WOMEN SAFETY INDIAN CITIES USING MACHINE LEARNING ON TWEETS

M.Pradeep Kumar[1]., Jillapalli Sirivennela[2].,Kodimala Ruchitha[3].,Mekala Ala[4].,Shaik Greeshma[5]

1 Assistant Professor, Department Of CSE., Malla Reddy College Of Engineering For Women., Maisammaguda.,
Medchal.,Ts, India (pradeepit09@gmail.com)
2, 3, 4, 5 B.Tech CSE, (19RG1A0579, 19RG1A0587, 19RG1A0599, 19RG1A05B3),
Malla Reddy College Of Engineering For Women., Maisammaguda., Medchal., Ts, India

ABSTRACT:

Stalking is only the beginning of a pattern of public violence and harassment against women and girls that often culminates in verbal or physical abuse in certain locations. This study primarily examines how social media platforms like Twitter, Facebook, and Instagram may be used to improve the security situation for women in major Indian cities. This study also explores methods for fostering social responsibility among ordinary Indians, which is necessary if we are to ensure the physical security of Indian women. Tweets, which often include photos and text as well as written words and quotations, may be used to send a message among the Indian Youth Culture and educate people about the need of taking strong action against individuals who harass women in Indian cities. Twitter and other Twitter handles, including hash tag messages that are widely disseminated across the globe, sir as a platform for women to express their views on how they feel while we go out to work or travel in public transportation, on what is the state of their mind when they are surrounded by unknown men, and on whether these women feel safe or not.

INTRODUCTION

Staring and casual remarks are examples of the passive-aggressive forms of harassment and violence that are unfortunately accepted as part of city life. Several studies have been done in different cities in India, and they all find that women experience the same kinds of sexual harassment and passing off from strangers. Sixty percent of Indian women report feeling dangerous while using public transportation or going out alone for work, according to a research done in three of the country's most populous metropolitan areas: Delhi, Mumbai, and Pune. Whether it's to a center of learning or somewhere else, women have the right to the city and may travel anytime they like. Women, however, often report feeling threatened and dangerous when walking through public venues like shopping malls and other public places on their route to and from work. The primary motivation for harassing girls is the perceived lack of danger or the absence of real-world repercussions for women. It's not uncommon for girls to be sexually harassed by neighbors on the way to school or for a lack of safety to instill a sense of fear in the minds of young girls. These experiences can leave a lasting impact on these girls, who may never fully recover from the trauma of being coerced into doing something they knew was wrong or of being the target of sexual harassment. Safest cities consider women's security from the point of view of women's rights to participate fully in city life without experiencing sexual harassment or assault. It is the responsibility of society to address the need of protection of women and also acknowledges that women and girls also have a right same as men have to be safe in the City, rather than placing limits on women that society generally imposes. Twitter messages have been analyzed to reveal the identities of men and women who have spoken out against sexual harassment and unethical behavior by males in Indian cities. For the purpose of obtaining a clear and original view of the safety status of women in Indian society, we ran the data set obtained through Twitter through machine learning algorithms to smooth it out by getting rid of zero values and removing re tweets and redundant data using Laplace's and Porter's theories on data analysis. More than 500 million tweets (microbiology posts) are created every day on Twitter, making it the largest social network of its kind in the world. Twitter's large user base has encouraged its members to share their opinions on any and all topics covered online, making the service a valuable resource for businesses, government agencies, and other groups of any kind. In the tweets part of Twitter, people will express their thoughts and perspectives.

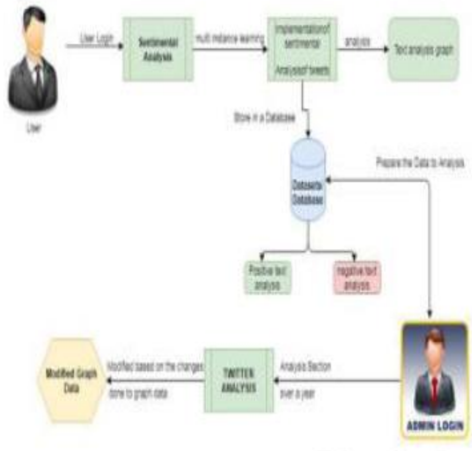

Fig.1: Example figure

Users are forced to condense their communications with the use of acronyms, slang, shot forms, emoticons, etc., since each tweet may only include 140 characters. Polysemy and sarcasm are two more methods by which many individuals express their ideas. Therefore, we can classify the language used on Twitter as informal. The mood of the original tweet is determined. The process of sentiment analysis is used to obtain the desired information.

