentitled ‘Emotion Estimation’
Experimententitled ‘Experiment’
Result & Discussionentitled ‘Result & Discussion’
Conclusion entitled ‘Conclusion’
Future Work entitled ‘Future Plan’ describes the future plan of our project.

## II. LANGUAGE PROCESSING

2.1: Natural Language Processing: Natural language processing (NLP) is the computerized approach to analyze text that is based on both a set of theories and a set of technologies. It is concerned with the interactions between computers and human (natural) languages. NLP is presenting naturally occurring texts at one or more level of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications.
NLP has two major methods of analysis.
Keyword Analysis or Pattern matching technique.
Syntactic driven parsing technique.

2.1.1: Keyword Analysis: In keyword analysis or Pattern matching technique, the system scans the input sentences for “selective” keywords and once they are encountered, the system responds with a ‘’built-in” reply.

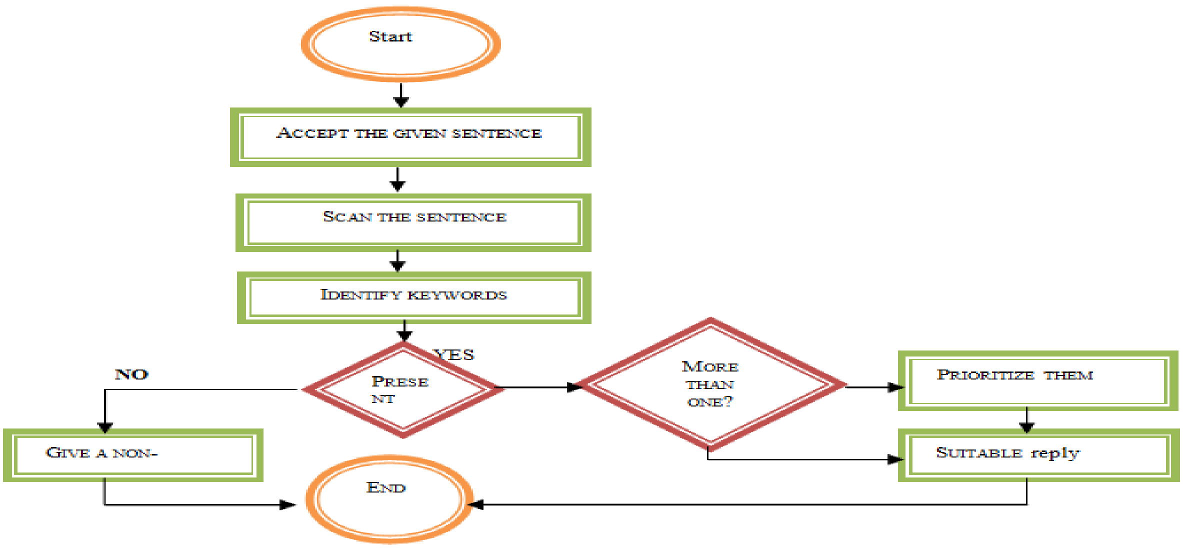



**Fig: Flow chart for Keyword Analysis**

2.1.2: Parsing: Parsing is the process of analyzing a sentence by taking it apart word-by-word and determining its structure from its constituent parts and sub-parts.
Parsing would seem to be a rather easy mechanical process. Given a lexicon telling the computer the Parts of Speech for a word, the computer would be able to just read through the input sentence word by word and in the end produce a structural description.
But problems arise for several reasons. First of all, a word may function as different parts of speech in different contexts. For example:

"He wanted some oil for his bicycle"

Here, the word "oil" treats as a noun, whereas

"This is an oil painting."

Here, the word "oil" treats as an adjective. So it is not possible to know how the word "oil" is used until we read the entire sentence.
So we have to determine which Parts of Speech is relevant in the particular context at hand.
2.2: Semantic Analysis: Semantics and its understanding as a study of meaning covers most complex tasks like: finding synonyms, word sense disambiguation, constructing question-answering systems, translating from one NL to another, populating base of knowledge. Basically one needs to complete morphological and syntactical analysis before trying to solve any semantic problem.
2.3: English Sentences (structures& examples): Sentence is the basic unit of language which expressed a complete thought. The first word of a sentence is capitalized and the sentence is terminated with a period, a question mark or an exclamation point. The basic parts of a sentence are the subject, the verb and (often, not but always) the object. The subject is usually a noun-a word that names a person, place, or thing. The verb (or predicates) usually follows the subject and identifies an action or a state of being. An object receives the action and usually follows the verb. In English for instance, subjects and verbs should be closed together or otherwise it would be impossible to understand the sentences.
The three basic sentence structures are the:
Simple Sentence
Compound Sentence
Complex Sentence
2.3.1: Simple Sentence: A simple sentence, also called an independent clause, contains a subject and a verb, and it expresses a complete thought. The basic syntactic orders of simple sentence are:
Subject + Verb + Complements.
Subject + Auxiliary Verb + Verb + Complements.
Examples:
I am very happy.
I have been in England before.
I come.
The boy cried.
Canada is a rich country.
The girl ran into her bedroom.
Some students like to study in the morning.
Murad and Mannan play football every afternoon.
Alicia goes to the library and studies everyday.
Riche reads newspaper.
Joe waited for the train.
The train was late.
You can give me a cheque.
The children were laughing.
John wanted a new bicycle.
All the girls are learning JAVA.
2.3.2: Compound Sentence: A compound sentence contains two independent clause joined by a coordinator. The coordinators are as follows: for, and, not, but, or, yet, so. (Hint: The first letter of each of the coordinators spells FANBOYS.) Except for very short sentences, coordinators are always preceded by a comma. The basic syntactic order of compound sentence is:
Subject + Verb + Complements + conjunct. + Subject + Verb + Complements
Examples:
You are the student whose exam was lost last year.
She works in the city but she lives in the suburbs.
My friend invited me to a birthday party, but I don't want to go.

