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Detection of Depression

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ABSTRACT

Depression is ranked as the largest contributor to global disability and is also a major reason for suicide. Still, many individuals suffering from forms of depression are not treated for various reasons. Previous studies have shown that depression also has an effect on language usage and that many depressed individuals use social media platforms or the internet in general to get information or discuss their problems. In particular, a convolutional neural network based on different word embeddings is evaluated and compared to a classification based on user-level linguistic metadata. An ensemble of both approaches is shown to achieve state-of-the-art results in a current early detection task. Furthermore, the currently popular ERDE score as metric for early detection systems is examined in detail and its drawbacks in the context of shared tasks are illustrated. A slightly modified metric is proposed and compared to the original score. Finally, a new word embedding was trained on a large corpus of the same domain as the described task and is evaluated as well.Social networks have been developed as a great point for its users to communicate with their interested friends and share their opinions, photos, and videos reflecting their moods, feelings and depressions. This creates an opportunity to analyze social network data for user's feelings and depressions to investigate their moods and attitudes when they are communicating via these online tools.
Keywords : Social network, Emotions, Depression, Depression analysis

I. INTRODUCTION

According to World Health Organization (WHO), more than 300 million people worldwide are suffering from depression, which equals about 4.4% of the global population. While forms of depression are more common among females (5.1%) than males (3.6%) and prevalence differs between regions of the world, it occurs in any age group and is not limited to any specific life situation. Depression is therefore often described to be accompanied by paradoxes, caused by a contrast between the self-image of a depressed person and the actual facts . Latest results from the 2016 National Survey on Drug Use and Health in the United States report that, during the year 2016, 12.8% of adolescents between 12 and 17 years old and 6.7% of adults had suffered a major depressive episode (MDE). Precisely defining depression is not an easy task, not only because several sub-types have been described and changed in the past , but also because the term "being depressed" has become frequently used in everyday language. In general, depression can be described to lead to an altered mood and may also be accompanied. The proliferations of internet and communication technologies, especially the online social networks have rejuvenated how people interact and communicate with beach other electronically.

The applications such as Facebook, Twitter, Instagram and alike not only host the written and multimedia contents but also offer their users to express their feelings, emotions and depressions about a topic, subject or an issue online. On one hand, this is great for users of social networking site to openly and freely contribute and respond to any topic online; on the other hand, it creates opportunities for people working in the health sector to get insight of what might be happen in gat mental state of someone who reacted to a topic in a specific manner. In order to provide such insight, machine learning techniques could potentially offer some unique features that can assist in examining the unique patterns hidden in online communication and process them to reveal the mental state (such as 'happiness', 'sadness' , 'anger', 'anxiety', depression) among social networks' users.

II. LITERATURE REVIEW

Previous studies have already shown that depression also has an effect on the language used by affected individuals. For example, a more frequent use of first person singular pronouns in spoken language was first observed in 1981. An examination of essays written by depressed, formerly-depressed, and non-depressed college students at University of Texas confirmed an elevated use of the word "I" in particular and also found more negative emotion words in the depressed group. Similarly, a Russian speech study found a more frequent use of all pronouns and verbs in past tense among depression patients. A recent study based on English forum posts observed an elevated use of absolutist words (e.g. absolutely, completely, every, nothing1) within forums related to depression, anxiety, and suicidal ideation than within completely unrelated forums as well as ones about asthma, diabetes, or cancer. The knowledge that language can be an indicator of an individual's psychological state has, for example, lead to the development of the Linguistic Inquiry and Word Count (LIWC) software. By utilizing a comprehensive dictionary, it allows researchers to evaluate written texts in several categories based on word counts. A more detailed description of LIWC. With a similar purpose, Differential Language Analysis Toolkit (DLATK) an open-source Python library, was created for text analysis with a psychological, health, or social focus. Driven by the growing availability of data, for example through social media, and the technological advances that allow researchers to work with this data, ethical considerations are becoming more and more important in the field of Natural Language Processing (NLP). Based on these developments, NLP has changed from being mostly focussed on improving linguistic analysis towards actually having an impact on individuals based on their writings. Although Institutional Review Boards (IRBs) have been well-established to enforce ethical guidelines on experiments that directly involve human subjects, the authors note that NLP and data sciences in general have not constructed such guidelines. They further argue that language "is a proxy for human behaviour, and a strong signal of individual characteristics" and that, in addition, "the texts we use in NLP carry latent information about the author and situation".

