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Women's Safety Analysis on social media using Machine Learning

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ABSTRACT

Some forms of harassment and violence, such as staring and making rude remarks, are considered typical in the modern city, even if they constitute a violation of civil liberties. To go anywhere in the city, whether it's to an educational institution or any other place ladies desire, is completely within their rights as citizens of the city. Because of the many unknowns in areas like malls and shopping centres, women believe they are at risk while making their way to work. These women's bodies are shamed and harassed by these men's eyes. Harassment of females occurs for a variety of reasons, chief among them being a lack of safety or the absence of tangible consequences.

The names of men and women who speak out against sexual harassment and other unethical behavior by men in Indian cities are also included in the analysis of the tweets collected from Twitter. It was decided to smooth the data by removing zero values and applying Laplace and Porter's theory, in order to develop a method of data analysis and remove retweet and redundant data from the data set that was obtained in order to provide an original and clear picture about the women safety. This is a similar study conducted by D. Kumar et al [11].

Keywords- Machine learning, women safety, social media, twitter.

1. Introduction

Many customers use social media like Twitter to share their thoughts, feelings, and assumptions with the rest of the world. Extraction of these tweets is possible, and they can be subjected to an extreme expressions test using comprehensive knowledge of how to determine the rating of female well-being in particular areas is possible as well. Tweeter, for example, is used by a significant number of customers to share their thoughts and feelings with the rest of the globe.

They can be easily deleted and put through an extreme trial of the phrases using deep understanding of how to rate female security in the specific territory in which they were posted. We used an API from tweeter to gather any tweets tagged with the hashtags "lady harassment" or "lady well-being" or terms like "lady harassments" or "lady security" that were posted on Twitter. After collecting all of the tweets, we separate them into datasets and prepare them for polarity before isolating them using our technique.

Investigations in the Emotion:

Extracting the emotional content of a remark or sentence is known as sentiment analysis. It's a method of classifying tweets that's employed to ascertain the public's thoughts. This point of view can be utilised to create a sentiment that can then be used to classify other people's feelings. Because each person's feelings on a subject are unique, we must decide what kind of specifications can be derived from them. In order to discover the class of entities in the tweets,

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the sentimental analyst uses a programming model. The algorithm's performance is heavily influenced by the sentimental class's size. For example, tweets can be divided into two categories based on their sentiment: positive and negative, or three categories: positive, negative, and neutral. Machine learning-based and lexicon learning-based approaches to sentimental analysis are the two primary categories of sentimental analysis. Extraction of features, programming model training using the dataset of features, is a part of the machine learning approach. While the lexicon-based approach relies on the vocabulary and scoring mechanism to identify viewpoints, We employ a machine learning strategy in this paper. The main phases in sentimental analysis are data collection, preprocessing, feature extraction, feature selection, sentiment detection, and sentiment classification utilizing machine learning algorithms or simple computations.

To find out where women are most at risk, researchers are analysing the posts, tweets, and messages that women leave on social networking sites to see where they are most likely to voice their fears and anxieties.

2. Methodology:

Social media can be utilized by malevolent people to boost the sales of products with phoney reviews or to raise suspicions about the country's safety for Indian women, which is the core problem of the proposed article.

An increasing number of women and girls are being harassed in public settings, starting with stalking and ending with sexual harassment or even sexual assault. For the most part, this study examines the role that social media plays in enhancing the safety of women in Indian cities, paying particular attention to Twitter, Facebook, and Instagram platforms.

These inappropriate behaviours, such as staring and making disparaging remarks, are often regarded as a regular part of daily life in urban areas. 1.6 Scope of work A number of studies have been carried out in cities all over India, and women report experiencing the same kind of sexual harassment and passing off comments from unknown people in each case. According to a research done in India's most populous metropolises, including Delhi, Mumbai, and Pune, 60% of women report feeling dangerous while leaving home for work or taking public transportation.

There are five chapters in the rest of the report, which are broken down into sections. Chap. 2 presents the survey of the existing system following this introductory chapter. This establishes a context for the current study in the subject of Sentimental Analysis of Women's Safety.