He ran out and fell over the suitcase.
Either the students or the teacher takes a day off every month.
He could neither eat nor sleep.
Do you want to stay here, or would you like to come with me?
She has five children, so she is incredibly busy.
Arunaate breakfast, thenshe went to school.
I tried to speak Spanish, and my friend tried to speak English.
Alejandro played football, for Aruna went shopping.
We stayed behind and finished the job.
We stayed behind and finished the job, then we went home.
Rini shouted and everybody waved.
We looked everywhere but we couldn’t find him.
They are coming by car so they should be here soon.
I like chocolate ice cream but my friend likes strawberry.
I am on a diet yet I really want a cookie.
They wanted to go to Canada, because they wanted to see Niagara Falls.
The above sentences are compound sentences. Each sentence contains two independent clauses and they are joined by a coordinator with a comma preceding it.
2.3.3 Complex Sentence: A complex sentence is a sentence consists of one independent clause and at least one dependent clause. A complex sentence always has a subordinator such as: because, since, after, although, when, as, as if, before, after, while, when, whenever, during, as soon as, as long as, until, unless, where, wherever, etc. When a complex sentence begins with a subordinator, a comma is required at the end of the dependent clause. When the independent clause begins the sentence with subordinators in the middle, no comma is required.The basic syntactic orders of complex sentence are:
Main clause + subordinating conjunction + adverbial clause
Main clause + subordinating conj. + Adv. clause + subordinating conj. + Adv. Clause
Subordinating conj. + Adv. Clause + Main Clause
Subordinating conj. + Adv. Clause + Main Clause + Subordinating Conj. + Adv. Clause + Coordinating Conj. + Adv. Clause
Examples:
John cannot set up his computer because the setting is complicated.
She became the queen when her father died, because she was the eldest child.
When he handed in his homework, he forgot to give the teacher the last page.
The teacher returned the homework after she noticed the error.
The students are studying because they have a test tomorrow.
After they finished studying, Juan and Maria went to the movies.
Juan and Maria went to the movies after the finished studying.
Her father died when she was very young.
She has a difficult childhood because her father died when she was very young.
Although a few snakes are dangerous most of them are quite harmless.
Although she has always lived in France, she speaks fluent English because her mother was American and her father was Nigerian.
Because my coffee was too cold, I heated it in the microwave.
Though he was very rich, he was still very unhappy.
When the cost goes up, the customers buy less clothing.
As she was bright and ambitious, she became manager in no time.
Wherever you go, you can find beauty.
After twenty years, she still had feelings for him.
2.4: Subjectivity: Emotion detection is a NLP application that benefits from being able to distinguish subjective from objective language. Subjective language is a language used to express opinions, evaluations, emotion or speculations. Objective language is unbiased and not influenced by the writer opinions. Both types of language are useful in text analysis: Subjective language is useful for automatic subjectivity analysis and Objective language is useful for information extraction.
Emotions are expressed in subjective language so it would appear that subjective analysis is the only area beneficial in emotion detection.

| Basic emotion's model | List of the basic emotions |
|---|---|
| **Ekman** | Anger, Disgust, Fear, Joy, Surprise, and Sadness |
| **Izard** | Anger, Contempt, Disgust, Distress, Fear, Guilt, Interest, Joy, Shame and Surprise. |
| **Plutchik** | Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise and Trust |

**Table 1: Basic Set of emotions**

## III. EMOTION ESTIMATION

Emotion detection is modeled as a classification problem where one or more nominal labels are assigned to a sentence from a pool of target emotion labels.

Our emotion detection framework contains two main modules:

1. Word-processing module and
2. Sentence Analysis.

The module named sentence analysis which is an easy but a lengthy process. In this module, we take 1000 sentences for testing purpose. These sentences are without emotional keywords where emotions are to be set manually.

3.1: Word-processing Module: The Word-processing part consists of tokenization, Parts-of-speech tagging, negative sentence extracting, and searching keywords from positive sentence. This enables us to extract emotion-bearing words from a given sentence.

