IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Analysis of Women Safety in Indian Cities Using Machine Learning on Tweets

Author:
[1]Neha Kumari,
M.Tech. Scholar,
Department of Computer Science and Engineering,
School of Engineering,
Malla Reddy University,
Hyderabad, Telangana, India

Under the esteemed guidance of:
[2] Dr.G. Jose Moses,
Professor,
Department of Computer Science and Engineering,
School of Engineering,
Malla Reddy University,
Hyderabad, Telangana, India

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 sexual harassment or sexual 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 like X, Facebook and Instagram. This paper also focuses on how 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 X which usually contain 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 among the Indian Youth Culture and educate people to take strict action and public those who harass the women. X handle 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. Future research can enhance this work by employing advanced deep learning models for better sentiment detection, supporting multilingual analysis to cover regional perspectives, and developing real-time dashboards for law enforcement use. Integrating artificial intelligence with predictive analytics can further assist in forecasting potential safety risks and recommending preventive measures. In conclusion, this study underscores the importance of leveraging machine learning and social media analytics in assessing and improving women's safety in Indian cities. By analyzing public sentiment on social media, authorities can gain valuable insights into prevailing concerns and implement data-driven interventions. The findings contribute to the growing field of AI-driven public safety solutions and emphasize the need for continuous monitoring and policy enhancements to create safer urban environments for women in India.

Keywords- Sentiment Analysis, Women Safety, Sentiment Classification, Machine Learning

I. Introduction

1.1. INTRODUCTION TO WOMEN'S SAFETY

Safety Enterprises for women and girls both in private and public spaces are issues that are told by inter-sectional ties of gender, class, race, age, disability, sexual exposure, and religion. These enterprises manifest across a wide range of settings, including homes, requests, roads, transportation, workplaces, educational institutions, and more. They're eternalized by patriarchal morals and values that shape the actions and stations of both men and women.

Certain types of importunity and Violence are veritably aggressive including gaping and passing commentary and these inferior practices are generally seen as a normal part of civic life. There have been several studies that have been conducted in metropolises across India and women report analogous types of sexual importunity and passing off commentary by other unknown people. The study that was conducted across the most popular Metropolitan metropolises of India including Delhi, Mumbai, and Pune, showed that 60 of the women feel unsafe while going out to work or while traveling in public transport. Women have the right to the megacity which means that they can go freely whenever they want whether it be to an Educational Institute or any other place women want to go. But women feel that they're unsafe in places like promenades, and shopping promenades on their way to their job position because of the several unknown Eyes body smirching, and importunity these women point to Safety or lack of concrete consequences in the life of women the main reason of importunity of girls. There are cases when the importunity of girls was done by their neighbors while they were on the way to academy or there was a lack of safety that created a sense of fear in the minds of small girls who throughout their continuance suffer due to that one case that happed in their lives where they were forced to do commodity inferior or was sexually wearied by one of their neighbors or any other unknown person. Safest metropolises approach women's safety from the perspective of women's rights to affect the megacity without fear of violence or sexual importunity. Rather than assessing restrictions on women that society generally imposes it's the duty of society to squishy the need of the protection of women and also fete that women and girls also have a right same as men have to be safe in the City. Analysis of X textbooks collection also includes the names of people and names of women who stand up against sexual importunity and unethical gesture of men in Indian metropolises which make them uncomfortable to walk freely. The data set that was attained through X about the status of women's safety in Indian society was for the process through machine literacy algorithms to smoothen the data by removing zero values and using Laplace and Porter's proposition to develop a system of analysis of data and remove retweet and spare data from the data set that's attained so that a clear and original view of the safety status of women in Indian society is attained.

1.2. PROBLEM STATEMENT

Women's safety in Indian cities is compromised by various forms of violence and harassment. Traditional reporting methods are often ineffective in capturing real-time data and understanding public sentiment. The challenge is to analyze real-time data from social media to:

- Identify patterns and trends related to women's safety.
- Classify the nature of safety concerns using machine learning.
- Predict potential safety threats based on historical data.
- Provide actionable insights for policymakers and law enforcement.