A more detailed description of LIWC. With a similar purpose, Differential Language Analysis Toolkit (DLATK) an open-source Python library, was created for text analysis with a psychological, health, or social focus. Driven by the growing availability of data, for example through social media, and the technological advances that allow researchers to work with this data, ethical considerations are becoming more and more important

Year	authors	Data
1981	University of Texas	more frequent use of first person singular pronouns in spoken language
2017	Almeida, H., Briand, A., Meurs, M.J	Detecting early risk of depression from social media user-generated content. In: Proceedings Conference and Labs of the Evaluation Forum CLEF
2018	Cacheda, F., Fernandez, D., Novoa, F., Carneiro, V.:	Artificial intelligence and social networks for early detection of depression.
2017	Trotzek, M., Koitka, S., Friedrich, C.M	Linguistic metadata augmented classiers at the clef 2017 task for early detection of depression. In: Proceedings Conference and Labs of the Evaluation Forum CLEF
2014	Prieto, V.M., Matos, S., Alvarez, M., Cacheda, F., Oliveira, J.L.:	Twitter: a good place to detect health conditions.
2017	Aldarwish MM, Ahmad HF	Predicting depression levels using social media posts. In: 2017 IEEE 13th international Symposium on Autonomous decentralized system

Table 1. Summary of Literature review

III. DEPRESSION ANALYSIS

3.1. DEFINITION

Depression and Subjectivity are mainly context and do- main dependent. Not only the changes in vocabulary are the reason behind that but one more reason is the dual meaning or depressions of same expression in different domains. Consider the example of expression 'go and read the book'. In case of book reviews this expression gives the positive polarity about the product but in case of movie review the same expression gives negative polarity about the product. Depression Analysis is more focused on extraction of polarity about a particular topic rather than assigning a particular emotion to the text. Opinion Mining and Depression Analysis are the branches of Text Mining which refer to the process of extracting nontrivial patterns and interesting information from unstructured script documents. We can say that they are the addition to data mining and knowledge discovery. Opinion Mining and Depression Analysis focus on polarity detection and emotion recognition correspondingly. Opinion Mining has more marketable potential higher than data mining as it the most natural form of storing the information in text format. It is much complex task than data mining because it has to deal with unstructured and fuzzy data. It is a multi-disciplinary area of research because it constitutes adoption of techniques in information retrieval, text analysis and extraction, auto-categorization, machine learning, clustering, and visualization.

Though Depression Analysis and Opinion Mining might look the same as the fields like traditional text mining or fact based analysis, it varies because of following facts. Depression Classification is the binary polarity classification which deals with a relatively small number of classes. Depression classification is easy task compared to text auto-categorization. While Opinion mining exhibits many additional tasks other than depression polarity detection like summarization and all.

3.2. LEVELS

We can divide depression analysis in following levels. [5]

3.2.1. Document

The task at this level is classifying the depression for document. The document is on single topic is considered. Thus texts which comprise comparative learning cannot be considered under this level.

3.2.2. Sentence

The task at this level goes to the sentences; it deters- mines whether each sentence expresses a positive opinion, negative opinion, or neutral view. If a sentence states no opinion means it is a neutral. This level of analysis is closely related to subjectivity classification. The subjective statement displays the polarity of an entity in affirmative-negative terms i.e. good-bad terms. Hence it is easy to obtain depression from it. But Objective statement does not give separation directly by affirmative-negative terms.

