The Role of Social Media In Promoting The Safety Of Women in Indian Cities

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Abstract: In every city, harassment and violence becomes one of the major problems for women. Further, women's personal life is suffered by the bullying and abusive content presented in online social networking (OSN). Therefore, it is necessary to identify the women safety in OSN environment. However, the conventional methods failed to predict the maximum safety analysis. So, this work is focused on women safety prediction using decision tree (WSP-DT) classifier. Initially, twitter dataset is considered to implement the entire system, which is then pre-processed to remove the missing and unknown symbols. Then, natural language toolbox kit (NLTK) applied to perform the tokenization, conversion to lowercase, stop words identification, stemming and lemmatization of tweets. Then, text blob protocol is developed to identify sentiments of pre-processed tweets, which identifies the positive, negative and neutral polarities of tweets. Further, term frequency-inverse document frequency (TF-IDF) is applied to extract the data features based on word and character frequency. Finally, decision tree classifier applied to identify the fake or genuine tweet based on multi-level training. The simulations conducted on twitter dataset show that the proposed WSP-DT classifier resulted in superior performance than the other methods.

Keywords: Women Safety, Online Social Network, Natural Language Toolbox Kit.

1. INTRODUCTION

Staring and passing remarks are two examples of aggressive forms of harassment and violence, which are often seen as being a regular aspect of urban life [1]. Numerous studies have been undertaken in cities throughout India, and the results show that women report experiencing the same kinds of sexual harassment and passing remarks from other unidentified persons. According to research that was done in the most populated metropolises in India, including Delhi, Mumbai, and Pune [2], 60% of women report feeling dangerous when leaving the house for work or using public transportation. Women have the right to the city, which enables them to go anywhere they like, including to educational institutions and other destinations. However, because to the many unidentified Eyes body shaming and harassing these ladies, women feel frightened in settings like malls and shopping malls while traveling to their workplace [3].

Figure 1 shows the different types of abusive statics on women's in OSN environments. Here, the major cause of harassment of girls is safety or a lack of tangible repercussions in women's lives [4]. There are cases where girls are sexually harassed by their neighbours while they are walking to school. This is preferable than placing limits on women that society often places. With this method, we can automatically score the great majority of words in this input without the requirement for human labelling thanks to lexical scoring that is drawn from the Dictionary of Affect in Language (DAL) [5] and enhanced by WordNet. To account for the impact of context, they add n-gram analysis to the lexical scoring process. In order to extract n-grams of components from all sentences, they first integrate DAL scores with syntactic elements. Additionally, they employ the polarity of each syntactic element in the phrase as a feature [6]. A method to automatically identify feelings on Twitter communications (tweets) was suggested and analyses several writing characteristics of tweets as well as meta-information of the words that make up these messages. Additionally, they use sources of erratic labels as the training data. A couple emotion detection services over twitter data gave these noisy labels. Various trials demonstrate that machine learning technique [7] is superior to earlier ones and more resilient to skewed and noisy data, which is the kind of data offered by these sources, since these characteristics may capture a more abstract description of tweets.

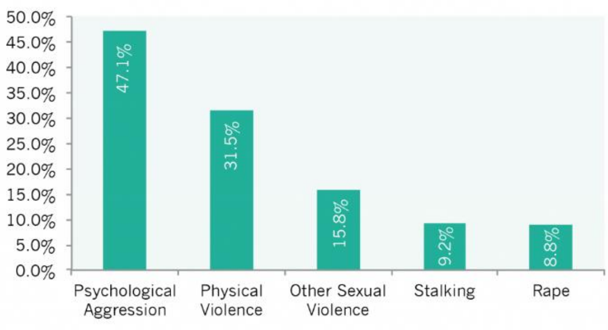


Fig. 1: Women safety statistics in OSN.

The conventional methods [8] failed to predict the maximum safety analysis. As a result, the focus of this article is on the WSP-DT classifier. The Twitter dataset is initially considered to implement the entire system, which is then pre-processed to remove missing and unknown symbols. Then, NLTK was used to perform tokenization, lowercase conversion, stop word identification, stemming, and lemmatization on tweets. The text blob protocol is then developed to identify sentiments in pre-processed tweets, identifying positive, negative, and neutral polarities. The findings of a sentimental analysis can be put to use in a wide variety of contexts, such as determining people's perspectives on women; analysing public sentiments regarding government policies; determining people's attitudes toward a particular brand or the introduction of a new product; and so on. The information that was gathered from Twitter has been the subject of a substantial amount of study, which has been carried out in order to carry out the classification of tweets and assess the findings. This study also covers a number of other studies on machine learning, as well as research on how to carry out emotional analysis by making use of data from Twitter and applying it to a particular topic.