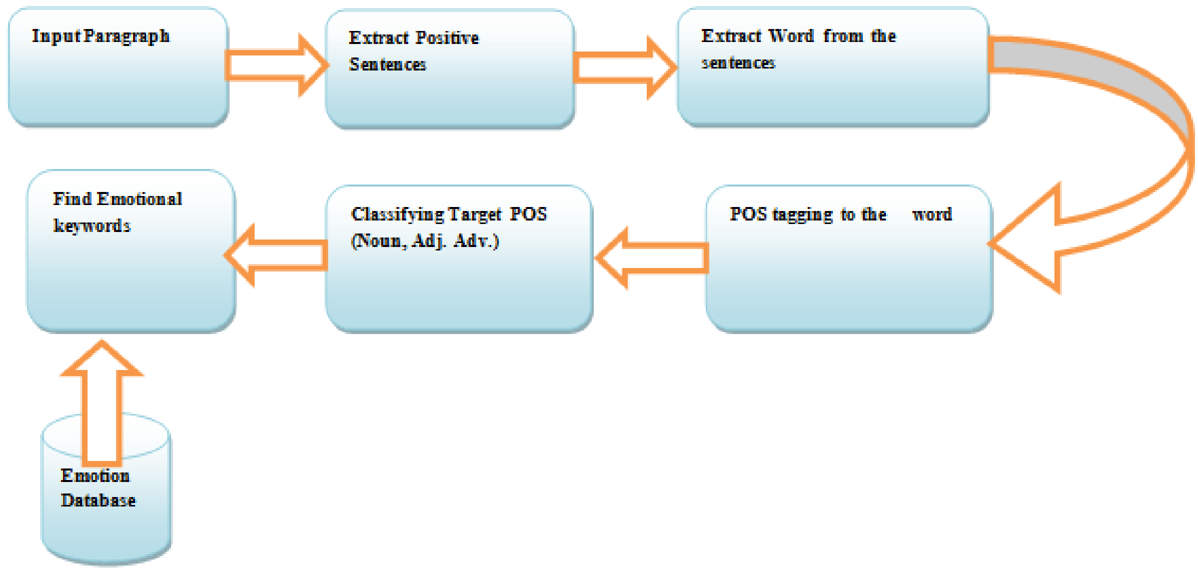
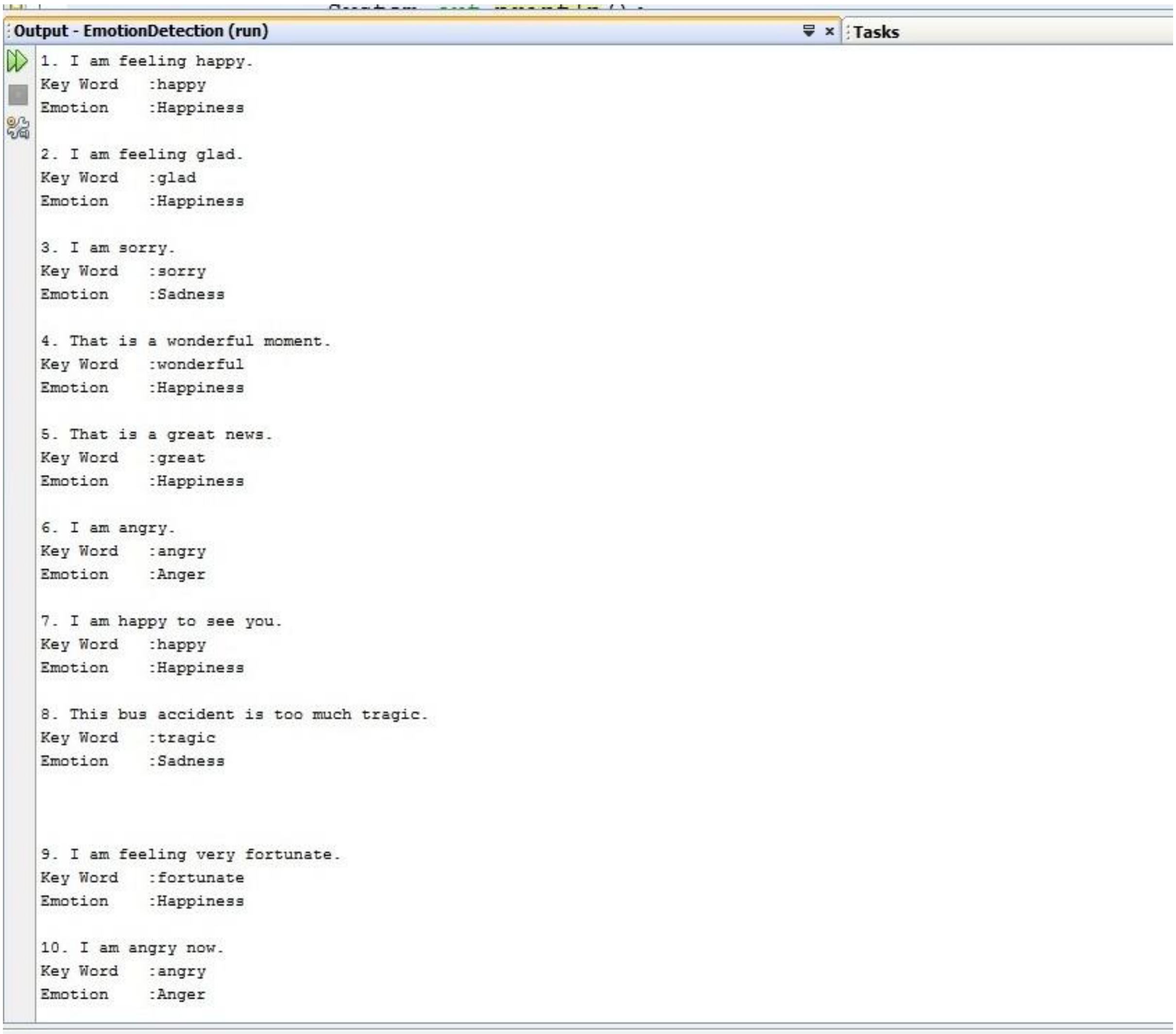



**Fig 1: Block Diagram of the Word-processing module**

3.1.1: Keyword Extraction: In this step we try to identify the basic emotional (happy, sad, angry, disgust, fear, surprise) key termsfrom the input sentences. Noun, Adverb and Adjectives are the useful POS to find emotion from text.