These are abstract sentences which are fact based.

3.2.3. Entity or Aspect

Aspect level gives detailed analysis. The core task of entity level is to identification of aspect of the text [1]. For example in a review of mobile if a customer says," Sound is good but the handset is not handy." In this review the aspect are sound and handiness. Here depression analysis becomes two level task i.e. finding the aspects in the text and then classifying in respective aspect. Aspect level depression analysis is superior to Document and Sentence level depression analysis. Depression analysis of topic or body which may or may not be hidden in the document is done. Thus comparative statements are also part of entity level depression analysis [6].Comparative study of detection analysis of depression is included in this paper.

3.3. APPROACHES

We can do opinion mining and depression analysis in following ways: keyword spotting, lexical affinity, statistical methods.

3.3.1. Keyword Spotting

In this technique the text is categorized based on the presence of fairly unambiguous words present in it. Thus the words or keywords present in the text have the importance with respect to depression analysis.

3.3.2. Lexical affinity

For a particular emotion, Lexical affinity assigns arbitrary words a probabilistic similarity.

3.3.3. Statistical methods

It calculates the valence or target of affective keywords and word co-occurrence frequencies on the base of a large training corpus. In early work it was aim to classify entire document into overall affirmative or negative. These systems mainly depend on supervised learning approaches which depend on manually labeled data. The examples of such systems are movie or product review databases. Many times depressions are not restricted to document level texts. It can be extracted from sentence level text. In such cases depression analysis can be done using detected opinion-bearing lexicon items. Or depressions are not limited to particular target, they can contrary towards same topic or multiple topics can be present in the same document [7]...

3.4. FEATURES

Depression features are as follows:

3.4.1. Terms presence and frequency

These features are nothing but individual words or word n-grams and their frequency counts. It either uses the term frequency weights or gives binary weighting to the words.

3.4.2. Parts of speech (POS)

It set up finding adjectives from the text, as they are important indicators of opinions.

3.4.3. Opinion words and phrases

These words themselves express opinion about the product or service in the text. For e.g. good or bad, like or hate. Some phrases also express opinions without using opinion words.

Negations: the presence of negative words may change the opinion orientation like not good is equivalent to bad.

3.5. METHODOLOGIES

Depression Classification techniques can be roughly divided into Lexicon based approach, Machine Learning approach and hybrid approach. The Machine Learning Approach (ML) applies the famous ML algorithms and it uses linguistic features. The Lexicon-based Approach depends on a depression lexicon. Lexicon is a collection of known and precompiled depression terms. It is again divided into dictionary-based approach and corpus- based approach which use semantic or statistical methods to find depression polarity of the text. The Hybrid Approach combines both approaches and it is very common with depression lexicons playing a key role in the majority of methods.

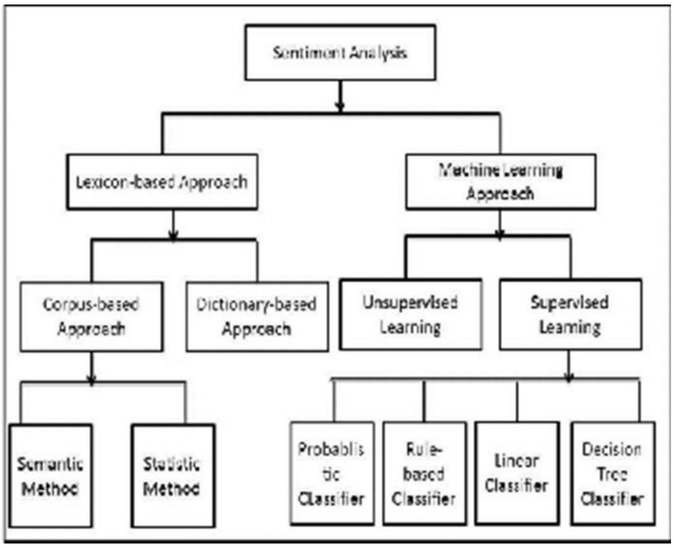


Fig. Depression Analysis Techniques [8]

Nearly all companies need Depression Analysis and Opinion Mining for different applications in different scenarios. In many product review websites like Yelp, Opinions reviews and feedbacks are explicitly asked in their web interfaces.