1.3. X ANALYSIS

As People communicate and share their opinions actively on social media, including Facebook and X, social networks can be considered a perfect platform to learn about people's views and sentiments regarding different events. There exist several opinion-oriented information gathering and analytics systems that aim to extract people's opinions regarding different topics. Since X contains short texts, people tend to use different words and abbreviations. These phrases are difficult to extract their sentiment by current NLP systems easily. Therefore, many researchers have used deep learning and machine learning techniques to extract and mine the polarity of the phrases. As a large number of people have been attracted towards social media platforms like Facebook, X, and Instagram point and most people are using it to express their emotions and also their opinions about what they think about the Indian cities and Indian society. Using X analysis for business is kind of like getting a monthly X analytics report card. X analytics compiles all the behavior and actions audiences take when they come across your posts or profile clicks, follows, likes, expands, and breaks down that data to help you track performance.

Women Safety Analysis, often referred to as "X Analysis" in advanced socio-technological studies, is a comprehensive approach that integrates multiple analytical methods to understand, assess, and improve the safety of women in public and private spaces. This multidisciplinary framework brings together sentiment analysis, crime data analytics, geospatial intelligence, and predictive modeling to identify patterns, evaluate risk factors, and support the development of informed safety policies and real-time interventions.

The first pillar of X Analysis in women safety is Crime Data Analysis. This involves collecting structured datasets from police reports, national crime records, and city surveillance systems to study the frequency, type, and location of gender-based violence. Statistical techniques such as frequency distribution, correlation analysis, and temporal analysis help uncover crime hotspots, peak hours of incidents, and areas with recurrent safety concerns. For example, analyzing a city's last five years of harassment reports might reveal unsafe zones near transit hubs or isolated streets, especially during late evening hours.

Secondly, Sentiment Analysis using Natural Language Processing (NLP) techniques is critical in understanding public perception and lived experiences. Social media platforms, complaint forums, and review sites often serve as outlets for women to express safety-related concerns. Sentiment analysis can detect keywords like "unsafe," "harassed," or "followed," and classify them as negative or alarming content. This real-time monitoring enables authorities and city planners to respond proactively to emerging threats, even when incidents go unreported through formal channels.

Another core component of X Analysis is Geospatial Analysis. By mapping incident reports and complaints onto digital city maps using GIS tools, analysts can create heatmaps and cluster diagrams showing high-risk zones. This geospatial intelligence is valuable for the strategic deployment of security resources such as street lighting, emergency helpline booths, CCTV cameras, and patrolling units. For instance, if an analysis reveals repeated harassment complaints near a university campus, authorities can use that data to increase nighttime patrolling and install surveillance cameras.

Predictive Modeling is also vital in this analytical framework. Machine Learning algorithms such as decision trees, random forests, or neural networks can be trained on historical data to predict the probability of incidents in specific regions based on time, population density, and past crime trends. This allows for the development of early warning systems and mobile safety apps that alert users when they enter high-risk areas.

In addition to technical analysis, qualitative insights are integrated from community surveys and stakeholder interviews. This ensures that the data interpretation is contextual and grounded in real-world social dynamics.

In conclusion, X Analysis in Women Safety is not a single method but a fusion of analytical strategies that work in tandem to improve urban safety infrastructure, public awareness, and governance. Through real-time monitoring, predictive intelligence, and community feedback loops, this approach enables smarter, data-driven decisions aimed at creating safer environments for women across cities and communities.

1.4. Sentiment Analysis Using Machine Learning

Sentiment analysis, often referred to as opinion mining, is an intriguing field that leverages the capabilities of machine learning to comprehend and evaluate human emotions, attitudes, and viewpoints expressed in text data. In the fast-paced and dynamic digital world we live in, a vast amount of text is produced daily across diverse online platforms like social media, customer reviews, and feedback. For enterprises, researchers, and organizations, sentiment analysis has emerged as a crucial tool for gaining valuable insights into public sentiments and opinions. Understanding how people perceive and feel about products, services, or events has become essential in making informed decisions and staying ahead in this highly competitive landscape.