In order to find them we applied POS taggeror Parts-Of-Speech tagger and extracted the key terms that we want. Parts-of-speech tagging is the process of assigning a parts-of-speech like noun, verb, adverb, preposition, adjective or other lexical class marker to each word in a sentence.

Then we need to identify the positive and negative sentences from the given paragraph. Then the next step is to search direct emotional keywords from the positive sentence. Otherwise, it will look for the synonyms of the six basic emotional words.



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Output - EmotionDetection (run)
1. I am feeling happy.
Key Word   :happy
Emotion    :Happiness

2. I am feeling glad.
Key Word   :glad
Emotion    :Happiness

3. I am sorry.
Key Word   :sorry
Emotion    :Sadness

4. That is a wonderful moment.
Key Word   :wonderful
Emotion    :Happiness

5. That is a great news.
Key Word   :great
Emotion    :Happiness

6. I am angry.
Key Word   :angry
Emotion    :Anger

7. I am happy to see you.
Key Word   :happy
Emotion    :Happiness

8. This bus accident is too much tragic.
Key Word   :tragic
Emotion    :Sadness



9. I am feeling very fortunate.
Key Word   :fortunate
Emotion    :Happiness

10. I am angry now.
Key Word   :angry
Emotion    :Anger
```

**Fig 2: Sample output of keyword analysis**

3.2: Sentence Analysis Module: In this sentence analysis module, our aim is to detect emotion from a sentence where there is no emotional keyword in the sentence. For this purpose, we analyze different categories of sentence.

3.2.1: Detecting emotion from exclamatory sentence: Any sentence expressing sudden emotion is called exclamatory sentence. The function of an exclamatory sentence is to show strong feelings. Exclamatory sentences are usually used to show feelings such as sadness, happiness, anger and frustration.

One of the easiest ways to convey a very strong feeling or opinion about something is to use an exclamatory word. These words are very similar to interrogative words, but instead of asking a question, they simply state an idea or opinion.

Exclamatory words that can stand alone as a sentence while expressing emotions or reactions are called interjections. Interjections don’t require a subject or verb to express a thought. They can be inserted in a sentence by using commas.

For example:

Wow, that was a thrilling ride!

Brilliant, you solved the puzzle!

Awesome, you got the job!

Ouch, that really hurts!

I don’t know what you feel but,sheesh, I think the food was too expensive!

Hurray, we won the game.

Damn, the car won't work!

Aww, it hit him right in the nuts!

Bah, I never liked him anyways.

Boo, get off the stage!

Oh! What a fool he is!
Ah! All the questions are easy.
Bravo! Well done.
Ahh, that feels wonderful.
Alas! I'm lost in the wilderness.
Alas! I am undone.
To detect emotional sense from a sentence we make a database that contains a lot of exclamatory words (alas, oh, oops etc.). If the sentence contains any of the exclamatory word, it will give the desired emotion based on thatexclamatory word.

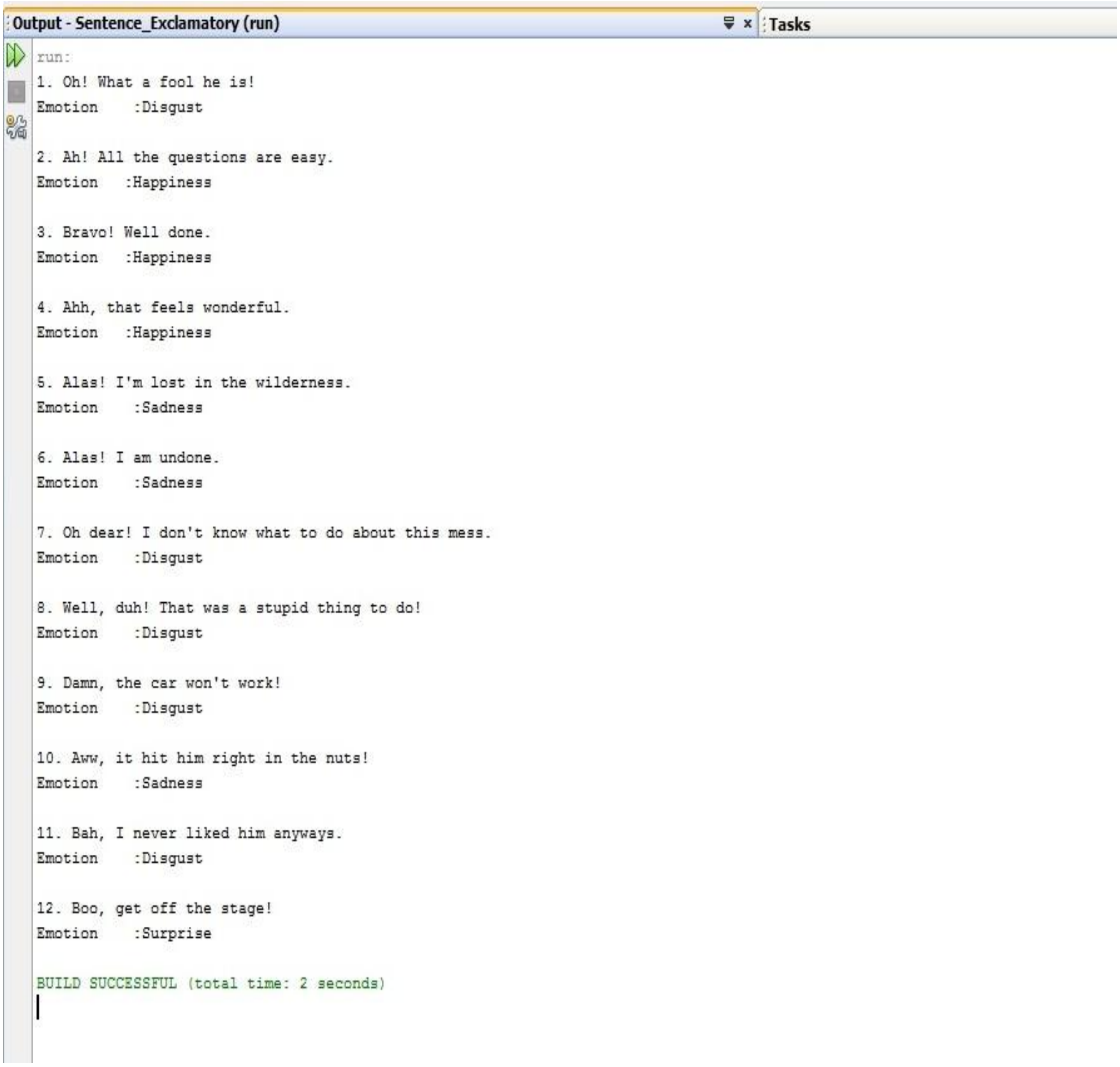


**Fig 3: Sample sentences with corresponding emotion.**

3.2.2: Detecting emotion from compound sentences: A compound sentence consists of two or more simple sentences joined by a comma followed by a coordinating conjunction (and, or, but, for, nor, yet, so). To detect emotion from compound sentence we have to consider the condition of the tense.