Scope

The algorithmic and model-based approaches to machine learning are the exclusive focus of this work. Some forms of violence and harassment, such as staring at women and making remarks, are commonplace even in urban settings, despite the fact that these behaviours, which are offensive and should not be tolerated, may be considered forms of violence and harassment. Numerous studies that have been carried out in India demonstrate that women have complained of being subjected to sexual harassment and other activities such as those mentioned above. Studies of this kind have also shown that the majority of women in populous metropolitan places such as Delhi, Pune, Chennai, and Mumbai have the feeling that they are in danger whenever they are surrounded by people they do not know.

Objective

In a number of different places around the country, the act of following and harassing women and girls may occasionally escalate into more serious kinds of assault and harassment in public spaces. Abuse, harassment, or assault are just examples of the sorts of violence and harassment that fall under this category. This research paper focuses the majority of its attention on the role that social media plays in promoting the safety of women in urban areas throughout India, with a particular reference to the role that social media websites and apps play, including the Twitter platform, Facebook, and Instagram. Specifically, this paper examines the function that social media plays in promoting the safety of women in urban areas throughout India. This research also focuses on the ways in which a sense of responsibility on the part of Indian society may be established among the common people of India so that we can concentrate on the protection of women in the situations in which they are most directly involved. Tweets on Twitter, which typically contain images and text as well as written messages and quotes that 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. This can be done by educating people to take strict action and punish those who harass the women. Tweets on Twitter contain written messages and quotes that focus on the safety of women in Indian cities. This may be accomplished by training people to take firm action against individuals who harass women and penalise them for their actions. Twitter and other Twitter handles that 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 or not these women feel safe or not are being used by women as a platform to talk about how they feel while we go out for work or travel in a public transport. Twitter and other Twitter handles that include has.

2. LITERATURE SURVEY

these brief papers than in lengthier ones was looked in their study [9]. They make a number of observations on the difficulty of supervised learning for sentiment analysis in microblogs and are surprised to discover that identifying sentiment in microblogs is simpler than in blogs. As an example of a data mining technique [10], discussion of the study of the Twitter dataset using machine learning algorithms and sentiment analysis. A method for automatically categorizing Tweet emotions from the Twitter dataset is shown. Regarding a search keyword, these messages or tweets are categorized as favourable, negative, or neutral. This is highly helpful for businesses seeking feedback on their product brands or for consumers seeking third-party reviews of products before making a purchase. The sentiment of tweets [11] will be categorized using machine learning algorithms under remote supervision. Twitter tweets with emoticons and acronyms that serve as noisy labels make up the training data. They look at Twitter data's sentiment analysis. In [12] authors explored the unique field of doing sentiment analysis on people's perceptions of the best colleges in India. Spelling correction, which is neglected in previous research papers, was handled using a probabilistic model based on Bayes' theory in addition to other preprocessing steps including the expansion of net jargon and elimination of duplicate tweets [13]. The outcomes achieved by using the following machine learning techniques are contrasted in this study as well. Multilayer Perceptron is a model of an artificial neural network that combines Naive Bayes, SVM, and SVM. Additionally, a comparison of the four distinct SVM kernels—RBF, linear, polynomial, and sigmoid—has been made.

In [14], evaluation of various works on research into sentiment analysis on Twitter included a description. The sample of tweets was then subjected to sentiment analysis using a Python algorithm that had been trained using data mining. This allowed the tweets to be categorized based on the emotions they exhibited. The Sustainable Development Goals (SDGs) [15] were then utilized to categorize the tweets, and a textual analysis was conducted to determine the main environmental and public health issues that Twitter users are most concerned about. They accomplished this by using the qualitative analysis program NVivo Pro 12. In order to secure the safety of women nearby, in [16] authors concentrated on fostering duties among the general public in different Indian towns. Tweets sent with the Twitter app include text messages, audio, video, pictures, emoticons, and hashtags. This tweet content may be utilized to spread awareness among the public, enlightening them to the need to take stern action in the event that harassing tweets are sent out to women, and ultimately, punishing such individuals [17]. Twitter and Instagram, two platforms that support hashtags, may be used to disseminate messages throughout the world and encourage women to voice their opinions and sentiments. This will allow them to determine if they feel comfortable or not when they go for work, ride in a public vehicle, or are surrounded by ominous guys. This essay also focuses on how understanding [18] certain cultural norms might benefit average Indian people, emphasizing the need to protect the security of women around them. Tweets on Twitter, which mostly consist of images, messages, and remarks on the wellbeing of girls in Indian urban neighbourhoods, getting out of a public vehicle for work or a trip, the state of their psyche when mysterious men surround them, and whether or not these women have a strong sense of security.