REVIEW OF AVAILABLE WORK

Using lexical affect scores and syntactic n-grams, we conduct a polarity analysis at the phrase level. We provide a classifier that can determine the subjective polarity of a statement based on its context. With our method, we can automatically score the vast majority of words in our input without resorting to manual labeling thanks to the lexical scoring derived from the Dictionary of Affect in Language (DAL) and expanded through Word Net. To account for the impact of context, we supplement lexical score using n-gram analysis. We take all of the sentences in the corpus and use a combination of DAL scores and syntactic elements to extract n-grams of constituents. The polarity of each syntactic element in the phrase is also taken into account. Both a majority-class and a more challenging lexical n-grams baseline are significantly outperformed by our findings.

Twitter sentiment analysis that can withstand biased and noisy data:

In this research, we offer a method for the automated detection of feelings in tweets by examining the linguistic and meta-informational properties of tweets. We also use noisy label sources as a kind of training data. Several sentiment detection websites over Twitter data provided these noisy labels. Our results demonstrate that our method outperforms prior attempts and is more resilient to skewed and noisy data, as is typical of the sort of data offered by various sources, since our features are able to capture a more abstract description of tweets.

Sentiment classification of customer feedback data: the importance of language analysis, the challenges of noisy data, and the size of feature vectors

We show that even in the very noisy area of customer feedback data, automated sentiment categorization is achievable. We demonstrate how to train linear support vector machines with good classification accuracy on data that presents classification issues even for a human annotator by employing large feature vectors in conjunction with feature reduction. We also demonstrate that, unexpectedly, a collection of surface-level word n-gram features supplemented with deep linguistic analysis features improves classification accuracy in this area.

A Python-based study on machine learning techniques for analyzing Twitter sentiment:

Twitter is a popular medium for individuals to share their thoughts and feelings on a variety of topics and events. The goal of sentiment analysis is to discover the underlying emotion in a body of data. Sentiment analysis is used to data from Twitter (tweets) to derive user emotions. The number of studies conducted in this area has steadily increased over the last several decades. This is because digesting tweets is tough due to their demanding format. Due to its compact nature, the tweet format introduces new challenges, such as the increased prevalence of slang and abbreviations. In this study, we will discuss an extended Python-based methodology, as well as examine various publications pertaining to research in Twitter sentiment analysis, outlining the techniques employed and models utilized.

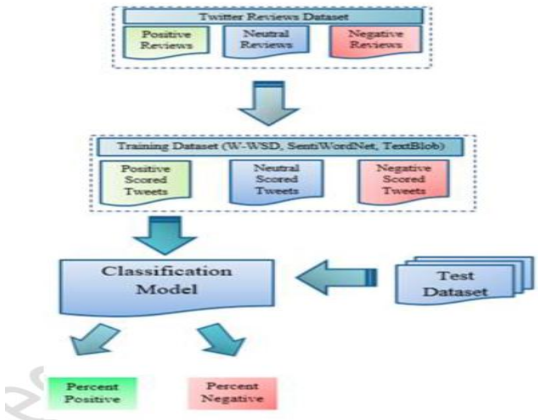

Fig.2: Twitter sentiment analysis.

Lexical affect scoring and syntactic n-grams for contextual phrase-level polarity analysis:

We provide a classifier that can determine the likely polarity of a sentence's subjective phrases based on its context. By including lexical scoring based on the DAL and enhanced by Word Net, we are able to automatically score the overwhelming majority of terms in our input without resorting to laborious human labeling. To account for the impact of context, we supplement lexical score using n-gram analysis. After extracting n grams of syntactic elements from each sentence, we integrate DAL scores with them. The polarity of each syntactic element in the phrase is also taken into account. Both a majority-class and a more challenging lexical n-grams baseline are significantly outperformed by our findings.

