ANALYSIS OF WOMEN SAFETY IN INDIAN CITIES BY USING MACHINE LEARNING ON TWEETS

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ABSTRACT

Women and girls have been experiencing a lot of violence and harassment in public places in various cities starting from stalking and leading to abuse harassment or abuse assault. This research paper basically focuses on the role of social media in promoting the safety of women in Indian cities with special reference to the role of social media websites and applications including Twitter platform Facebook and Instagram. This paper also focuses on how a sense of responsibility on part of Indian society can be developed the common Indian people so that we should focus on the safety of women surrounding them. Tweets on Twitter which usually contains images and text and also written messages and quotes which focus on the safety of women in Indian cities can be used to read a message amongst the Indian Youth Culture and educate people to take strict action and punish those who harass the women. Twitter and other Twitter handles which include hash tag messages that are widely spread across the whole globe sir as a platform for women to express their views about how they feel while we go out for work or travel in a public transport and what is the state of their mind when they are surrounded by unknown men and whether these women feel safe or not?

1 INTRODUCTION

Twitter in this modern era has emerged as a ultimate microblogging social network consisting over hundred million users and generate over five hundred million messages known as 'Tweets' every day. Twitter with such a massive audience has magnetized users to emit their perspective and judgmental about every existing issue and topic of internet, therefore twitter is an informative source for all the zones like institutions, companies and organizations. On the twitter, users will share their opinions and perspective in the tweets section. This tweet can only contain 140 characters, thus making the users to compact their messages with the help of abbreviations, slang, shot forms, emoticons, etc.

In addition to this, many people express their opinions by using polysemy and sarcasm also. Hence twitter language can be termed as the unstructured. From the tweet, the sentiment behind the message is extracted. This extraction is done by using the sentimental analysis procedure. Results of the sentimental analysis can be used in many areas like sentiments regarding a particular brand or release of a product, analyzing public opinions on the government policies, people thoughts on women, etc. In order to perform classification of tweets and analyze the outcome, a lot of study has been done on the data obtained by the twitter.

We also review some studies on machine learning in this paper and research on how to perform sentimental analysis using that domain on twitter data. The paper scope is restricted to machine learning algorithm and models. Staring at women and passing comments can be certain types of violence and harassments and these practices, which are unacceptable, are usually normal especially on the part of urban life.

Many researches that have been conducted in India shows that women have reported sexual harassment and other practices as stated above. Such studies have also shown that in popular metropolitan cities like Delhi, Pune, Chennai and Mumbai, most women feel they are unsafe when surrounded by unknown people.

On social media, people can freely express what they feel about the Indian politics, society and many other thoughts. Similarly, women can also share their experiences if they have faced any violence or sexual harassment and this brings innocent people together in order to stand up against such incidents.

From the analysis of tweets text collection obtained by the twitter, it includes names of people who has harassed the women and also names of women or innocent people who have stood against such violent acts or unethical behavior of men and thus making them uncomfortable to walk freely in public.

2. LITERATURE SURVEY AND RELATED WORK:

Expressing views on social media, expressing on micro blogging websites like tweeter is quite common in these days. A lot of people take it to social media to express their views about everything which is going right or wrong in our society and which is happening in day-to-day life. Woman safety is one of the many things which many people talk and express their views about on social media. Most people talk positive things, pointing out the certain change which is needed in our society that can drive the negativity out of our neighborhood and make women feel safe again. There will be X men and Y women who will tweet about women safety once or twice a day, across the country which can be used as a dataset. Using this dataset, it is quite common to run an analytical algorithm on the extracted data from social media and categorize them in positive and negative aspects.

2.1 Agarwal, Apoorv, Fadi Biadsy, and Kathleen R. Mckeown. "Contextual phrase-level polarity analysis using lexical affect scoring and syntactic n-grams." Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, 2009.