Depression Analysis is not only limited to product reviews but expands it wing to many fields like political/governmental issues. Opinion Mining can increase capabilities of Customer Relation- ship Management (CRM) and Recommendation Systems by collecting positive and negative depressions of the consumer. By using Depression Analysis techniques wired systems displaying advertisements can detect web pages that contain sensitive content inappropriate for trailers placement.

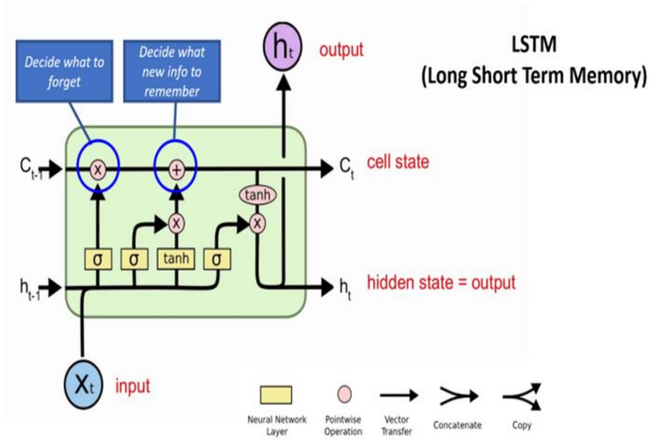
Companies are applying different marketing strategies like collecting opinions of general public about the products and services.

These depressions can be mined using Depression Analysis for Business Intelligence. Not only the commercial market but government intelligence also uses opinion mining to monitor the negative communications over social media.

IV. SYSTEM ARCHITECTURE

There are a number of ways to analyze the information, but the reality is that mental health, specifically depression, is a subjective and complex topic. While it may be possible to quantify the degree to which one might be depressed based on a Tweet, the only real question that matters for this project is, is an individual exhibiting linguistic markers indicative of depression? Knowing the question and the subjective nature of mental illness, a binary classification model made the most sense for this project. While a logistic regression model made sense as a benchmark model, a Long Short Term Memory network (LSTM) model wound up being the most robust for the project at hand. A recurrent neural network allows information to be passed from one step of a network to another, and are ideal for sequences, lists, and other language processing problems. A LSTM is capable of learning long-term dependencies and work incredibly well on a large variety of problems. The LSTM + CNN model takes in an input and then outputs a single number representing the probability that the tweet indicates depression. The model takes in each input sentence, replaces it with its embeddings, and then runs the new embedding vector through a convolutional layer. The convolutional layer passes the structure that it learns from the sequential data into a LSTM layer. The output of the LSTM layer is then fed into a Dense model for prediction.

Once the model was designed and built, the issue then became refining the model to achieve the best results.



The system will send the tweets to be analyzed and stored the results in the database. The tweets will be analyzed in all three models. The system will return the predicted depressions which are Positive, Negative or Neutral. When the system returns two Positive results and one Negative or Neutral result, the system will take the Positive predicted depression as for the Overall Predicted Depression, same as for two Negative results and two Neutral results. The tweets are then analyzed using three different techniques which are Naïve Bayes Classifier technique, NLP techniques and Deep Learning technique.

After the depression of each user tweets is calculated, the depression percentage is then calculated based from the total positive and total negative tweets. If the users have a high percentage of positive tweets, it will classify the users as an optimistic person that implies the user is no depression related. Meanwhile, users that have a high percentage of negative tweets, it will classify the users as an optimistic person that can implies the users might be depression related.