In [19] authors explored how the use of machine learning methods in the investigative process may be used to study the pattern of crimes and criminal characteristics in India, such as rape, sexual assault, kidnapping, etc. The datasets collected from each state in the nation have been studied and worked on using the potent Python package pandas. In [20] authors scope includes an analysis of crime patterns as well as a focus on the fundamental causes of these patterns and the steps that should be done to avoid them going forward by using a decision tree's machine learning algorithm.

Analysis of polarity at the phrase level based on the context, consuming lexical affect score and syntactic n-grams

Apoorv Agarwal, Fadi Biadsy, and Kathleen R. Mckeown are the authors of this piece.

We introduce a classifier that can determine the contextual polarity of subjective statements based on their location inside a sentence. In order to account for the influence of the setting, we supplement lexical score using n-gram analysis. We begin by combining the DAL scores with the syntactic parts of each phrase, and then we extract the n-grams of each ingredient from each sentence. The polarity of all syntactic parts inside the sentence is also taken into consideration as a property of the phrase. Both an easier baseline composed of lexical n-grams and a more challenging baseline consisting of a majority class demonstrate considerable improvement when compared to our findings.

robust identification of sentiment on Twitter using data that is both skewed and noisy

Luciano Barbosa and Junlan Feng are credited with writing this.

In this paper, we propose an approach to automatically detect sentiments on Twitter messages (tweets) that explores some characteristics of how tweets are written and meta-information of the words that compose these messages. This approach is based on the idea that certain characteristics of how tweets are written and information about the words that compose these messages are related. Specifically, this approach focuses on the relationship between the words that make up the tweets and their context. In addition, we make use of data sources that provide noisy labels for our training purposes. A few websites that identify sentiment using Twitter data were responsible for providing these noisy labels. Because our features are able to capture a more abstract picture of tweets, our trials reveal that our approach is more successful than others that came before it. It is also more resilient in the face of skewed and noisy data, which is the sort of data that is offered by these sources.

Classifying customers' feelings based on their feedback involves dealing with noisy information, a high number of feature vectors, and the need of linguistic research.

Michael Gamon is the author of this work.

We demonstrate that it is possible to carry out automatic sentiment classification in the very noisy field of customer feedback data. We demonstrate that it is possible to train linear support vector machines that achieve high classification accuracy on data that present classification challenges even for a human annotator by making use of large feature vectors in combination with feature reduction. This is possible by training the linear support vector machines on data that present classification challenges even for a human annotator. In order to achieve this goal, it was necessary to demonstrate that it is feasible to train linear support vector machines. We also show that the addition of features produced from in-depth linguistic research to a collection of features derived from surface-level word n-grams consistently contributes to gains in classification accuracy within this domain, which came as a surprise to us.

An research into the usage of machine learning methods on the programming language Python for the purpose of doing sentiment analysis on tweets from the social media platform Twitter.

Authors: Gupta B, Negi M, Vishwakarma K, Rawat G & Badhani P

Abstract: Twitter is a platform that is used extensively by individuals to share their ideas and convey their feelings on a variety of subjects and events. An strategy of analysing data and retrieving the sentiment that the data represents is known as sentiment analysis. Over the course of the last several decades, there has been a steady expansion of study in this area. The complex nature of tweets, which makes it harder to digest the information contained inside them, is the root cause of this issue. Because the tweet format is so compact, there is a whole new level of issues that arise, such as the usage of slang and abbreviations, among other things. In this study, we seek to evaluate various publications related to research in Twitter sentiment analysis, outlining the methodology taken and models implemented, as well as proposing a generalised approach that is based on Python.

3. PROPOSED SYSTEM

In the work that was proposed, we downloaded tweets from Twitter using the TWEEPY package that is available for the Python programming language. However, every time we tried to download tweets online, the Internet was unavailable. As a result, we downloaded MEETOO tweets on women's safety and stored them in a dataset folder. This application will read these tweets in order to determine how ladies are feeling.