The suggested system is described in detail in Chapter 3. This begins with the introduction of the dataset and the models utilised in the report. After then, the structure of the suggested system is discussed. This section explains how the research was done, including the algorithms and tools utilised. This study's evaluation parameters are also described here.

The experiment and its outcomes are detailed in Chapter 4. The comparison graph and each model's confusion network are clearly visible. This allows us to determine which ML and DL algorithm-based model is the best effective for predicting stock market trends.

In Chapter 5, the results of all the models in this research report are summarised, and recommendations are provided for when to utilise each model. It provides a fresh path for the future.

To obtain tweets from Twitter, we used the TWEEPY programme from Python. However, because the Internet was unavailable, we downloaded the MEETOO tweets about women's safety and security and stored them in a dataset folder instead. In order to identify the feelings of women, an application will read this tweet.

Author uses NLTK (natural language tool kit) to clean up tweets by removing special symbols and stop words.

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A dictionary and corpus of texts from the TEXTBLOB corpus were used by the author to determine the polarity of tweets, with tweets with polarity values less than 0 being considered negative, tweets with values greater than 0 being considered neutral, and tweets with polarity values less than 0.5 being considered positive.

3. System Recommendations:

For the most part, this study examines the role that social media plays in enhancing the safety of women in Indian cities, paying particular attention to Twitter, Facebook, and Instagram platforms.

While utilising the TWEEPY python programme to get tweets from Twitter, the author's proposal calls for using MEETOO tweets about women's safety and security instead, which were downloaded and placed in the dataset folder because the INTERNET was unavailable at the time. Women's feelings will be detected by reading tweets through the application.

NLTK (natural language tool kit) is being used by the author to clean up tweets by removing special symbols and stop words.

3.1 Algorithms:

Sentimental analysis, TFIDF (term frequency inverse frequency document) and Decision Tree method are all employed in this investigation.

Feelings are analyzed in this section.

Step 1: First Things First: Get Things Going!

Step 2: Load the dataset in step 2.

Step 3: Eliminate stop words and other distracting elements from your tweets, such as repetitive letters.

When a word is compared to a positive or negative feelings word dictionary, the whole phrase's count is either increased or decreased accordingly.

To conclude based on the positive and negative counts, we can determine the polarity, which is classed into Positive, Negative, and Neutral.

As the name suggests, TF-IDF (term frequency-inverse document frequency) measures how important a word is in terms of the number of times it is used in a text. How many times a term is used in a document is multiplied by how many times the word is used in other documents. In this way, the average frequency of each tweet's words will be represented as a numeric vector.

3.2 Algorithm based on the Decision Tree

The goal is to create a model that can accurately predict a target value from simple decision rules derived from the available data. Using this strategy has the advantage of being simple to interpret and comprehend, as well as being capable of solving problems involving several outputs. For both regression and classification issues, Decision Trees are a typical supervised learning technique that can be used. Its purpose is to predict a target using simple decision rules derived from the dataset and its related attributes. There are two advantages to utilising this model: it is simple to read and can solve issues with various outputs; on the other hand, building overly complicated trees that lead to overfitting is a typical downside..

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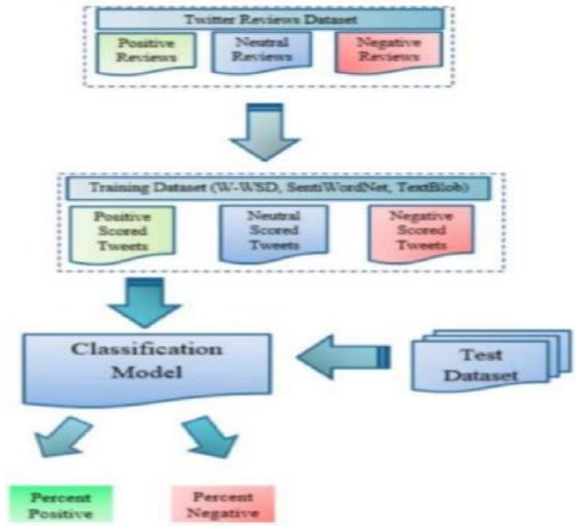