V. DEPRESSION ANALYSIS IN TWITTER

Depression analysis is all about extracting opinion from the text. There are various aspects, reasons, orientation of extracting these emotions according to reason behind the analysis. Event detection, location detection etc. tasks can be done on tweets.

When this task is accomplished on twitter data, the framework or architecture to do depression analysis varies according to what type of result one want to achieve from the tweets. One more important factor behind the varying nature of flow of twitter depression analysis is use of different methodologies and techniques.

Many times researchers derive their own framework or flow to do depression analysis to increase efficiency of the result. Some of common steps in twitter depression analysis and the keywords in it are defined below:

5.1. PREPROCESSING

Despite of these generalized orientation of framework of twitter depression analysis, we can frame up this topic into the following workflow. Thus the generalized steps involved in this framework are as follows:

Before starting depression analysis, the data preprocessing need to be done.

5.1.1. Removal of Non-English Tweets

When the tweets are extracted from big datasets like TREC or Clue web dataset, it contains English as well as non-English tweets.

Therefore, we have to run language identification on each tweet, and have to delete from our collection all tweets that are assigned a 0-probability of being English.

5.2. FEATURE SELECTION

5.2.1. Lexicon Features

Based on the subjectivity of the word we can classify the words into positive, negative and neutral lexicons. We have to compare each word with predefined word net libraries.

5.2.2. Part-of-speech Features

Parts-of speech features i.e. nouns, adverbs, adjectives, etc. in each tweets are tagged.

5.2.3. Micro-blogging Features

By creating binary features we can detect the presence of positive, negative, and neutral emotions. By the presence of abbreviations and intensifiers we can classify tweets in positive, negative and neutral. Online available slang dictionaries can be used for emotions and abbreviations [11].

5.2.4. Steps to Extract Features

5.2.8.1. Case Normalization

In this step entire document is converted into lowercase.

5.2.8.2. Tokenization

Tokenization is splitting up the systems of text into personal terms or tokens. This procedure can take many

5.2.5. Removal of Re-tweets

We have to delete any text that followed an RT token (as well as the RT token itself), since such text typically corresponds to quoted (retweeted) material.

5.2.6. Conversion to ASCII

Many tweets contain unusual or non-standard characters, which can be problematic for down-stream processing. To address these issues, we have to use a combination of BeautifulSoup5 and Unidecode6 to convert and transliterate all tweets to ASCII.

5.2.7. Removal of Empty Tweets

After completing all of the other pre-processing, we have to delete any empty tweets.

5.2.8. Restoration of Abbreviations

We can restore popular abbreviations used in the tweets, to their corresponding original forms using a lexicon of abbreviations (e.g. “wknd" to “week-end").Punctuations are kept since people often express depression with tokens such as “:)”, “:-)". These emotions can also be used for depression classification [10]. types, according to the terminology being examined. For English, effective tokenization technique is to use white space and punctuation as token delimiters.

5.2.8.1. Stemming (Snowball)

Stemming is the procedure of decreasing relevant to-kens into a single type of token. This procedure contains the recognition and elimination of suffixes, prefixes, and unsuitable pluralizations.

5.2.8.2. Generate n-Grams

Character n-grams are ‘n’ nearby figures from a given feedback sequence. For example, a 3- gram of a phrase ’FORM’ would be ‘_ _ F’, ’_FO’, ‘FOR’, ‘ORM’,