We present a classifier to predict contextual polarity of subjective phrases in a sentence. Our approach features lexical scoring derived from the Dictionary of Affect in Language (DAL) and extended through WordNet, allowing us to automatically score the vast majority of words in our input avoiding the need for manual labeling. We augment lexical scoring with n-gram analysis to capture the effect of context. We combine DAL scores with syntactic constituents and then extract grams of constituents from all sentences. We also use the polarity of all syntactic constituents within the sentence as features. Our results show significant improvement over a majority class baseline as well as a more difficult baseline consisting of lexical n-grams.

1 Introduction Sentiment analysis is a much-researched area that deals with identification of positive, negative and neutral opinions in text. The task has evolved from document level analysis to sentence and phrasal level analysis. Whereas the former is suitable for classifying news (e.g., editorials vs. reports) into positive and negative, the latter is essential for question-answering and recommendation systems. A recommendation system, for example, must be able to recommend restaurants (or movies, books, etc.) based on a variety of features such as food, service or ambience. Any single review sentence may contain both positive and negative opinions, evaluating different features of a restaurant. Consider the following sentence (1) where the writer expresses opposing sentiments towards food and service of a restaurant. In tasks such as this, therefore, it is important that sentiment analysis be done at the phrase level. (1) The Taj has great food but I found their service to be lacking. Subjective phrases in a sentence are carriers of sentiments in which an experiencer expresses an attitude, often towards a target. These subjective phrases may express neutral or polar attitudes depending on the context of the sentence in which they appear. Context is mainly determined by content and structure of the sentence. For example, in the following sentence (2), the underlined subjective phrase seems to be negative, but in the larger context of the sentence, it is positive.1 (2) The robber entered the store but his efforts were crushed when the police arrived on time. Our task is to predict contextual polarity of subjective phrases in a sentence.

A traditional approach to this problem is to use a prior polarity lexicon of words to first set priors on target phrases and then make use of the syntactic and semantic information in and around the sentence to make the final prediction. As in earlier approaches, we also use a lexicon to set priors, but we explore new uses of a Dictionary of Affect in Language (DAL) (Whissel, 1989) extended using WordNet (Fellbaum, 1998). We augment this approach with n-gram analysis to capture the effect of context. We present a system for classification of neutral versus positive versus negative and positive versus negative polarity (as is also done by (Wilson et al., 2005)). Our approach is novel in the use of following features:

• Lexical scores derived from DAL and extended through WordNet: The Dictionary of Affect has been widely used to aid in interpretation of emotion in speech (Hirschberg 1We assign polarity to phrases based on Wiebe (Wiebe et al., 2005); the polarity of all examples shown here is drawn from annotations in the MPQA corpus. Clearly the assignment of polarity chosen in this corpus depends on general cultural norms. 24 et al., 2005). It contains numeric scores assigned along axes of pleasantness, activeness and concreteness. We introduce a method for setting numerical priors on words using these three axes, which we refer to as a "scoring scheme" throughout the paper. This scheme has high coverage of the phrases for classification and requires no manual intervention when tagging words with prior polarities.

• N-gram Analysis: exploiting automatically derived polarity of syntactic constituents We compute polarity for each syntactic constituent in the input phrase using lexical affect scores for its words and extract n-grams over these constituents. N-grams of syntactic constituents tagged with polarity provide patterns that improve prediction of polarity for the subjective phrase.

• Polarity of Surrounding Constituents: We use the computed polarity of syntactic constituents surrounding the phrase we want to classify. These features help to capture the effect of context on the polarity of the subjective phrase. We show that classification of subjective phrases using our approach yields better accuracy than two baselines, a majority class baseline and a more difficult baseline of lexical n-gram features. We also provide an analysis of how the different component DAL scores contribute to our results through the introduction of a "norm" that combines the component scores, separating polar words that are less subjective (e.g., Christmas, murder) from neutral words that are more subjective (e.g., most, lack). Section 2 presents an overview of previous work, focusing on phrasal level sentiment analysis. Section 3 describes the corpus and the gold standard we used for our experiments. In section 4, we give a brief description of DAL, discussing its utility and previous uses for emotion and for sentiment analysis. Section 5 presents, in detail, our polarity classification framework. Here we describe our scoring scheme and the features we extract from sentences for classification tasks.