Tense is a category that locates a situation in time, indicating when the situation takes place. Tenses are especially important because they tell us not only about the aspect of the verb.

There are basically three types of English tenses:
Present Tense
Past Tense
Future Tense

Present tense is used to express actions that occur in the present. Past tense is a verb tense expressing activity, action state or being in the past. Futurity in English is expressed either by using words that imply future action or by employing an auxiliary construction combined with the main verb which represents the true action of the sentence. The most common auxiliary verbs are used to express futurity are “will”, “can”, “should”, “may”, “ must” , and “shall’.

Here, we only consider the present and past tenses to detect the emotion from compound sentence.

If there is an emotional keyword found in a clause of a compound sentence, at first we will try to identify the situation of tense of that clause. If the clause’s tense is present tense, we will take the emotion from that clause. If the sentence is negative sentence and the negation word is present just before the keyword, the emotion will be neutral.

Methodologies

Emotion detection methodologies use the concepts and algorithm that are created for subjectivity and sentiment analysis. There are so many emotion detection approaches that are being explored, but there are no fore-running methods.

4.1: Emotional Lexicon: The first step in detecting emotion from text is discovering keywords or phrases that associate with emotions. A list of emotions and words that express each emotion is called emotional lexicon. In general, these lists start with identifying seed words, or words that highly associate with one emotion, and expand by using synonyms.

Often different emotions are expressed through different words. For example, delightful and yummy indicates the emotion of joy, gloomy and cry indicates the emotion of sadness etc. Words may evoke different emotions in different contexts, and emotion evoked by a phrase or a sentence is not simply the sum of emotions conveyed by the words in it. The emotion lexicon will be useful for evaluating automatic methods that identify the emotion evoked by a word.

The WordNet Affect Lexicon is a manually created collection of words. The creation process involved annotating a few seed words with Ekman’s six basic emotions then expanding the basic collection by marking the WordNet synonyms of the each word with the same emotion. The full list reached a few hundred of words.

The General Inquirer is an emotional lexicon that classifies words into a lager number of categories. The collection contains 11,788 emotion labeled words and 182 word tags, which include positive and negative semantic and affect categories like pleasure, arousal, feeling and pain that have not been analyzed yet.

Even though a growing emotion lexicon would be beneficial in detecting emotion, an annotated collection of words and phrases would only increase detection accuracy to a certain extent. Emotional lexicons by themselves are not successful in classifying sections of text to their appropriate emotion. In fact, most of the time emotion is not expressed through the emotion-labeled words.