Twitter sentiment analysis with biased and noisy data

In this research, we offer a method for the automated detection of feelings in tweets by examining the linguistic and meta-informational properties of tweets. In addition, we use noisy label sources as our training data. Several sentiment detection websites over Twitter data provided these noisy labels. Our results demonstrate that our method outperforms prior attempts and is more resilient to the kinds of skewed and noisy data that are offered by these sources because our features are able to capture a more abstract picture of tweets. Sentiment classification on customer feedback data: the importance of language analysis, noisy data, and big feature vectors We show that even in the very noisy area of customer feedback data, automated sentiment categorization is achievable. We demonstrate how to train linear support vector machines with good classification accuracy on data that presents classification issues even for a human annotator by employing large feature vectors in conjunction with feature reduction. We also demonstrate that, unexpectedly, a collection of surface-level word n-gram features supplemented with deep linguistic analysis features improves classification accuracy in this area.

APPLICATION

Concept for combining social media postings and machine learning algorithms to assess the security of women. The vast majority of individuals nowadays use some kind of social media to share their thoughts and emotions with others. If a woman has a poor experience in a certain location, she may communicate her concerns online. Women, however, often report feeling threatened and uncomfortable when walking through public venues like shopping malls on their route to work. Because the author of the proposed work uses the TWEEPY package of the Python programming language to retrieve tweets from Twitter, it is important that she feel safe and secure at all times. This application will analyze the tweets in order to identify the feelings of women. Author using NLTK (natural language toolkit) to clean up tweets by excluding unnecessary symbols and stop words. The author uses the TEXTBLOB corpora package and dictionary to determine the polarity of tweets, classifying those with a value of less than 0 as negative, those with a value of greater than 0 but less than 0.5 as neutral, and those with a value of greater than 0.5 as positive.

Advantages:

The names of men and women who speak out against the abuse, harassment, and unethical behavior of males in Indian cities that restricts their freedom of movement have been collected and analyzed from a collection of tweets. Second, the Twitter-collected data set on the security of Indian women.

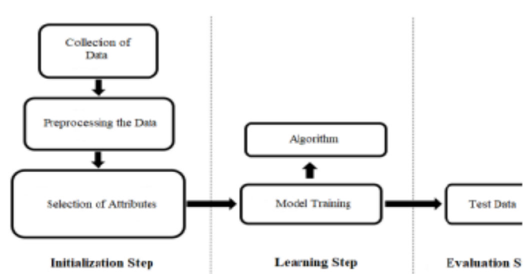

Fig.3: System architecture

MODULES:

In this section, we will learn how to upload datasets. Using this module, we can search for missing data and replace it with the mean or a value of 0 to clean the dateset. The data-set will be divided into training and testing halves using the •Train & Test Split module. To train a classifier, all machine learning algorithms need around 80% of the data, while the remaining 20% is utilized to evaluate how well the classifier predicts.

MACHINE INTELLIGENCE

To complete its mission, an AI system employs a machine learning algorithm, which, in most cases, predicts output values based on input data. Classification and regression are the two primary operations of machine learning algorithms. The two main types of machine learning (ML) algorithms are supervised and unsupervised. Data for both input and intended output is labeled for supervised learning algorithms, whereas unlabeled data is processed by unsupervised algorithms. For instance, an unsupervised algorithm may use similarities and differences to sort unsorted data into groups. Semi-supervised algorithms are more accurately used in various ML techniques, such as transfer learning and active learning. Active learning enables an algorithm to ask the user or another source for further information, whereas transfer learning applies knowledge obtained from one task to help tackle a separate but related issue. Both methods are frequently employed when labeled data is in short supply. To guide unsupervised machine learning, reinforcement learning (often considered a fourth category) uses incentives and punishments to incentive desired behaviors and discourage undesirable ones. The pros and cons of supervised and unsupervised learning Separate from these categories are the supervised and unsupervised varieties of machine learning algorithms. In supervised learning, you give the computer a set of examples that already have correct answers—for instance, a series of animal pictures labeled with their names. The trained model would be expected to accurately identify an unseen image (representing a species of animal included in the training set). In unsupervised learning, the algorithm is responsible for sifting through data and generating insights on its own. One possible outcome is groups of data points that have similarities among themselves. When there is no overlap between the clusters, that works well. Supervised learning algorithms are transformed into models via training and assessment by adjusting their parameters to reflect the data's true state as closely as possible. Stochastic gradient descent (SGD) is basically repeated runs of steepest descent from randomly chosen starting points and is often used as an optimizer in these algorithms. Common improvements to SGD include including momentum-based gradient direction correction or epoch-based progress adjustment to the learning rate.