Experimental set-up and results are presented in Section 6. We conclude with Section 7 where we also look at future directions for this research. 2 Literature Survey The task of sentiment analysis has evolved from document level analysis (e.g., (Turney., 2002); (Pang and Lee, 2004)) to sentence level analysis (e.g., (Hu and Liu., 2004); (Kim and Hovy., 2004); (Yu and Hatzivassiloglou, 2003)). These researchers first set priors on words using a prior polarity lexicon. When classifying sentiment at the sentence level, other types of clues are also used, including averaging of word polarities or models for learning sentence sentiment. Research on contextual phrasal level sentiment analysis was pioneered by Nasukawa and Yi (2003), who used manually developed patterns to identify sentiment. Their approach had high precision, but low recall. Wilson et al., (2005) also explore contextual phrasal level sentiment analysis, using a machine learning approach that is closer to the one we present. Both of these researchers also follow the traditional approach and first set priors on words using a prior polarity lexicon.

Wilson et al. (2005) uses a lexicon of over 8000 subjectivity clues, gathered from three sources ((Ridloff and Wiebe, 2003); (Hatzivassiloglou and McKeown, 1997) and The General Inquirer2). Words that were not tagged as positive or negative were manually labeled. Yi et al. (2003) acquired words from GI, DAL and WordNet. From DAL, only words whose pleasantness score is one standard deviation away from the mean were used. Nasukawa as well as other researchers (Kamps and Marx, 2002)) also manually tag words with prior polarities. All of these researchers use categorical tags for prior lexical polarity; in contrast, we use quantitative scores, making it possible to use them in computation of scores for the full phrase

While Wilson et al. (2005) aims at phrasal level analysis, their system actually only gives "each clue instance its own label" [p. 350]. Their gold standard is also at the clue level and assigns a value based on the clue's appearance in different expressions (e.g., if a clue appears in a mixture of negative and neutral expressions, its class is negative). They note that they do not determine subjective expression boundaries and for this reason, they classify at the word level. This approach is quite different from ours, as we compute the polarity of the full phrase. The average length of the subjective phrases in the corpus was 2.7 words, with a standard deviation of 2.3.

Like Wilson et al. 2 http://www.wjh.harvard.edu/ inquirer 25 (2005) we do not attempt to determine the boundary of subjective expressions; we use the labeled boundaries in the corpus. 3 Corpus We used the Multi-Perspective QuestionAnswering (MPQA version 1.2) Opinion corpus (Wiebe et al., 2005) for our experiments. We extracted a total of 17,243 subjective phrases annotated for contextual polarity from the corpus of 535 documents (11,114 sentences).

These subjective phrases are either "direct subjective" or "expressive subjective". "Direct subjective" expressions are explicit mentions of a private state (Quirk et al., 1985) and are much easier to classify. " Expressive subjective" phrases are indirect or implicit mentions of private states and therefore are harder to classify. Approximately one third of the phrases we extracted were direct subjective with non-neutral expressive intensity whereas the rest of the phrases were expressive subjective. In terms of polarity, there were 2779 positive, 6471 negative and 7993 neutral expressions.

3 EXISTING SYSTEM

People often express their views freely on social media about what they feel about the Indian society and the politicians that claim that Indian cities are safe for women. On social media websites people can freely Express their view point and women can share their experiences where they have faced abuse harassment or where we would have fight back against the abuse harassment that was imposed on them. The tweets about safety of women and stories of standing up against abuse harassment further motivates other women data on the same social media website or application like Twitter. Other women share these messages and tweets which further motivates other 5 men or 10 women to stand up and raise a voice against people who have made Indian cities and unsafe place for the women. In the recent years a large number of people have been attracted towards social media platforms like Facebook. It is a common practice to extract the information from the data that is available on social networking through procedures of data extraction, data analysis and data interpretation methods. The accuracy of the Twitter analysis and prediction can be obtained by the use of behavioral analysis on the basis of social networks.