- Author is cleaning up tweets by using a programme called NLTK, which stands for natural language tool kit, in order to eliminate special symbols and stop words.
- The author uses the TEXTBLOB corpora package and dictionary to count positive, negative, and neutral polarity. Tweets with a polarity value of less than 0 are considered to have a negative polarity, while tweets with a polarity value of greater than 0 and less than 0.5 are considered to have a neutral polarity. Tweets with a polarity value of greater than 0.5 are considered to have a positive polarity.

every city is the prevalence of sexual harassment and assault. In addition, the harassing and violent content that can be found in online social networking sites can have a negative impact on the personal lives of women. As a result, it is essential to determine whether or not the OSN environment is safe for women. The conventional methods, on the other hand, were not successful in predicting the maximum safety analysis. Figure 2 shows the proposed WPC-DT block diagram. Initially, dataset is collected using “TWEEPY” package, which download tweets from internet. The dataset mostly contains the “MEETOO” hashtag-based tweets. These tweets are specially focused on women safety issue. Then, the dataset is pre-processed using NLTK. Here, NLTK is used to identify stop words, and remove special symbols from tweet dataset. The NLTK also eliminates unknown characters, symbols, special letters from dataset. The empty samples are replaced by zeros, which resulted in pre-processed and normalized data. Then, Textblob is used to count the positive, negative, and neutral polarity tweets. Tweets with polarity values less than 0 are considered negative, tweets with polarity values greater than 0 are considered neutral, and tweets with polarity greater than 0.5 are considered positive. Further, TF-IDF method is used to extract the data specific features. In addition, DT classifier trained with TF-IDF features. Finally, The DT classifier predicts the tweet status as “Genuine tweet” or “Fake tweet” by using sentiment analysis.

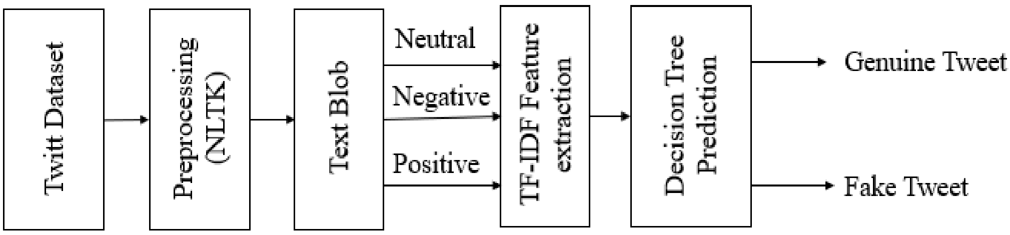


Fig. 2: Block diagram of proposed system.

NLTK-Pre-processing

The NLTK offers us several test datasets and different text processing frameworks. The NLTK used to carry out a wide range of operations, including tokenization, lower case conversion, Stop Words removal, stemming, and lemmatization.

Tokenization: Tokenization is the division of text into smaller pieces. There are just a few tokens in that text. The goal is to break down each word in a phrase and develop a vocabulary that will allow us to express each word in a list in a distinctive way. Tokens include words, numbers, and other objects.

converting to lowercase Our goal is to prevent our model from being confused when it encounters the same term in two distinct circumstances, such as one beginning in capital letters and the other not. To prevent repetition in the token list, we thus lowercase all terms.

Stop Words deletion: There will be a lot of noise when we model using textual characteristics. These are stop words, such as the, he, her, etc., that should simply be eliminated prior to processing in order to facilitate cleaner processing within the model. All of the stop words that are accessible in the English language may be seen using NLTK.

Stemming: Many terms with the root word play, such as playing, played, playfully, etc., may be found in our text and all have the same meaning. Therefore, we just need to eliminate the remainder and extract the root term. Here, the term that is generated from the root is called "stem," although this word need not really exist or have any significance. We produce the stems simply by committing the suffix and prefix.

Lemmatization: Here, we wish to get the word's root form. Lemma is the name of the word that was extracted and is a term that is in the dictionary. The lemma that was constructed will be accessible in the WordNet corpus, which we already have. NLTK gives us the WordNet Lemmatizer, which searches the WordNet Database for word lemmas.

Text blob

For processing text data, TextBlob is an open-source Python module that is relatively simple to use. It has a wide variety of built-in techniques for typical natural language processing jobs. Spelling correction, part of speech tagging, and text categorization are some of the activities using Python tools. However, it may also be used for a number of NLP tasks, including: spelling correction, n-grams, parsing, word inflexion, phrase frequencies, word frequencies, tokenization, text classification, sentiment analysis, part of speech tagging, and noun phrase extraction. The Textblob is used to count the positive, negative, and neutral polarity tweets. Tweets with polarity values less than 0 are considered negative, tweets with polarity values greater than 0 are considered neutral, and tweets with polarity greater than 0.5 are considered positive.