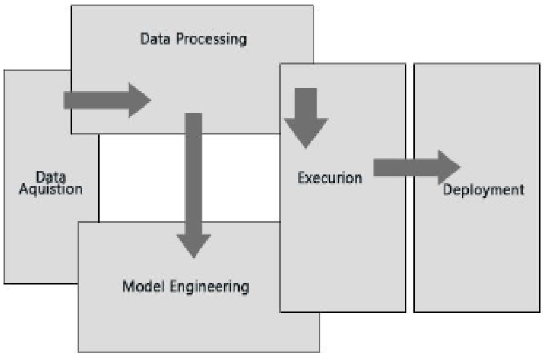

Fig.4: Machine learning algorithms process steps

From simple linear regression and logistic regression to complicated deep neural networks, machine learning algorithms come in a wide variety of degrees of complexity systems consisting of interconnected nodes and multi-model ensembles. Some of the most widespread algorithms, however, are:

- Linear regression, also known as least-squares regression (when dealing with numerical data),
- Logistic regression (used for categorizing data into two groups)
- Multi-category categorization using linear discriminant analysis.
- Classification and regression tree decisions
- Both Naive Bayes classifiers and regression models are completely naive.
- For both classification and regression, we recommend K-Nearest Neighbors, or KNN.
- (Classification and Regression) LVQ (Learning Vector Quantization)
- SVM (Support Vector Machines) are used for categorizing data into two groups.
- Random Forests are an ensemble approach (for both classification and regression) that uses a "bagging" technique.
- Boosting techniques, such as Ada Boost and Boost, are examples of ensemble algorithms that generate a sequence of models in which each subsequent model attempts to repair faults made by the prior model.

All this talk about neural networks and deep neural networks, where are they? You should only use them for specific issues like image classification and voice recognition that aren't well-suited to simpler methods since they tend to be compute-intensive to the point that they require GPUs or other specialist hardware. Keep in mind that the term "deep" refers to a neural network with numerous hidden layers

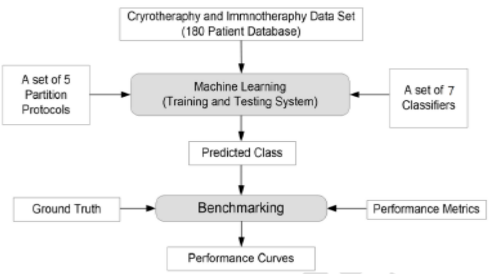

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Fig.5: Machine learning algorithms architecture

RESULTS OF EXPERIMENTS

Staring at women and making derogatory remarks are forms of aggression and harassment that are unfortunately common in urban settings. Numerous studies done in India have revealed the aforementioned instances of sexual harassment and other mistreatment of women. Many women in large urban centers like Delhi, Pune, Chennai, and Mumbai report feeling threatened by strangers, according to surveys. People in India are able to voice their opinions on a wide range of topics, from the country's politics and culture to their personal lives. Women who have experienced assault or sexual harassment may also speak out by sharing their stories, which unites the community to take a stance. Twitter's text analysis of user tweets reveals both the identities of males who have harassed women and the names of women and bystanders who have spoken out against men's unethical or violent behavior that has made it difficult for women to feel safe in public.

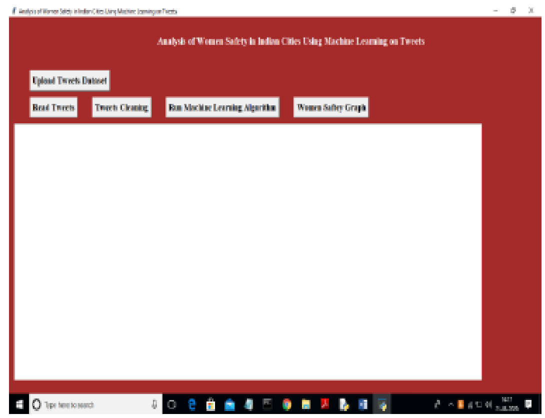

Fig.6: Home screen

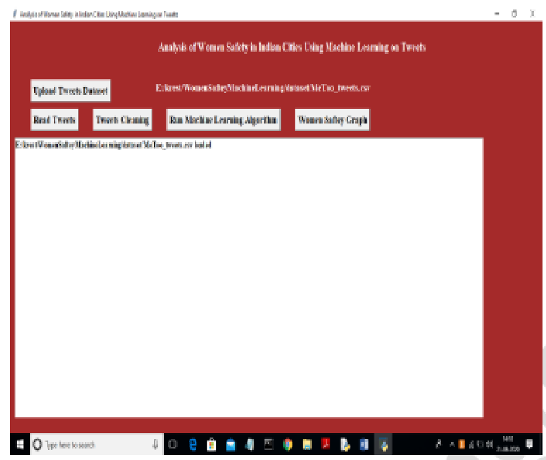

Fig.7: Data loading screen

Meet_tweets.csv file will be uploaded to the above page, and the 'Open' button will be clicked to load the dataset.