DISADVANTAGES:

i. Twitter and Instagram point and most of the people are using it to express their emotions and also their opinions about what they think about the Indian cities and Indian society.

ii There are several methods of sentiment that can be categorized like machine learning hybrid and lexicon-based learning.

iii. Also, there are another categorization Janta presented with categories of statistical, knowledge-based and age wise differentiation approaches

4 PROPOSED WORK AND ALGORITHM

Women have the right to the city which means that they can go freely whenever they want whether it be too an Educational Institute, or any other place women want to go. But women feel that they are unsafe in places like malls, shopping malls on their way to their job location because of the several unknown Eyes body shaming and harassing these women point Safety or lack of concrete consequences in the life of women is the main reason of harassment of girls. There are instances when the harassment of girls was done by their neighbors' while they were on the way to school or there was a lack of safety that created a sense of fear in the minds of small girls who throughout their lifetime suffer due to that one instance that happened in their lives where they were forced to do something unacceptable or was abusely harassed by one of their own neighbors or any other unknown person. Safest cities approach women safety from a perspective of women rights to the affect the city without fear of violence or abuse harassment. Rather than imposing restrictions on women that society usually imposes it is the duty of society to imprecise the need of protection of women and also recognizes that women and girls also have a right same as men have to be safe in the City.

ADVANTAGES:

i. Analysis of twitter texts collection also includes the name of people and name of women who stand up against abuse harassment and unethical behaviors of men in Indian citieswhich make them uncomfortable to walk freely.

ii. The data set that was obtained through Twitter about the status of womensafety in Indian society.

5. METHODOLOGIES

MODULES

PYTHON

Python is a high-level, interpreted scripting language developed in the late 1980's by Guido van Rossum at the National Research Institute for Mathematics and Computer Science in the Netherlands. The initial version was published at the alt. Sources newsgroup in 1991, and version 1.0 was released in 1994.

Python 2.0 was released in 2,000, and the 2.x versions were the prevalent releases until December 2008. At that time, the development team made the decision to release version 3.0, which contained a few relatively small but significant changes that were not backward compatible with the 2.x versions. Python 2 and 3 are very similar, and some features of Python 3 have been back ported to Python 2. But in general, they remain not quite compatible. Both Python 2 and 3 have continued to be maintained and developed, with periodic release updates for both. As of this writing, the most recent versions available are 2.7.15 and 3.6.5. However, an official End of Life date of January 1, 2020 has been established for Python 2, after which time it will no longer be maintained. If you are a newcomer to Python, it is recommended that you focus on Python 3, as this tutorial will do.

DJANGO

Django is a high-level Python Web framework that encourages rapid development and clean, pragmatic design. Built by experienced developers, it takes care of much of the hassle of Web development, so you can focus on writing your app without needing to reinvent the wheel. It's free and open source.

Django's primary goal is to ease the creation of complex, database-driven websites. Django emphasizes reusability and "pluggability" of components, rapid development, and the principle of don't repeat yourself. Python is used throughout, even for settings files and data models.