Using advanced language processing methods and machine learning algorithms, sentiment analysis can easily classify text into positive, negative, or neutral sentiments without any difficulty. This is accomplished by thoroughly examining patterns, contextual hints, and linguistic characteristics, empowering these models to accurately detect and evaluate the emotions expressed within the text.

Sentiment analysis can be categorized into several types, each with its own specific approach. For instance, document-level sentiment analysis aims to understand sentiments expressed throughout entire documents. On the other hand, sentence-level sentiment analysis hones in on individual sentences to grasp the emotions conveyed within them. Additionally, sub-sentence or phrase-level sentiment analysis delves into sentiments at a more granular level, providing a deeper understanding of the emotions behind smaller textual units.

2. LITERATURE SURVEY

2.1. Contextual phrase-level polarity analysis using lexical affect scoring and syntactic n-grams [1]

AUTHORS: Agarwal, Apoorv, FadiBiadsy, and Kathleen R. Mckeown.

We present a classifier to predict the 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 n-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.

2.2. Robust sentiment detection on Twitter from biased and noisy data [2]

AUTHORS: Barbosa, Luciano, and Junlan Feng

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. Moreover, we leverage sources of noisy labels as our training data. These noisy labels were provided by a few sentiment detection websites over Twitter data. In our experiments, we show that since our features can capture a more abstract representation of tweets, our solution is more effective than previous ones and also more robust regarding biased and noisy data, which is the kind of data provided by these sources.

2.3. Study of Twitter sentiment analysis using machine learning algorithms on Python [3]

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

Twitter is a platform widely used by people to express their opinions and display sentiments on different occasions. Sentiment analysis is an approach to analyzing data and retrieving the sentiment that it embodies. Twitter sentiment analysis is an application of sentiment analysis on data from Twitter (tweets), to extract sentiments conveyed by the user. In the past decades, the research in this field has consistently grown. The reason behind this is the challenging format of the tweets which makes the processing difficult. The tweet format is very small which generates a whole new dimension of problems like use of slang, abbreviations etc. In this paper, we aim to review some papers regarding research in sentiment analysis on Twitter, describing the methodologies adopted and models applied, along with describing a generalized Python-based approach.

2.4. Sentiment classification on customer feedback data: noisy data, large feature vectors, and the role of linguistic analysis [4]

AUTHORS: Gamon, Michael

We demonstrate that it is possible to perform automatic sentiment classification in the very noisy domain of customer feedback data. We show that by using large feature vectors in combination with feature reduction, we can train linear support vector machines that achieve high classification accuracy on data that present classification challenges even for a human annotator. We also show that, surprisingly, the addition of deep linguistic analysis features to a set of surface-level word n-gram features contributes consistently to classification accuracy in this domain.

2.5. Sentiment analysis of top colleges in India using Twitter data. [5]

AUTHORS: Mamgain, N., Mehta, E., Mittal, A., & Bhatt, G.

Sentiment analysis is used for identifying and classifying opinions or sentiments expressed in source text. Social media is generating a vast amount of sentiment rich data in the form of tweets, status updates, blog posts etc. Sentiment analysis of this user generated data is very useful in knowing the opinion of the crowd. Due to the presence of slang words and misspellings, twitter sentiment analysis is difficult compared to general sentiment analysis. Sentiments from the source text will be analyzed by using a machine learning approach. Mining opinions and analyzing sentiments from social network data which will help in several fields such as even prediction, analyzing overall mood of public on a particular social issue. The accuracy of classification can be increased by using Natural Language Processing (NLP) Techniques. We present a new feature vector for classifying the tweets as positive, negative, neutral and undefined. The mined text information is subjected to Ensemble classification to analyze the sentiment. Ensemble classification involves combining the effect of various independent classifiers on a particular classification problem. Multi-Layer Perceptron (MLP) is used to classify the features extracted from the reviews. A Decision Tree-based Feature Ranking is used for feature selection. Based on Manhattan Hierarchical Cluster Criterion the ranking will be done.