Fig.8: Read tweets

Each line in the window above represents a tweet, and you may see them all by scrolling down the text area of the window. In the aforementioned window, you can see all tweets that contain special symbols and stop words; to remove them, simply click the 'Tweets Cleaning' button.

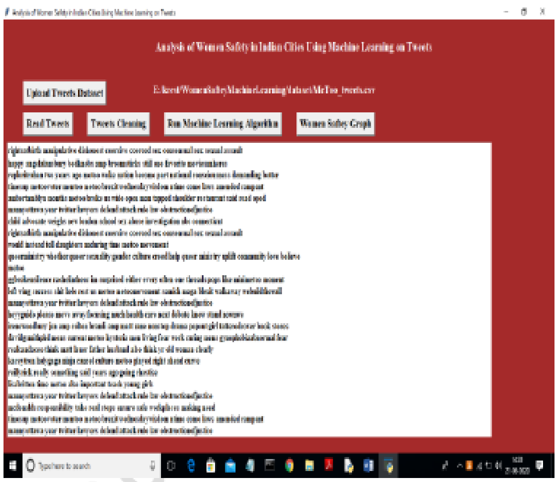

Fig.9: Tweet cleaning

All alphabetic characters and symbols are shown above. Once you've cleaned up your tweets by removing any stop words, you can use the 'Run Machine Learning Algorithm' button to see if your predictions matched the actual sentiments conveyed in the tweets.

Fig.10: Machine learning algorithm

On the previous screen, you can see the text of each tweet along with its sentiment and polarity score. To see all tweets, please scroll down above the text. After clicking the "Women's Safety Graph" button, the user will be able to quickly and easily determine if the area is safe for women. More individuals will congregate in a safe environment. Tweet either something good or neutral; if you can't, more people will focus on the bad.

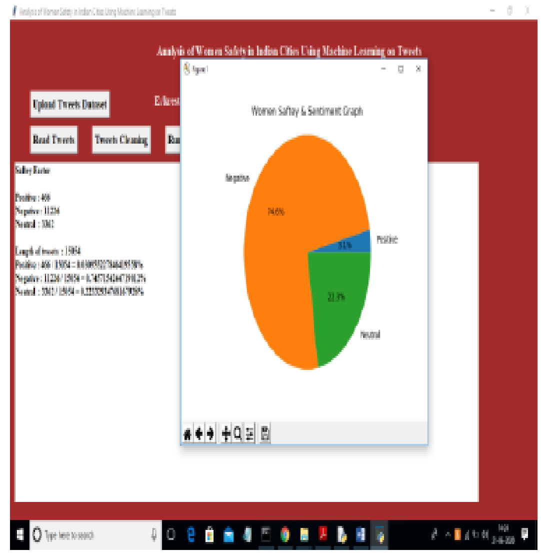

Fig.11: Women safety graph

Multiplying the percentage shown on the previous screen (0.74) by 100 indicates that 74% of respondents feel that the neighborhood is unsafe, while the remaining 22% and 3% express optimism.

Conclusion

In this article, we've covered a variety of machine learning techniques that may help us make sense of the millions of tweets and texts sent and received every day on Twitter. The SPC method and linear algebraic Factor Model techniques are two of the most powerful and helpful machine learning algorithms for evaluating vast amounts of data and classifying the results into meaningful categories. Another prominent machine learning technique for gleaning insights on the safety of women in Indian cities from Twitter is based on so-called support vector machines.

LONG-TERM IMPACT

Since only Twitter is considered in this project, there is room for expansion into applying these machine learning algorithms to other social media platforms in the future. The suggested philosophy of the present may be included into the user interface of the Twitter program to expand its reach and conduct sentiment analysis to millions of tweets in order to increase security.

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