6 RESULTS AND DISCUSSION

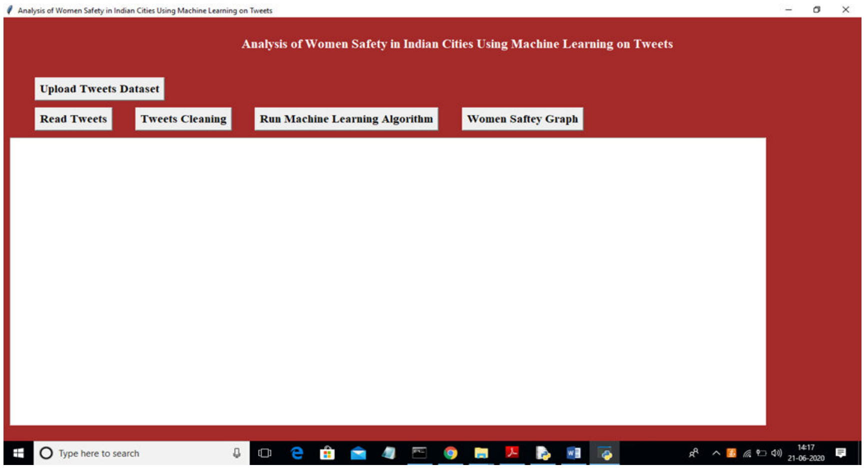

FIG1 : In above screen click on 'Upload Tweets Dataset' button and upload tweet

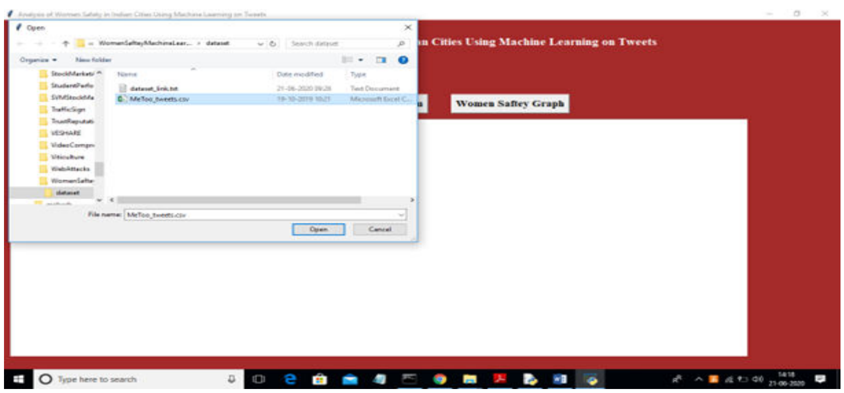

FIG 2 UPLOADING TWEETS DATASET

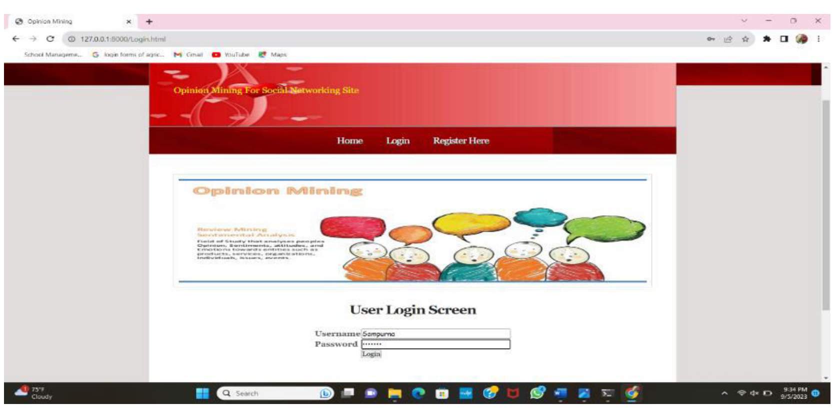

FIG3 USERLOGIN PAGE

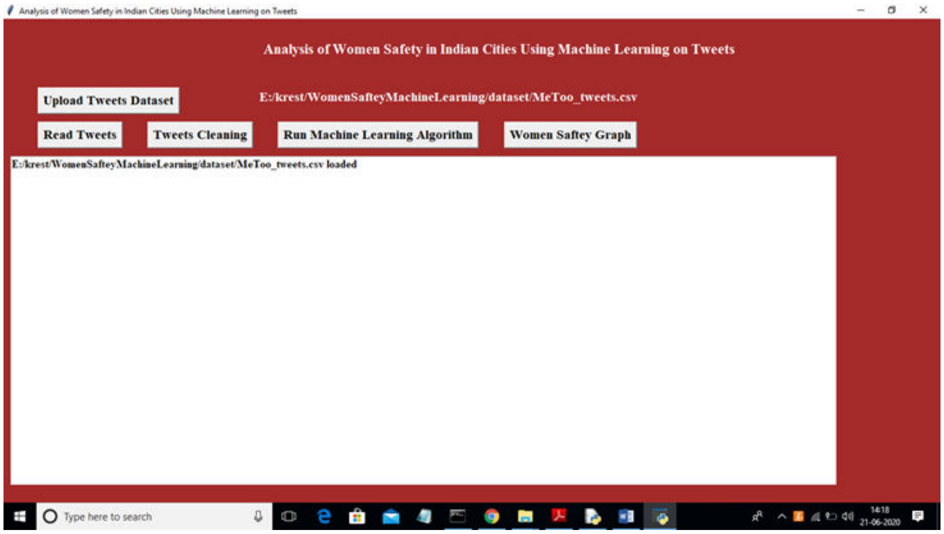

FIG 4 UPLOADED TWEETS DATA

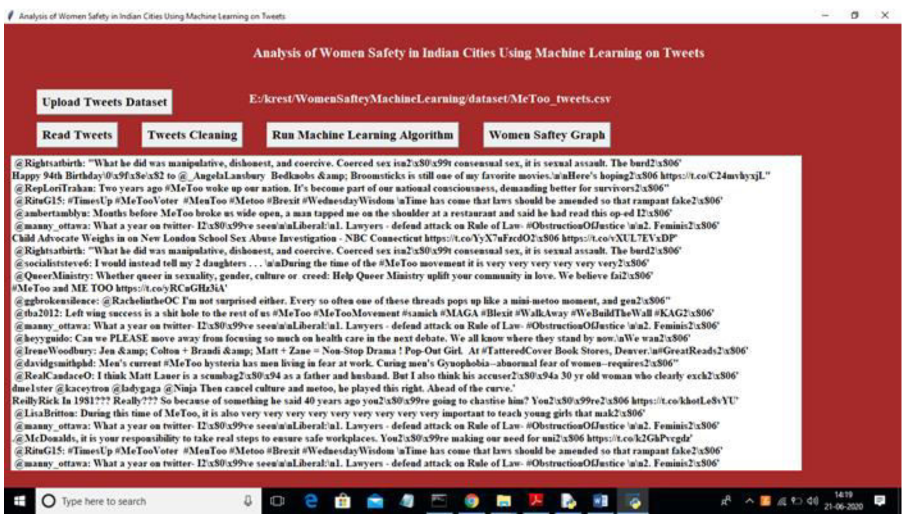

FIG 5 READING TWEETS

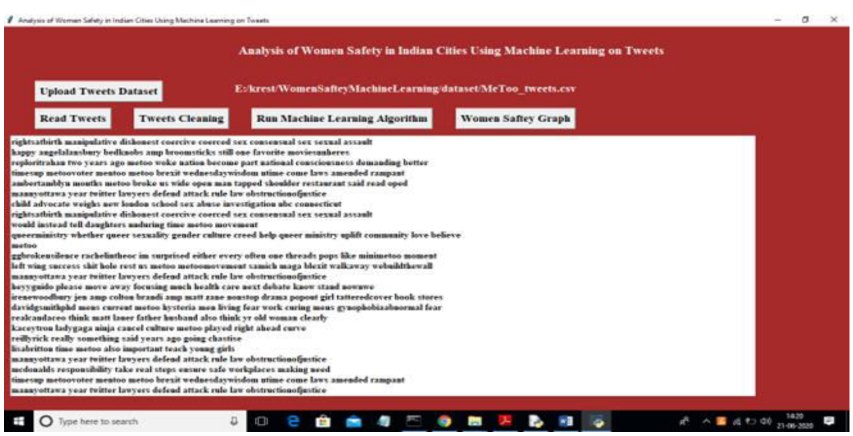

FIG 6 TWEETS CLEANING

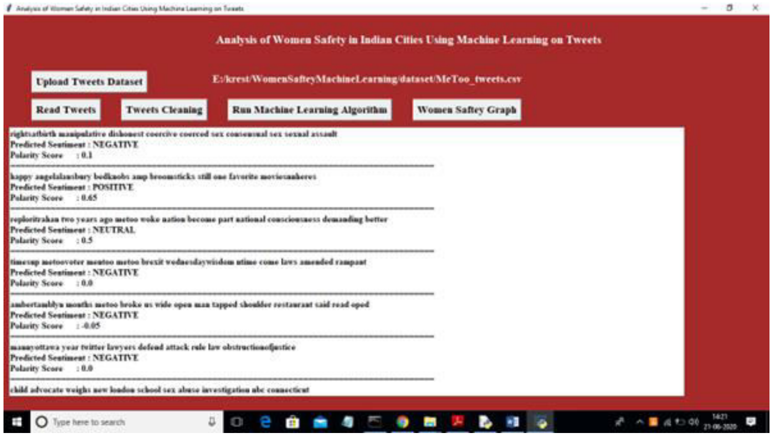

FIG 7 RUNNING MACHINE LEANING ALGORITHM

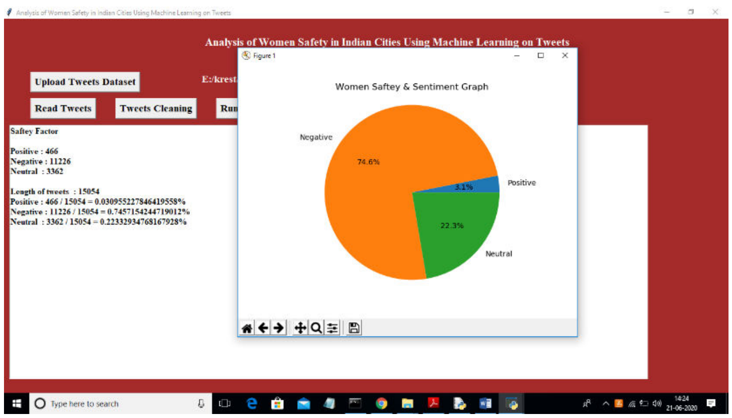

FIG 8 WOMEN SAFETY GRAPH

6.CONCLUSION AND FUTURE SCOPE

CONCLUSION

Throughout the paper various algorithms have been discussed about deep learning and machine learning which can help in analyzing huge amount of data accumulated via tweeter to help determine the safety of women in the society. The machine learning algorithms used are very effective