3. SYSTEM ANALYSIS

This chapter discusses the theories and some background study on Analysis of Women Safety in Indian Cities Using Machine Learning on Tweets

3.1. EXISTING SYSTEM

People often express their views freely on social media about what they feel about Indian society and the politicians who claim that Indian cities are safe for women. On social media websites, people can freely express their viewpoint and women can share their experiences where they have faced abuse harassment or where they would have fought back against the abuse harassment that was imposed on them. The tweets about the safety of women and stories of standing up against abuse and harassment further motivate other women to 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 an unsafe place for the women. In recent years a large number of people have been attracted to 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 Twitter analysis and prediction accuracy can be obtained by using behavioral analysis based on social networks.

3.2. DISADVANTAGES OF EXISTING SYSTEM

- X and Instagram point out that most people are using it to express their emotions and also their opinions about what they think about the Indian cities and Indian society.
- Several methods of sentiment can be categorized like machine learning hybrid and lexicon-based learning.
- Also, there is another categorization Janta presented with categories of statistical, knowledge-based, and age-wise differentiation approaches

3.3. PROPOSED SYSTEM

Women have the right to the city which means that they can go freely whenever they want whether it be to an Educational Institute or any other place women want to go. But women feel that they are unsafe in places like malls, and shopping malls on their way to their job location because of the several unknown Eyes body shaming, and harassment these women point to Safety or lack of concrete consequences in the life of women the main reason of harassment of girls. There are instances when their neighbours did the harassment of girls 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 abused harassed by one of their neighbor or any other unknown person. Safest cities approach women's safety from the perspective of women's rights to affect the city without fear of violence abuse harassment. Rather than imposing restrictions on women that society usually imposes it is the duty of society to imprecise the need of the protection of women and also recognize that women and girls also have a right same as men have to be safe in the City.

3.4. ADVANTAGES OF PROPOSED SYSTEM

- Analysis of X texts collection also includes the names of people and names of women who stand up against abuse harassment and unethical behavior of men in Indian cities which make them uncomfortable to walk freely.
- The data set that was obtained through X about the status of women's safety in Indian society.

4. SYSTEM DESIGN AND IMPLEMENTATION

4.1. SYSTEM REQUIREMENTS

Hardware Requirements:

- System : Pentium i3 Processor.
- Hard Disk : 500 GB.
- Monitor : 15’’ LED
- Input Devices : Keyboard, Mouse
- Ram : 4 GB

Software Requirements:

- Operating system : Windows 7 Ultimate/8/10/11
- Coding Language : Python 3.7.1
- Python Modules : numpy, Pandas, scikit-learn, matplotlib, Pillow
- Web Framework : Flask
- Frontend : Tkinter API
- Dataset : TwitterData.csv (www.kaggle.com)