VI. PROJECT SNAPSHOTS

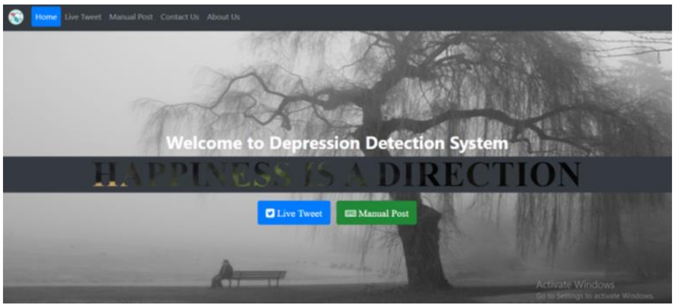


Fig. represents Homepage

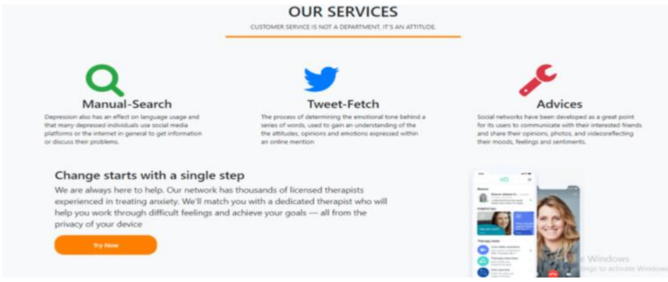


Fig. represents Our Services

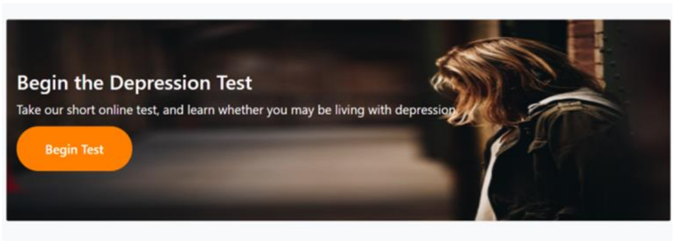


Fig. represents Depression Test

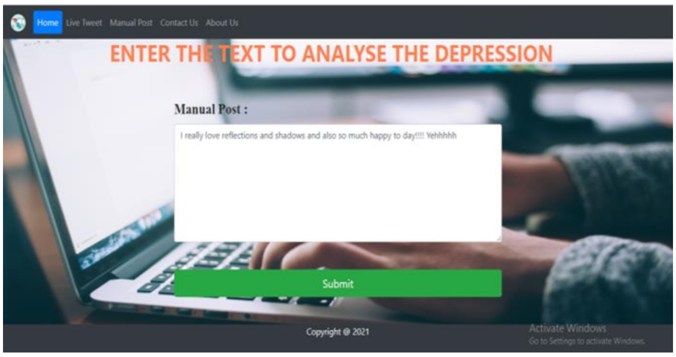


Fig. represents Manual Post

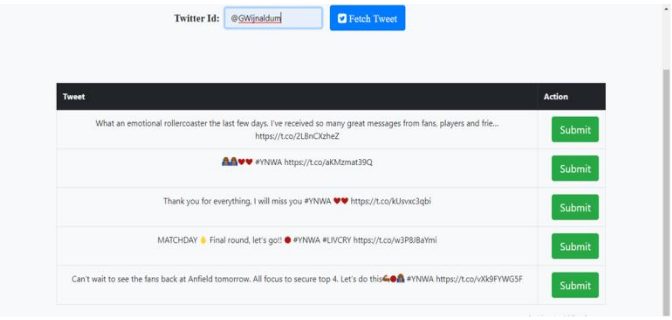


Fig. represents Twitter posts

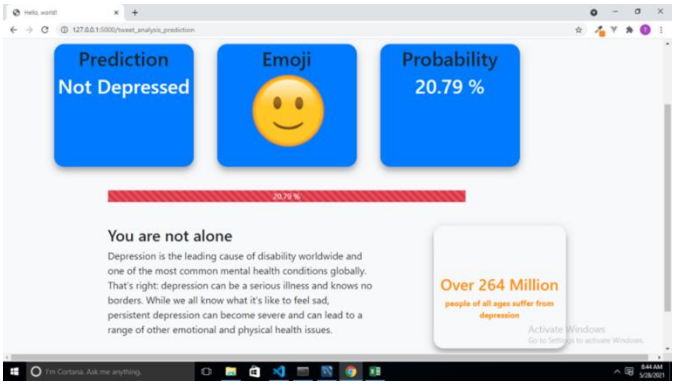


Fig. represents result

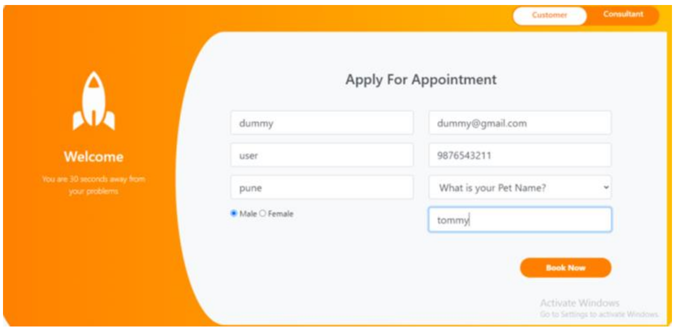


Fig. represents Appointment Registration

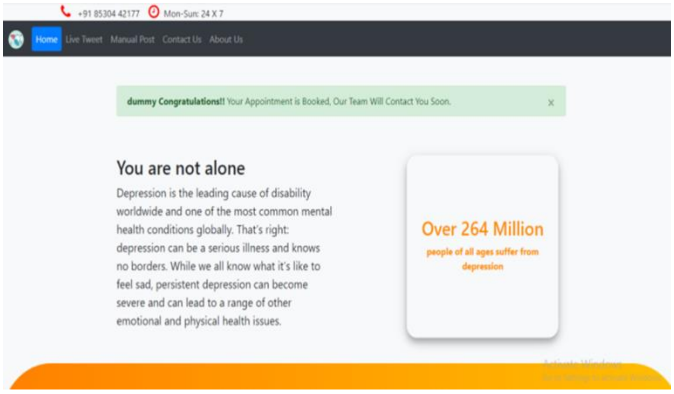


Fig. represents Appointment

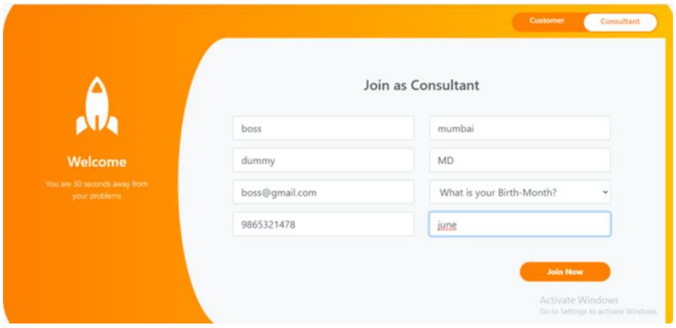


Fig. represents Consultant Registration

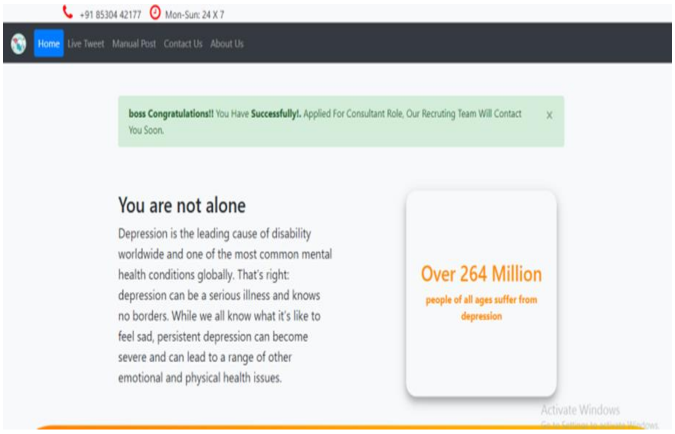


Fig. represents Consultation result

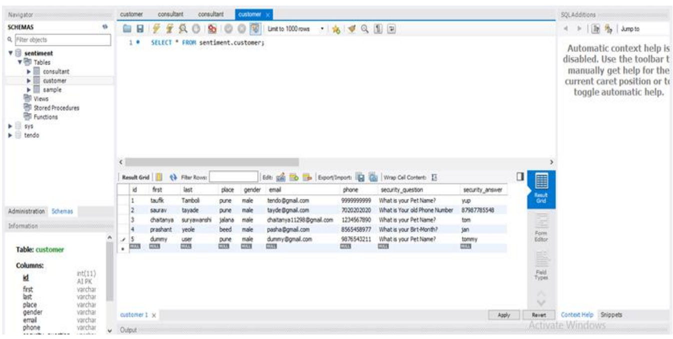


Fig. represents Appointment Database

VII. FUTURE SCOPE

The propose approach is currently incapable of interpreting sarcasm. It can be overcome by exhaustive study of fundamentals in depression detection. Currently not feasible to develop a multi-language base system.

It can be overcome by further study.

In the future, depression detection will deliver deeper, beyond the concept of the number of likes, comments, and shares in a post, to reach and comprehend the significance of social media conversations and what they reveal about consumers.

As a result, depression detection tools like Bytes View are becoming necessary for these businesses to survive in such a competitive market.

Right now we have worked with only the very simplest unigram models; we can improve those models by adding extra information like closeness of the word with a negation word.