and work efficiently on various platforms when it comes to handling the large amount of data from social media platforms. These algorithms can really help make a dent in women safety and extracting information and create various datasets to work with. We look forward to work more and tweak it to work even more efficiently in the coming near future.

FUTURE SCOPE:

For the future enhancement, we can extend to apply these machine learning algorithms on different social media platforms like Facebook and Instagram also since in our project only twitter is considered. Present ideology which is proposed can be integrated with the twitter application interface to reach large extend and apply sentimental analysis on millions of tweets to provide more safety.

7 REFERENCES

[1]. Agarwal, Apoorv, Fadi Biadsy, and Kathleen R. Mckeown. "Contextual phrase-level polarity analysis using lexical affect scoring and syntactic n-grams." Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, 2009.

[2]. Barbosa, Luciano, and Junlan Feng. "Robust sentiment detection on twitter from biased and noisy data." Proceedings of the 23rd international conference on computational linguistics: posters. Association for Computational Linguistics, 2010.
[3]. Bermingham, Adam, and Alan F. Smeaton. "Classifying sentiment in microblogs: is brevity an advantage?" Proceedings of the 19th ACM international conference on Information and knowledge management. ACM, 2010.
[4]. Gamon, Michael. "Sentiment classification on customer feedback data: noisy data, large feature vectors, and the role of linguistic analysis." Proceedings of the 20th international conference on Computational Linguistics. Association for Computational Linguistics, 2004.
[5]. Kim, Soo-Min, and Eduard Hovy. "Determining the sentiment of opinions." Proceedings of the 20th international conference on Computational Linguistics. Association for Computational Linguistics, 2004.