4.2. SYSTEM ARCHITECTURE

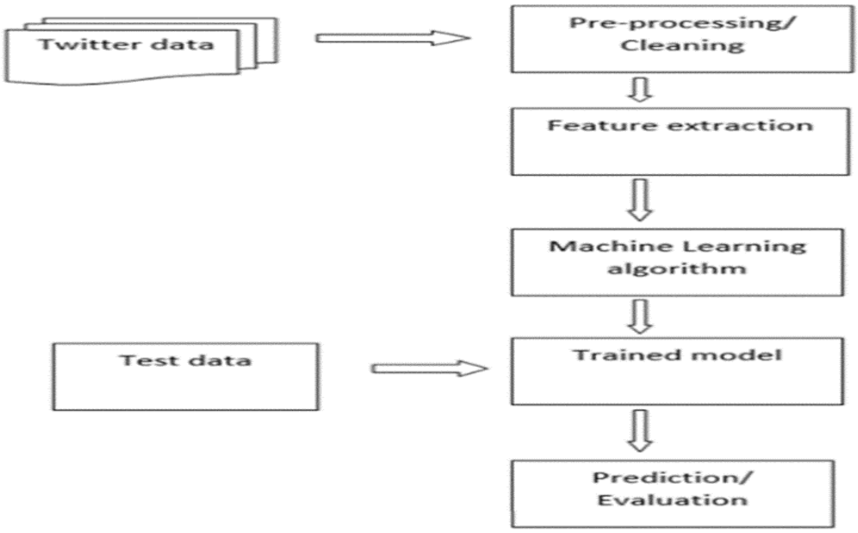


Figure 7. Overview Architecture

Every user data such as credentials, new tweets, re-tweets and tweet score will be stored in the database for the admin to monitor and perform the analysis. The sentiment analysis is applied on the user data in order to monitor and confirm whether any tweets are abusive to women or not. Admin performs this analysis on each and every user tweet to provide safety for the women. Sentimental analysis will be implemented on the tweets of user that are stored in the database. Admin can now prepare the data to perform the analysis. The tweets made by every user of the application will be called as the initial input for the sentiment analysis and hence they will be the dataset. Along with this, text analysis graph can also be shown. Admin will store the filters in the database. Filters are the keywords for which the tweet context will be searched for in order to declare as abusive or not. There can be two types of filters – positive keyword and negative keyword. Positive keywords are those words which are abusive or disrespect the women by any means. Negative keywords are the words which are normal and will not abuse the women.

There can be 'n' number of positive and negative keywords stored in the database. When the admin implements the sentimental analysis, every keyword in the database will be compared with each and every word in the tweet of the user. If any one of the positive keywords is found in the tweet, that tweet will be classified as positive sentimental analysis and these are abusive to women. If negative keyword is found in the tweet, it will be classified as the negative sentimental analysis which is not abusive to women. Hence, by this stage there will be two types of sentimental analysis made based on the filter in the database. Under positive sentimental analysis, there will be a list of all the tweets in the application that are abusive to women. Similarly, under negative sentimental analysis there will be a list that is clean and are not abusive tweets. Along with the tweet context, user details will also be provided at each of the analysis list.

Analysis of twitter texts collection also includes the name of people and name of women who stand up against sexual harassment and unethical behavior of men in Indian cities which make them uncomfortable to walk freely. The data set that was obtained through X about the status of women safety in Indian society was for the processed through machine learning algorithms for the purpose of smoothening the data by removing zero values and using Laplace and porter's theory is to developer method of analyzation of data and remove retweet and redundant data from the data set that is obtained so that a clear and original view of safety status of women in Indian society is obtained.

4.3. SYSTEM IMPLEMENTATION

The process of obtaining the sentiments of tweet includes following steps:

- Data Collection
- Data extraction
- Data Cleaning
- Machine Learning Algorithm
- Sentiment Analysis
- Sentiment Classification
- Output Presentation

4.3.1. Data Collection

- In the first module of the Analysis of Women Safety in Indian Cities Using Machine Learning on Tweets, we make the data collection process. This is the first real step towards the real development of a machine learning model, collecting data. This is a critical step that will cascade in how good the model will be, the more and better data that we get, the better our model will perform
- There are several techniques to collect the data, like web scraping, manual interventions. The dataset is located in the dataset folder. The dataset is referred to from the popular dataset repository called Kaggle. The following is the link of the dataset:
- Kaggle Dataset Link: https://www.kaggle.com/datasets/sudhanvahg/indian-crimes-dataset

4.3.2. Data Extraction

In this project, data is extracted from X to gather public opinions, incidents, and discussions surrounding women's safety in Indian cities. Using the X API and tools like Tweepy (a Python library), tweets are collected by searching for relevant keywords such as **"women safety," "harassment," "unsafe city," "rape,"** and other related terms. Filters like language (English), location, and date range can be applied to narrow the dataset. The extracted data typically includes:

- Tweet text
- Timestamp
- User location
- Hashtags and mentions

This unstructured data is saved in a structured format (e.g., CSV, JSON) for further processing like cleaning, sentiment analysis, and visualization.

4.3.3. Data Cleaning

Data cleaning is the process of preparing raw X data for analysis by removing noise and irrelevant elements. Tweets often contain URLs, mentions, hashtags, emojis, numbers, and inconsistent text formats that can negatively impact the performance of machine learning models. Cleaning ensures that only meaningful, standardized, and analysable text remains.