4.2: Emotion Labeled Datasets: Emotion labeled datasets are blocks of text that have been annotated with emotion tags. Manually annotating datasets of text is expensive and time consuming. However, because comparing results to annotated texts is the most stabilized method of checking the accuracy of an algorithm, annotated datasets have been established and consistently used throughout emotion detection studies.

One of the most common dataset, used in many emotion detection studies, is SemEval-2007-Task, an effective text that consists of newspaper headlines. The annotations are labeled with Ekman’s six basic emotions along with a neutral category. Additionally, this dataset allowed one sentence to be tagged with multiple emotions. The dataset is composed of 1,250 annotated headlines that is split between a developmental set of 250 headlines and a test set of 1000 news headlines.

Another annotated dataset is the International Survey on Emotion Detection Antecedents and Reactions (ISEAR). The ISEAR is the compilation of 7,666 sentences provided by 1,096 culturally divergent participant who were questioned about experiences and reactions that are related to the emotions of anger, joy, sadness, fear, disgust and guilt.

Even though there are annotated datasets out there to test algorithms on, the necessity of an annotated dataset decreases the text used in emotion detection fields, especially for machine learning algorithms that require a large annotated datasets for training.

4.3. Our emotion detection model: Our emotion detection model includes two main modules: Word-processing and Sentence Analysis. This emotion detection model helps us to extract six basic emotional keywords and their synonyms, relevant emotion-bearing words and syntactic relations among them.

4.3.1. Extracting emotional keywords (KW Analysis): In this step the input sentence is tokenized into single words. These words are tagged with a POS tagger. The tagger learns a sentence structure for a language as a set of transition rules. These rules are then applied to the words to label each word as a noun, adjective, verb etc. Once they are labeled they are checked for emotional keywords. We have created SIX_EMOTIONS database for this checking purpose which contains 210 emotional keywords. Once an emotional keyword is found from comparison, then that emotional key word is assigned to an emotional result.

| Emotion Class | Related keywords |
|---|---|
| **Joy** | Happiness, happy, joyous, blissful, great, good, glad etc. |
| **Anger** | Wild, furious, bad, livid, hot, stormy, sore, angry etc. |
| **Sadness** | Sad, sorry, tragic, depressed, unhappy, pensive, pitiful etc. |
| **Disgust** | Disturbed, annoying, suck, repel, offended, disgust etc. |
| **Fear** | Panic, fear, worship, terror, horror, alarm, fright etc. |
| **Surprise** | Surprise, break, seek, amazement, wonder, astonished, popeyed etc. |