TF-IDF Feature extraction

TF-IDF is one of the most crucial methods for information retrieval, which is the representation of the significance of a word or phrase inside a given text. Figure 3 shows the feature extraction process using TF-IDF method. The Inverse Document Frequency (IDF) and Term Frequency (TF) are the two statistical techniques used by TF-IDF. The phrase “TF” refers to the total number of times a certain term (t) occurs in the text (doc) in comparison to the total number of words in the text. The amount of information a word conveys is measured by its IDF. It gauges how important a certain word is across the whole text. IDF display a word's frequency or rarity across all publications. The formula for TF-IDF is TF * IDF. Further, the TF-IDF does not immediately transform raw data into helpful features. First, each word is given its own vector after being converted from raw strings or a dataset. The characteristic will then be retrieved using a specific method, such as Cosine Similarity, which operates on vectors, etc.

TF: The first step Let's say we have a collection of English text papers and want to determine which one best answer the statement "Data Science is wonderful." Starting off simply by removing any papers that do not have all three words—"Data is," "Science is," and "awesome"—leaves countless documents. We may count the number of times each phrase appears in each document to further separate them; the frequency at which a term looks in a document is referred to as TF. A term's weight in a text is just proportionate to how often it appears.

$$tf(t,d) = (d)_w/N \tag{1}$$

Here, (d)_w represents the number of repetitive words (w) in document (d) and N represents the total number of words.

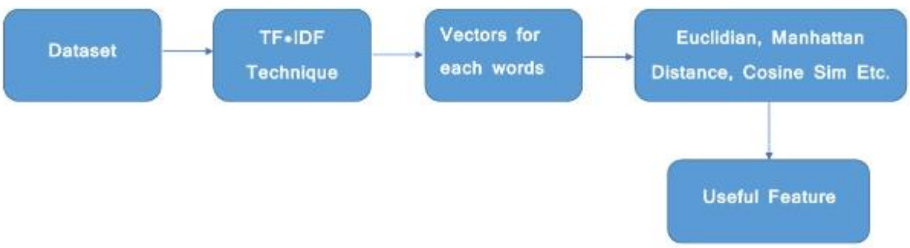


Fig. 3: Feature extraction using TF-IDF.

Document Frequency (DF): We count a phrase as occurring once if it appears in the text at least once; the exact number of instances is irrelevant.

$$idf(t) = N / DF \quad (2)$$

There were a few additional problems with IDF. For example, the IDF levels expand when applied to a big corpus, like 100,000,000. When a word from the vocabulary appears during the query, the DF will be 0. Because we are unable to perform a division by zero, we round the number off by adding one to the denominator.

$$idf(t) = N/(df + 1)/ log(idf(t)) \quad (3)$$

The TF-IDF was currently the appropriate metric to assess a word's significance to a document inside a corpus or collection and generate the features.

Decision tree classification

A flowchart is a kind of tree structure that might be analogous to a decision tree, which is another type of tree structure. The central nodes of this form of tree structure each represent a feature (or characteristic), the branches each represent a decision rule, and the leaf nodes each indicate the predicted outcome. Fig. 4 shows the prediction process using decision tree classification.

The node that is considered to be the "root" of a decision tree is called the "root node." It gains the capacity to split in accordance with the significance of the traits. This approach of slicing the tree into portions is known as recursive partitioning, and it has been given that name. The structure of a flowchart is presented for reference, which may more easily make choices. It is a graphical representation that may easily simulate human level thinking, and it looks somewhat like a flowchart diagram. Because of this, comprehending decision trees and making sense of what they mean may be accomplished with relative ease.

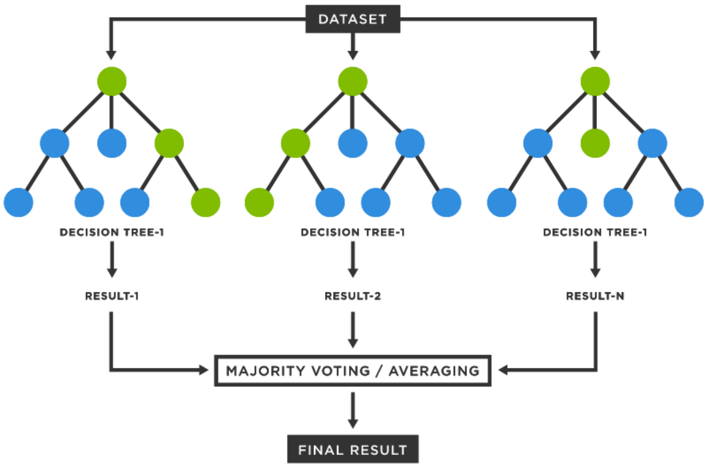


Fig. 4: Decision Tree classification.