We could specify a window prior to the word (a window could for example be of 2 or 3 words) under consideration and the effect of negation may be incorporated into the model if it lies within that window.

The closer the negation word is to the unigram word whose prior polarity is to be calculated, the more it should affect the polarity.

For example if the negation is right next to the word, it may simply reverse the polarity of that word and farther the negation is from the word the more minimized ifs effect should be.

VIII. CONCLUSION

In this paper exhibited the capability of using or measuring and detecting major depression among its users. To give a clear understanding of our work, numbers of research challenges were stated at the start of this paper. The analytics performed on the selected dataset, provide some insight on the research challenges: What depression is and what are the common factors contributing toward depression. While we feel moody, sad or low from time to time, few people encounter these emotions seriously, for drawn out stretches of time (weeks, months or even years) and in some cases with no apparent reason. Despondency is something other than a low state of mind—it's a genuine condition that influences someone's physical and emotional feelings. Depression can influence any of us anytime. However, some phases or events make us more vulnerable to depression. Physical and emotional changes associated with growing-up, losing a loved one, beginning a family, retirement may trigger some emotional influx that could lead toward depression for few people. What are the factors to look for depression detection in social networking comments?

It is important to remember that depressive emotions have several signs and symptoms spread across various categories as reported in Based on signs and symbols divided dataset into 5 emotional variables (positive, negative, sad, anger, anxiety), 3 temporal categories (present focus, past focus and future focus), 9 standard linguistic dimensions (e.g., articles, prepositions, auxiliary verb, adverbs, conjunctions, pronoun, verbs and negations)How to extract these factors from social sites comments? To extract the above-mentioned factors, we applied Linguistic Inquiry and Word Count (LIWC) on our dataset. The LIWC2015 Dictionary is the heart of the text analysis strategy. It processes our comments on a 'line by line' basis within and across columns of spread sheet and accesses a single text within a spread sheet and analyse each line sequentially and reads one target word at a time.

What is the relationship between these factors and attitudes toward depression?

The relationship between the above-mentioned issues with the attitudes towards depression are varies from person to person. When is the most influential time to communicate within depressive Indicate Facebook user? In this study, got 54.77% depressive indicative

Facebook users communicate with their friends from midnight to midday and 45.22% from midday to midnight.

Depression can influence any of us anytime. However, some phases or events make us more vulnerable to depression.

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