Key Steps in Data Cleaning:

- **Lowercasing:** Converts all text to lowercase to maintain consistency.
- **Removing URLs:** Eliminates links that do not contribute to sentiment or topic analysis.
- **Removing Mentions and Hashtags:** Strips out `@usernames` and # symbols to clean the content.
- **Removing Punctuation and Special Characters:** Gets rid of non-alphanumeric characters to reduce noise.
- **Removing Numbers:** Removes digits unless contextually important.
- **Tokenization:** Breaks down sentences into individual words.
- **Stop word Removal:** Removes common words like "is", "the", "in" that carry minimal meaning.
- **Lemmatization/Stemming:** Reduces words to their root form for uniformity (e.g., “walking” → “walk”).

After cleaning, tweets are transformed into structured, simplified text suitable for sentiment analysis or classification.

4.3.4. Machine Learning Algorithm

In this technique the following functions will work which describe below.

- Click on “Upload Twitter Dataset” button, initially the given TwitterData.csv file will be uploaded to the application successfully.
- Apply “Data preprocessing” module. Preprocessing is the process of doing a pre-analysis of data, in order to transform them into a standard and normalized format. It Identify, Drop and replace the missing values.
- Apply “Feature Extraction” module, it identifying and extracting relevant features (columns) from raw data.
- Apply “Feature Classification” module, it splits the structured dataset (100%) into two parts. Those are train dataset (90%) and test dataset (10%). it follows scikit-learn python library.
- Apply Support Vector Machine algorithm; it contains business logic to predict the result. It takes the input like train dataset and test dataset. It follows scikit-learn python library. It finds the overall accuracy (in terms of Performance) of the algorithms. To calculate the accuracy, firstly we need to generate Performance metrics’ (Like Precision, Recall, f1-score, support). To calculates the

Performance metrics', firstly we need to generate confusion matrix (it provides TP, TN, FP, FN Values)

4.3.5. Sentiment Analysis

Sentiment analysis is a Natural Language Processing (NLP) technique used to determine the emotional tone behind a body of text. In the context of this project, sentiment analysis is applied to tweets related to women's safety in Indian cities. The goal is to classify each tweet as **positive**, **negative**, or **neutral**, based on the user's opinion or emotional expression.

This is achieved by pre-processing the tweet text and then using machine learning models (like Logistic Regression, SVM, or LSTM) to analyze the linguistic features of the text. The model learns to recognize patterns in word usage that indicate sentiment. For example:

- Tweets describing harassment or unsafe experiences are marked as **negative**.
- Tweets promoting safety initiatives or positive experiences are marked as **positive**.
- Informative or general tweets without strong emotion are marked as **neutral**.

The output of sentiment analysis helps in identifying emotional trends, high-risk areas, and public reactions, providing valuable insights for policymakers and safety authorities.

4.3.6. Sentiment Classification

Sentiment classification is the process of categorizing text into predefined sentiment categories—typically **positive**, **negative**, or **neutral**. In this project, sentiment classification is applied to tweets about women's safety in Indian cities to understand public emotions and concerns.

After cleaning and pre-processing the tweet text, machine learning models such as **Support Vector Machine (SVM)**, **Random Forest**, or **Deep Learning (LSTM)** are trained to detect sentiment patterns in the data. These models analyze features like word frequency, context, and polarity to assign a sentiment label to each tweet.

For example:

- **Positive** sentiment: "The new women's helpline is very helpful."
- **Negative** sentiment: "I don't feel safe walking alone at night in Delhi."
- **Neutral** sentiment: "A women's safety seminar was held today."

Sentiment classification helps uncover trends in public perception, identify areas of concern, and support proactive decision-making by authorities.

4.3.7. Output Presentation

To generate useful and meaningful information out of the raw data, sentimental analysis plays vital role. Once the algorithm is completed, the outcome of the analysis can be visualized by creating different types of graphs. Bar graphs, Time series and Pie charts are some of the examples which can be used to display the output. To measure the sentiment of the tweets in terms of Positive and Negative, Bar graphs can be used. Similarly, to measure in terms of likes, dislikes, average length of tweet for a certain period, Time series can be used. To obtain the initial source of the tweet, pie charts can be used.

5. RESULTS AND DISCUSSION

5.1. Web output for Analysis of Women Safety in Indian Cities Using Machine Learning on Tweets

5.1.1. Select the Dataset and Upload

Click on "Upload X Dataset" button, initially the given TwitterData.csv file will be uploaded to the application successfully.