The following is the overarching principle that underlies each and every decision tree algorithm:

1. Before begin to separate the data, establish characteristic function. This is the most essential by using the Attribute Selection Measures, or ASM.

2. Make a decision node out of that attribute, and then divide the dataset up into a number of different, smaller subsets using those decision nodes.

3. The process of building the tree is initiated by repeatedly applying this approach to each child in a recursive fashion until one of the following requirements is satisfied:

Each and every one of the tuples is associated with the identical attribute value.

There are no more characteristics that can be acquired.

There are no further examples to be found and generates the predicted outcome from test samples.

Advantages

- The analysis of the collection of texts on Twitter contains the names of persons as well as the names of women who speak out against abuse, harassment, and unethical behaviour on the part of men in Indian cities, which makes it unpleasant for them to move freely. These women say that the behaviour of men in these cities makes it difficult for them to move freely.

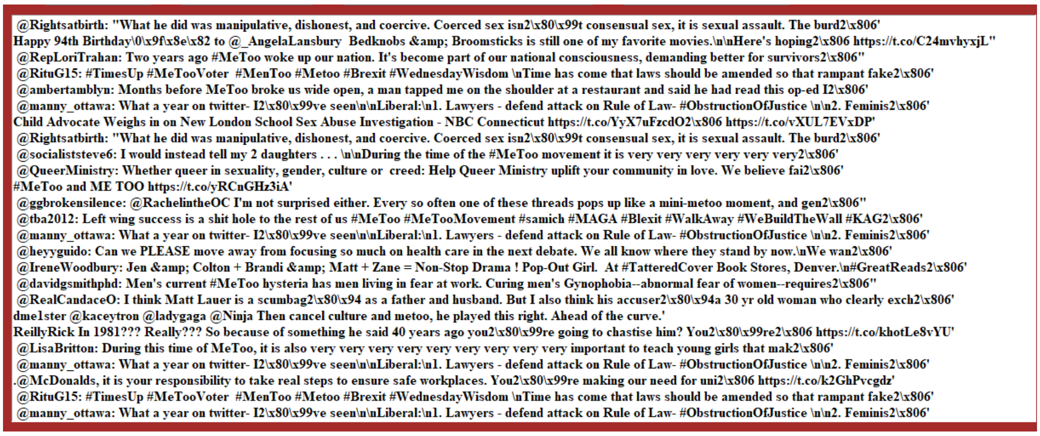
- The collecting of data that was obtained on the precarious position of women in Indian society via the use of Twitter.

4. Results and discussions

This section gives the detailed results analysis of proposed method, which are implemented using WPC-DT model.

Datasets

This research explores the #MeToo hashtag on Twitter and reveals some of the information it contains. Approximately 15,000 tweets are included in the data set. I made an effort to demonstrate what is occurring in relation to this hashtag (at least in my sample). After removing any stop words, the most common terms being used in conjunction with this hashtag are as follows: The bigrams that occur most often. The Tre-grams that occur the most often. The most widely used platform is that is being used by the Twitterverse. Fig. 5 shows the sample tweets from MeToo dataset.