**Table 2: Some examples from the SIX_EMOTIONS dataset**

4.3.2. Extracting affect-word & phrases (ABW Analysis): The second step of our emotion detection model is to extract the content-word and phrases. Sometimes words in a sentence affect more than a single keyword. Consider a sentence, “The players of Bangladesh Cricket Team were greeted with joyless cheer”. Our lexical resource SIX_EMOTIONS lists the word ‘cheer’ under the emotion category “happiness”. However in this sentence, emotional keyword ‘cheer’ is highly influenced by the word ‘joyless’, which make the emotional state of this sentence completely different. To solve this problem we make an emotion labeled dataset named SENTENCE_DB with 151 sentences for testing purpose. In this dataset, an input sentence is tagged with an emotion manually. The input sentence is tokenized into 2-words, 3-words, 4-words and 5-words phrases. Then these phrases or affect bearing word are compared with the phrases of the emotion labeled dataset. Once an emotional phrase is found in the dataset then that sentence is assigned to a corresponding emotional result.

| Emotional Class | Related Sentences |
|---|---|
| **Joy** | We won the game. |
| **Anger** | You didn’t have the permission to stay out this late. |
| **Sadness** | I am lost in the wilderness. |
| **Disgust** | We were stuck in traffic jam for almost three hours. |
| **Fear** | My mother is scared stiff of heights. |
| **Surprise** | The minister’s resignations came as a bolt from the blue. |

**Table 3: Some examples from the Sentence_DB dataset**

4.3.3: Extracting exclamatory keywords (EXLA Analysis): To detect emotion from exclamatory sentences, our emotion detection model aims to find out exclamatory keywords. This method is almost as similar as “extracting keywords” method but the POS tagging feature is absent in this method. First of this step, the input sentence is tokenized into single words. Then each word is compared with the elements of another emotion labeled dataset named Excla_DB. Once a matched is detected between an input word and an element of the dataset, then that entire sentence is tagged with an emotional reply by the method itself.

| Emotion Class | Related exclamatory keywords |
|---|---|
| **Joy** | Yahoo, yay, yaay, hurrah, etc. |
| **Anger** | Grrr, grr. |
| **Sadness** | Oww, alas, aw, ouch, etc. |
| **Disgust** | Do’h, ewww, piff, yuck, oh, uff, etc. |
| **Fear** | Aah, yikes |
| **Surprise** | Boo, wow, ooh-la-la, oops, whoa etc. |

**Table 4: Some examples from the Excla_DBdatase**

Experiment

To test the emotion detection result, we make some experiments. There are almost 154 sentences in our emotional dataset with 500 words. All of the sentences were labeled with different emotion state manually. Following table shows the tagged result.

| **Emotion** | **Joy** | **Sadness** | **Anger** | **Disgust** | **Fear** | **Surprise** |
|---|---|---|---|---|---|---|
| **Number** | 31 | 34 | 28 | 25 | 17 | 11 |

**Table 5: The number of manually emotion labeled sentences**

To get more accurate emotion estimation, we need to consider that, how the content words behave in the sentence. The first comparing is conducted between an input sentence and the emotional state description column of our emotional datasets. The testing result is shown in the following figure:


**Fig 4: Sample input data with corresponding emotion state**

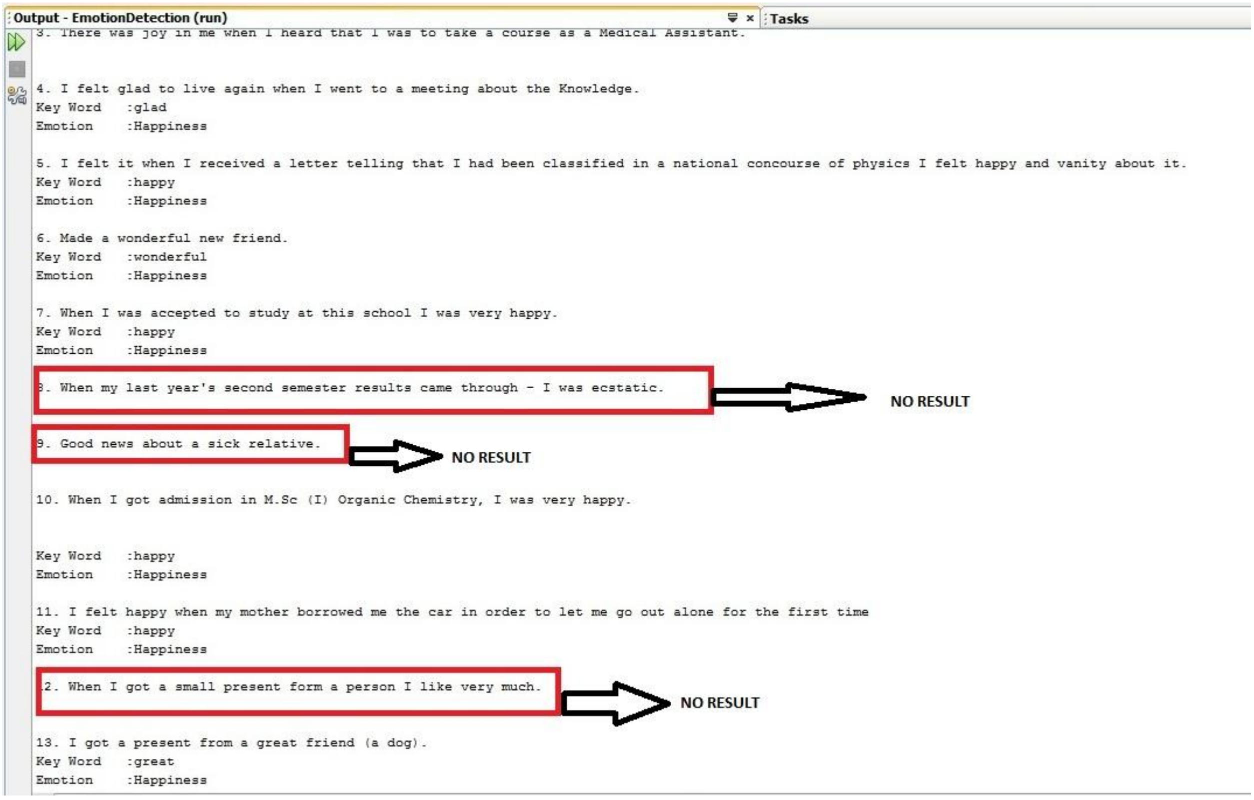


**Figure 6: Sample output for our experiments**

The above figure shows that, for some sentences our emotion detection model doesn't produce any result. This is because of the absence of a particular keyword in our dataset. This is one of the drawbacks of our system.