Fig-1 **Architecture/Framework**:

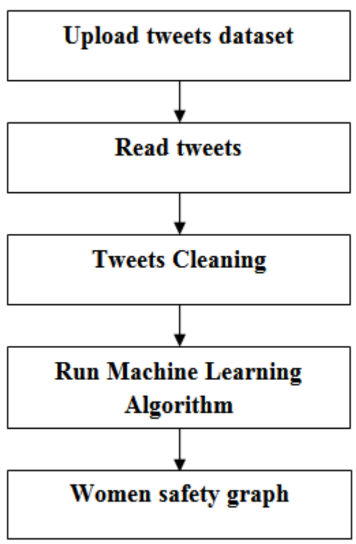

Fig-2 Algorithm and Process Design:

Using this module, we'll be able to upload a twitter dataset.

When we use this module, we'll see all of the tweets in our dataset, and we'll be able to detect if any of them contain special symbols or stop words, such as periods.

Special symbols and stop words can be removed from tweets using this module.

A machine learning algorithm is used to analyse tweets and present feelings with a polarity score based on the tweet's text.

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Graph 4 shows the results of employing this module in terms of women's safety. Outcomes and Methodology

Collection of data

While utilising the TWEEPY python programme to get tweets from Twitter, the author's proposal calls for using MEETOO tweets about women's safety and security instead, which were downloaded and placed in the dataset folder because the INTERNET was unavailable at the time. In order to identify the feelings of women, an application will read this tweet.

Terms associated with human emotions are incorporated into the language. Hybrid learning, the third strategy, combines machine learning and lexical learning in order to improve the classifier's performance.

Classification of Feelings:

The dataset is ready for categorization at this point. The tweet's subjectivity will be examined and an opinion formed based on each of the tweet's sentences. Sentences with subjective expressions are retained, whereas those with objective expressions are omitted. Techniques like metagrams, Negation and Lemmas, etc., are used at various levels of sentiment analysis. Negative and positive emotions can be categorised into two major groups: positive and negative. Each of the remaining subjective claims is graded as great, awful, like, dislike, or positive and negative at this level of sentimental analysis.

Text Blob (TEXTBLOB)

A dictionary and corpus of texts from the TEXTBLOB corpus were used by the author to determine the polarity of tweets, with tweets with polarity values less than 0 being considered negative, tweets with values greater than 0 being considered neutral, and tweets with polarity values less than 0.5 being considered positive.

In order to get the most useful and relevant information from raw data, sentiment analysis is required. Analyses can be presented in a variety of graph formats after the approach has been applied.

4. Sample Implementation code:

```
import tkinter
from textblob import TextBlob
from tkinter import *
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from string import punctuation
from nltk.corpus import stopwords


text.insert(END,'==================================================================
==============\n')
    if blob.polarity > 0.2 and blob.polarity <= 0.5:
      neu = neu + 1
      text.insert(END,tweet+"\n")
      text.insert(END,"Predicted Sentiment : NEUTRAL\n")
      text.insert(END,"Polarity Score      : "+str(blob.polarity)+"\n")
      text.insert(END,"Tweet Predicted As  : "+tweet_type+"\n")
```

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```
text.insert(END,'======================================================================
==============\n')
        if blob.polarity > 0.5:
            pos = pos + 1
            text.insert(END,tweet+"\n")
            text.insert(END,"Predicted Sentiment : POSITIVE\n")
            text.insert(END,"Polarity Score      : "+str(blob.polarity)+"\n")
            text.insert(END,"Tweet Predicted As  : "+tweet_type+"\n")

text.insert(END,'======================================================================
==============\n')
        text.update_idletasks()