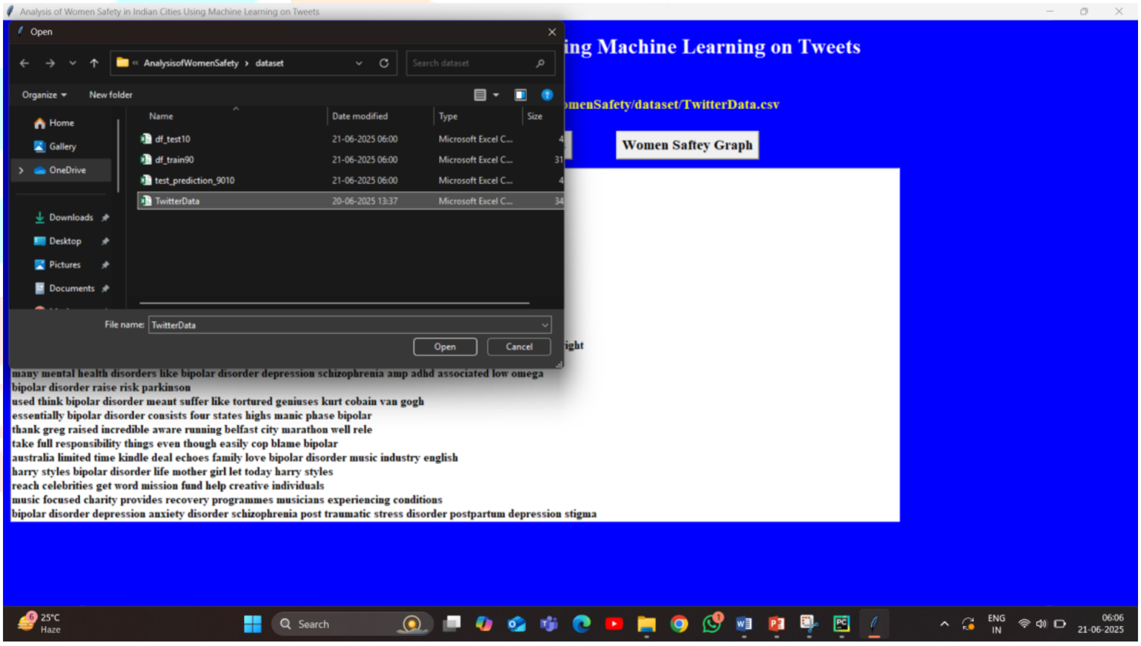


Figure 8: Select the Dataset and Upload

5.1.2. Tweets Cleaning

During the data Cleaning stage, once the data is extracted from the X source as datasets, this information has to be passed to the classifier. The classifier cleans the dataset by removing redundant data like stop words, emoticons in order to make sure that non-textual content is identified and removed before the analysis.