## IV. RESULT & DISCUSSION

The testing phase of our emotion detection model is done by taking some sample sentences from the ISEAR dataset. The testing results are shown in the figure 5:
In this figure the blue line denotes the total number of input data, the red line denotes the total number of correct sentence which was detected by the methods and the green line denotes the success rate of our three methods.

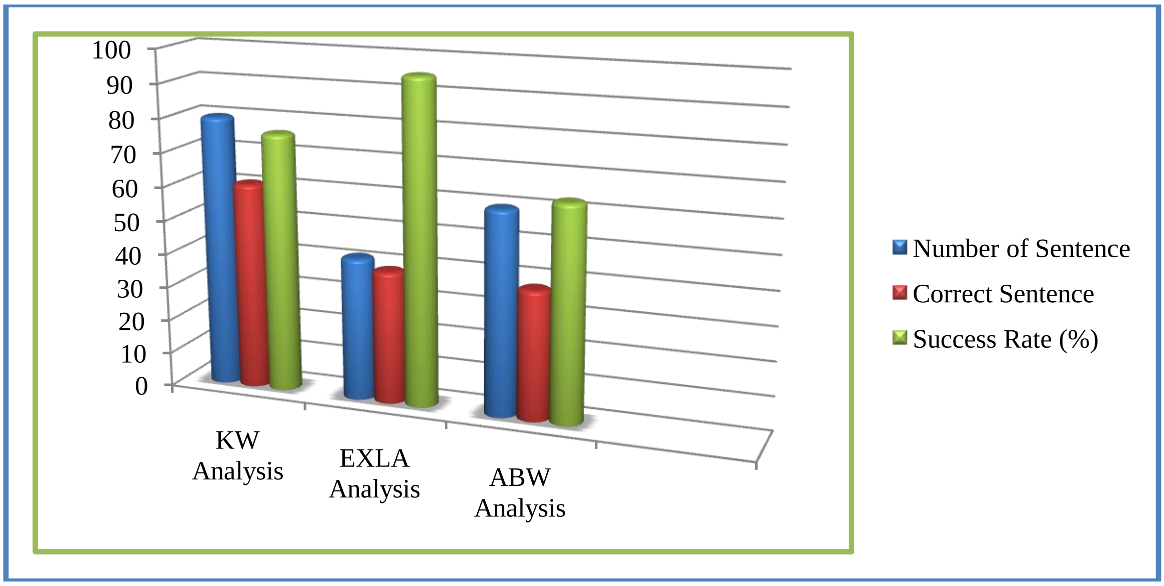


**Figure 5: Emotion Detection Graph**

In most emotion detection approaches, the results are presented with the common measures of precision, recall and f-score. In our experiments, we use only precision to present the results. Here precision is the number of correctly detected sentence retrieved by the methods divided by all the input sentences retrieved by the methods.

The overall results of our methods are shown in the Table 2:

| Methods | Number of sentence | Precision |
|---|---|---|
| **KW Analysis** | 100 | 0.7623 |
| **EXLA Analysis** | 100 | 0.9523 |
| **ABW Analysis** | 100 | 0.6333 |

**Table 6: Result for the three methods using precision.**

In our emotion detection model, when there are two direct emotional keywords a present then the KW Analysis method is failed to detect the correct emotion. This problem is also happened in case of EXLA Analysis and ABW Analysis too. This is probably due to the inability to develop adequate models for less represented emotions because of scarcity of data. Nonetheless our emotion detection model's performance is 78% average for precision of the emotional class. The success rate of our emotion detection methods are shown in the following figure:

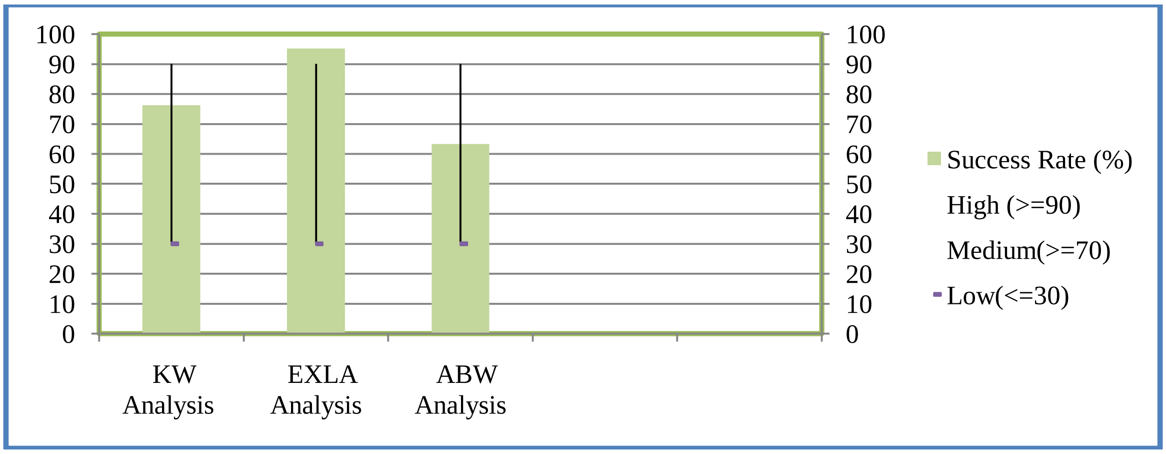


**Fig 6: Success Rate of the emotion detection methods.**

## V. CONCLUSION

In our project, we propose three emotion detection methods to extract emotion from text input. Both the keywords and Affect Bearing Word (ABW) are the main topic of our project to detect emotion from text. Experiments proved that human emotion was deeply depended on the content word of the sentence. As we know, it is still difficult to do the semantic parsing with machine learning method. Nevertheless, some part of the semantic information and emotional keywords such as exclamatory keywords & direct emotional keywords have been work out in the system. The result shows that we have got relatively good results for emotion detection from text input.

**Future Work**

The future of emotion detection is promising. Although not enough time has spent to have established standards in this field, the algorithms are continuing to increase in accuracy. In future we will try to increase the resources of our affect lexicon and emotional dataset to increase the performance of our methods as well as to increase the accuracy of the entire system.

There are many advantages in being able to identify emotion from text input. To being able to build such kind of applications, the ability to detect emotion from text can enhance the human-computer interaction. If the computer can tell a person's mood or emotional state, it would be able to switch to an accommodating form of interaction.

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