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@Rightsatbirth: "What he did was manipulative, dishonest, and coercive. Coerced sex isn2\x80\x99t consensual sex, it is sexual assault. The burd2\x806'
Happy 94th Birthday\0\x9f\x8e\x82 to @_AngelaLansbury  Bedknobs &amp; Broomsticks is still one of my favorite movies.\n\nHere's hoping2\x806 https://t.co/C24mvhyxjL"
@RepLoriTrahan: Two years ago #MeToo woke up our nation. It's become part of our national consciousness, demanding better for survivors2\x806"
@RituG15: #TimesUp #MeTooVoter  #MenToo #Metoo #Brexit #WednesdayWisdom \nTime has come that laws should be amended so that rampant fake2\x806'
@ambertamblyn: Months before MeToo broke us wide open, a man tapped me on the shoulder at a restaurant and said he had read this op-ed I2\x806'
@manny_ottawa: What a year on twitter- I2\x80\x99ve seen\n\nLiberal:\n1. Lawyers - defend attack on Rule of Law- #ObstructionOfJustice \n\n2. Feminis2\x806'
Child Advocate Weighs in on New London School Sex Abuse Investigation - NBC Connecticut https://t.co/YyX7uFzcdO2\x806 https://t.co/vXUL7EVxDP'
@Rightsatbirth: "What he did was manipulative, dishonest, and coercive. Coerced sex isn2\x80\x99t consensual sex, it is sexual assault. The burd2\x806'
@socialiststeve6: I would instead tell my 2 daughters . . . \n\nDuring the time of the #MeToo movement it is very very very very very very2\x806'
@QueerMinistry: Whether queer in sexuality, gender, culture or  creed: Help Queer Ministry uplift your community in love. We believe fai2\x806'
#MeToo and ME TOO https://t.co/yRCnGHz3iA'
@ggbrokensilence: @RachelintheOC I'm not surprised either. Every so often one of these threads pops up like a mini-metoo moment, and gen2\x806"
@tba2012: Left wing success is a shit hole to the rest of us #MeToo #MeTooMovement #samich #MAGA #Blexit #WalkAway #WeBuildTheWall #KAG2\x806'
@manny_ottawa: What a year on twitter- I2\x80\x99ve seen\n\nLiberal:\n1. Lawyers - defend attack on Rule of Law- #ObstructionOfJustice \n\n2. Feminis2\x806'
@heyyguido: Can we PLEASE move away from focusing so much on health care in the next debate. We all know where they stand by now.\nWe wan2\x806'
@IreneWoodbury: Jen &amp; Colton + Brandi &amp; Matt + Zane = Non-Stop Drama ! Pop-Out Girl.  At #TatteredCover Book Stores, Denver.\n#GreatReads2\x806'
@davidgsmithphd: Men's current #MeToo hysteria has men living in fear at work. Curing men's Gynophobia--abnormal fear of women--requires2\x806"
@RealCandaceO: I think Matt Lauer is a scumbag2\x80\x94 as a father and husband. But I also think his accuser2\x80\x94a 30 yr old woman who clearly exch2\x806'
dme1ster @kaceytron @ladygaga @Ninja Then cancel culture and metoo, he played this right. Ahead of the curve.'
ReillyRick In 1981??? Really??? So because of something he said 40 years ago you2\x80\x99re going to chastise him? You2\x80\x99re2\x806 https://t.co/khotLe8vYU'
@LisaBritton: During this time of MeToo, it is also very very very very very very very very very important to teach young girls that mak2\x806'
@manny_ottawa: What a year on twitter- I2\x80\x99ve seen\n\nLiberal:\n1. Lawyers - defend attack on Rule of Law- #ObstructionOfJustice \n\n2. Feminis2\x806'
.@McDonalds, it is your responsibility to take real steps to ensure safe workplaces. You2\x80\x99re making our need for uni2\x806 https://t.co/k2GhPvcgdz'
@RituG15: #TimesUp #MeTooVoter  #MenToo #Metoo #Brexit #WednesdayWisdom \nTime has come that laws should be amended so that rampant fake2\x806'
@manny_ottawa: What a year on twitter- I2\x80\x99ve seen\n\nLiberal:\n1. Lawyers - defend attack on Rule of Law- #ObstructionOfJustice \n\n2. Feminis2\x806'
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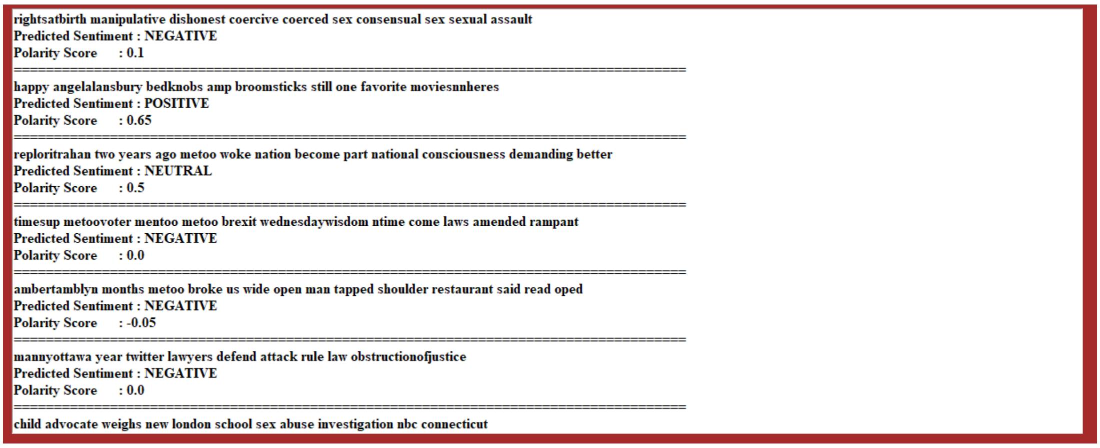
Fig. 5: Sample dataset.

Fig. 6 represents the prediction outcome of each tweet, and the test tweets are predicted with sentiment as "Neutral", "Negative", and "Positive". Further, tweet polarity score also identified.