def graph():
    label_X = []
    category_X = []
    text.delete('1.0', END)
    text.insert(END,"Saftey Factor\n\n")
    text.insert(END,'Positive : '+str(pos)+"\n")
    text.insert(END,'Negative : '+str(neg)+"\n")
    text.insert(END,'Neutral  : '+str(neu)+"\n\n")
    text.insert(END,'Length of tweets  : '+str(len(clean_list))+"\n")
    text.insert(END,'Positive : '+str(pos)+' / '+ str(len(clean_list))+' = '+str(pos/len(clean_list))+'%\n')
    text.insert(END,'Negative : '+str(neg)+' / '+ str(len(clean_list))+' = '+str(neg/len(clean_list))+'%\n')
    text.insert(END,'Neutral  : '+str(neu)+' / '+ str(len(clean_list))+' = '+str(neu/len(clean_list))+'%\n')
    label_X.append('Positive')
    label_X.append('Negative')
    label_X.append('Neutral')
    category_X.append(pos)
    category_X.append(neg)
    category_X.append(neu)
```

5. Outcome:

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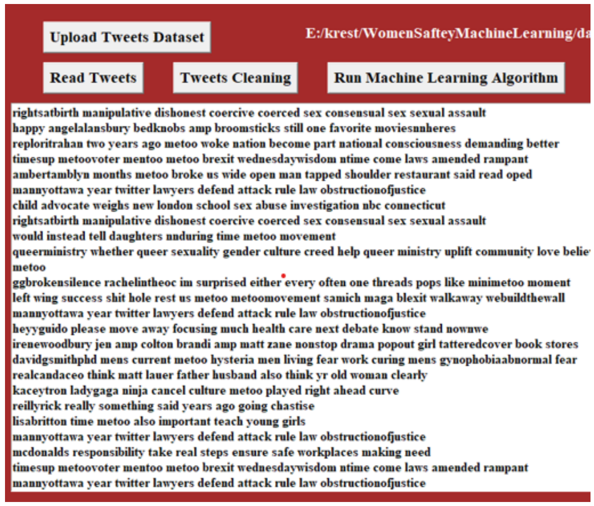

Fig-3 : Here we can see all special symbols and stop words remove from tweets and only clean words are there and now by using Machine Learning Algorithm' we predict sentiments from tweets.

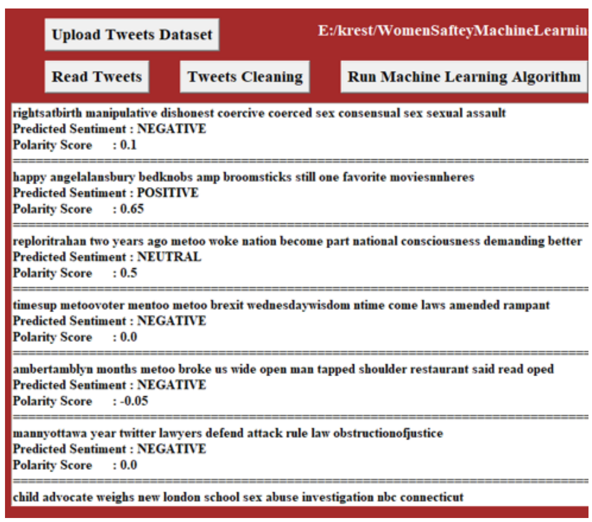

Fig-4: Here it is shown each tweet having tweet text and then displaying tweets sentiments with polarity score. Scroll down above text area to see all tweets.

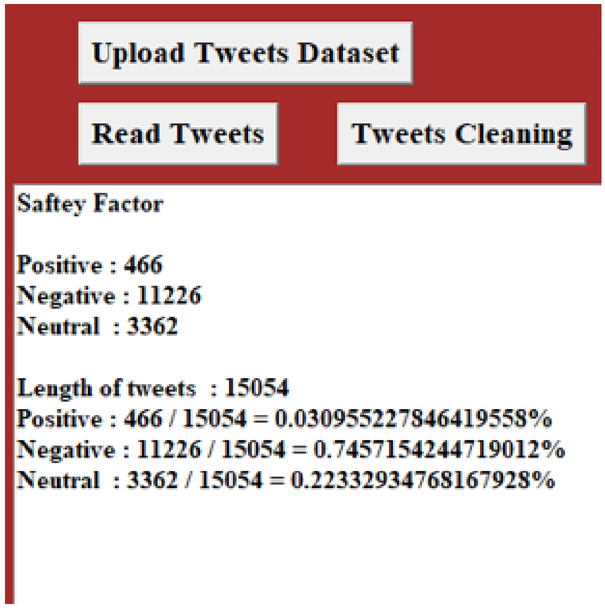

Fig-5: result user can easily understand whether area is safe or not.

If area is safe then more peoples will express either positive or neutral tweets and if not safe then more peoples will discuss negative tweets.

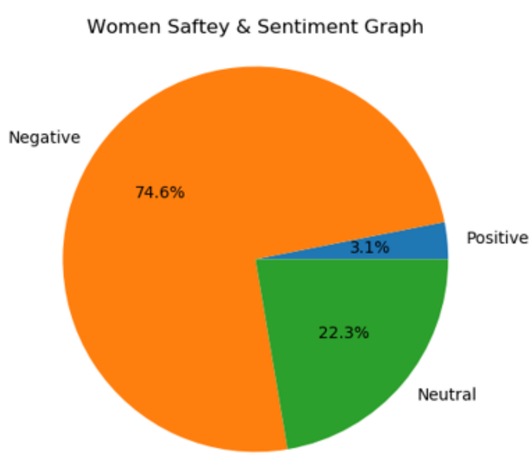

Fig-6: Women Safety and Sentiment Graph

Here 0.74 multiply by 100 will give 74% which means 74% peoples are talking negative and area is not safe and only 22 and 3% peoples are talking positive and neutral.