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rightsatbirth manipulative dishonest coercive coerced sex consensual sex sexual assault
Predicted Sentiment : NEGATIVE
Polarity Score     : 0.1
================================================================================
happy angelalansbury bedknobs amp broomsticks still one favorite moviesnnheres
Predicted Sentiment : POSITIVE
Polarity Score     : 0.65
================================================================================
reploritrahan two years ago metoo woke nation become part national consciousness demanding better
Predicted Sentiment : NEUTRAL
Polarity Score     : 0.5
================================================================================
timesup metoovoter mentoo metoo brexit wednesdaywisdom ntime come laws amended rampant
Predicted Sentiment : NEGATIVE
Polarity Score     : 0.0
================================================================================
ambertamblyn months metoo broke us wide open man tapped shoulder restaurant said read oped
Predicted Sentiment : NEGATIVE
Polarity Score     : -0.05
================================================================================
mannyottawa year twitter lawyers defend attack rule law obstructionofjustice
Predicted Sentiment : NEGATIVE
Polarity Score     : 0.0
================================================================================
child advocate weighs new london school sex abuse investigation nbc connecticut
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Fig. 6: Tweet sentiments with polarity score.

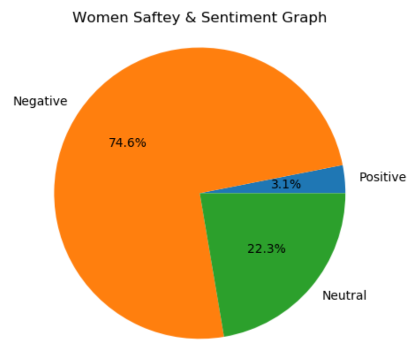

Fig. 7: Graphical representation of Women safety sentiment.

In Fig. 7, value of 0.74 multiplied by 100 gives a percentage of 74%, which indicates that 74% of residents feel that the neighborhood is unsafe, but just 22% and 3% of residents feel that the neighborhood is about the same. Figure 6 presents the tweet status with sentiment and its authenticity as FAKE or GENUINE by using decision tree algorithm.

Table. 1: Performance comparison.

Model	Accuracy (%)
KNN [12]	63.6363
Random forest [13]	70.1298
SVM [15]	74.6753
Naive bayes [18]	75.3246
ANN [19]	59.0909

5. CONCLUSION

One of the most significant challenges that women face in any community is the prevalence of sexual harassment and assault. In addition, the women's private lives are negatively impacted because of the bullying and abusive information that is displayed in OSN. As a result, it is essential to determine whether or not the OSN environment is safe for women. The standard approaches were not successful in predicting the maximum safety analysis. Therefore, the WSP-DT classifier is the primary focus of our study. At first, it is thought that the Twitter dataset would be used to build the whole system. After that, the dataset will be pre-processed to get rid of any unknown or missing symbols. Following that, NLTK was applied to tweets in order to accomplish the tasks of tokenization, conversion to lowercase, detection of stop words, stemming, and lemmatization. Then, a text blob protocol is built to detect the feelings of tweets that have already been pre-processed. This protocol determines the positive, negative, and neutral polarities of tweets. In addition, TF-IDF is used in order to extract the data characteristics based on the frequency of individual words and characters. In the end, a decision tree classifier was used to determine whether a tweet was phony or authentic based on the previous multi-level training. The simulations that were run on the Twitter dataset reveal that the suggested WSP-DT classifier produced better results than the other approaches when compared to those results.

Throughout the whole of this research work, we have spoken about a wide range of machine learning techniques. These algorithms can provide us with assistance in organising and analysing the vast quantity of data that we have gotten from Twitter. This data consists of the millions of tweets and text messages that are exchanged on a daily basis. These techniques of machine learning are highly effective and beneficial when it comes to the processing of enormous volumes of data. This comprises the SPC method and strategies based on the linear algebraic Factor Model. Both of these assist in further classifying the data into appropriate categories and are included below. In the process of collecting meaningful information from Twitter and acquiring an idea about the present scenario surrounding the safety of women in metropolitan areas in India, support vector machines are yet another sort of machine learning technique that is very popular.

Future Enhancement

Because this study is just focusing on Twitter, there is a possibility that in the not-too-distant future we may be able to extend the applicability of these machine learning algorithms to other social media platforms. Twitter is the only platform currently being considered for this study. Facebook and Instagram are two examples of these websites. It is possible that the current concept, which is being supplied, will be included into the user experience of the Twitter programme. This would allow Twitter to reach a wider audience and do sentiment analysis on millions of tweets in order to provide further safety.

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