In propose paper author is analysing social media tweets to detect women's safety but the main problem is social media can be used by malicious users who will give fake ratings to worst products to boom their sale or can write fake tweets to raise finger at country safety towards Indian women and to overcome from this problem we have modified propose work with two algorithms which will check weather given tweets are fake or genuine. So by getting tweets authenticity peoples will comes to real conclusion on women safety.

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In extension work we have added TFIDF (term frequency inverse frequency document) algorithm which will convert all tweets words into numeric vector which will contains average frequency of each tweet words.

This TFIDF vector will be input to Decision Tree algorithm which will predict weather given tweet is FAKE or GENUINE. Decision Tree algorithm is already trained on FAKE and REAL words so it can easily predict authenticity of each tweet.

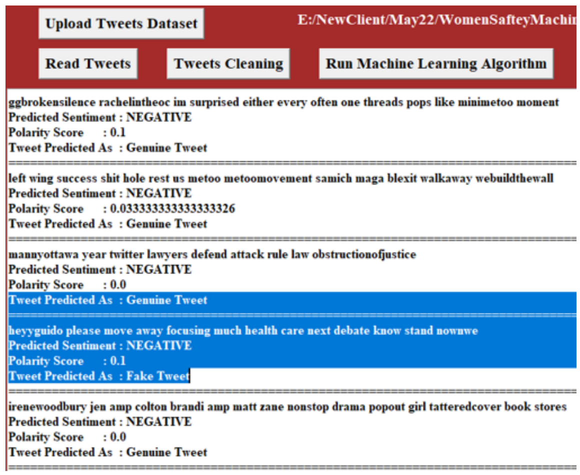

Fig-7: displaying tweets with sentiment and its authenticity as FAKE or GENUINE by using decision tree algorithm

CONCLUSION

The main problem with this approach is that social media can be exploited by malicious users who give false ratings to inferior products in order to boost sales or who write false tweets about national security in an attack on Indian women. To combat this issue, we've modified our proposal to include two algorithms that verify whether or not a given tweet is genuine. By verifying the validity of tweets, individuals can arrive to an informed conclusion on the safety of women. There is a new feature in our extension work that will transform all tweets words into a numeric vector that provides the average frequency of each word in each tweet. The Decision Tree algorithm will use this TFIDF vector to determine if a given tweet is FAKE or GENUINE. Each tweet's authenticity can be determined using a Decision Tree algorithm that has been taught to distinguish between fake and real terms.

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