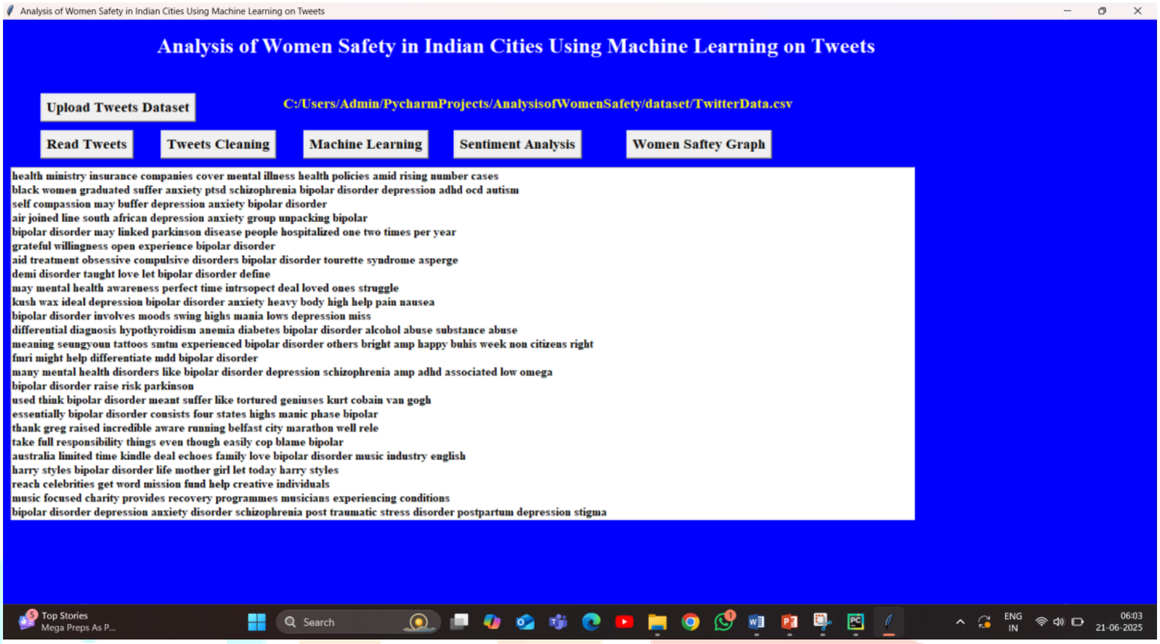


Figure 9: Tweets Cleaning

5.3.3. *Run Machine learning Algorithm*

Running a machine learning algorithm involves training a model on pre-processed data to perform tasks like sentiment classification. In this project, the cleaned tweets are transformed into numerical features using techniques like TF-IDF or word embeddings, and then fed into algorithms such as:

- **Logistic Regression**
- **Support Vector Machine (SVM)**
- **Random Forest Classifier**

The model learns patterns from labelled tweet data (positive, negative, neutral) and uses this knowledge to predict the sentiment of new, unseen tweets. After training, the model is evaluated using metrics like **accuracy**, **precision**, **recall**, and **F1-score** to ensure its effectiveness. The final model helps automate large-scale sentiment analysis of tweets related to women's safety.

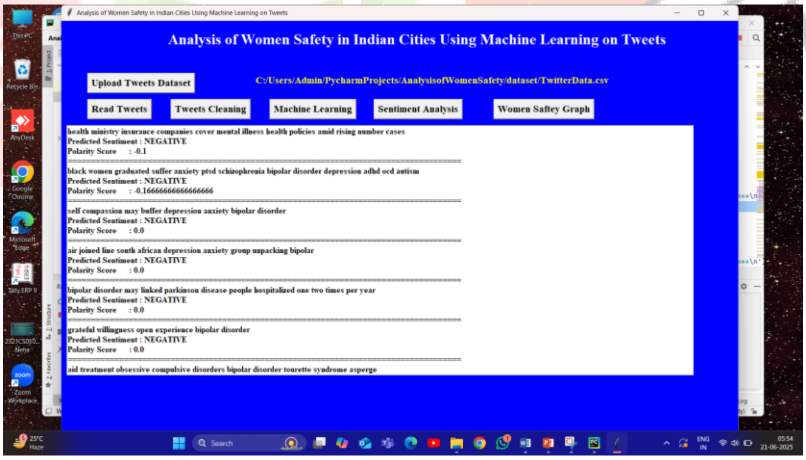
Figure 10: Run Machine Learning Algorithm

5.1.3. *Sentiment analysis (Extract X Sentiment)*

Sentiment Analysis (Extract X Sentiment) involves identifying and classifying emotions or opinions in text. In short:

- Input: Cleaned tweets or text data.
- Processing: Use a trained machine learning or NLP model.
- Output: Classify sentiment as Positive, Negative, or Neutral (X sentiment).

This helps understand public opinion, customer feedback, or social trends based on textual data.



5.1.4. *Sentiment Classification*

At this step, the dataset is ready for classification. Every sentence of the tweet will be examined, and an opinion will be formed accordingly for subjectivity. Subjective expression sentences are retained, and those of objective expression sentences are rejected. Techniques like Unigrams, Negation, Lemmas, and so on are used at different levels of sentiment analysis. Sentiments can be distinguished broadly into two groups – Positive and Negative. At this point of sentimental analysis, each of the subjective sentences that will be retained are classified into good, bad or like, dislike or positive and negative.

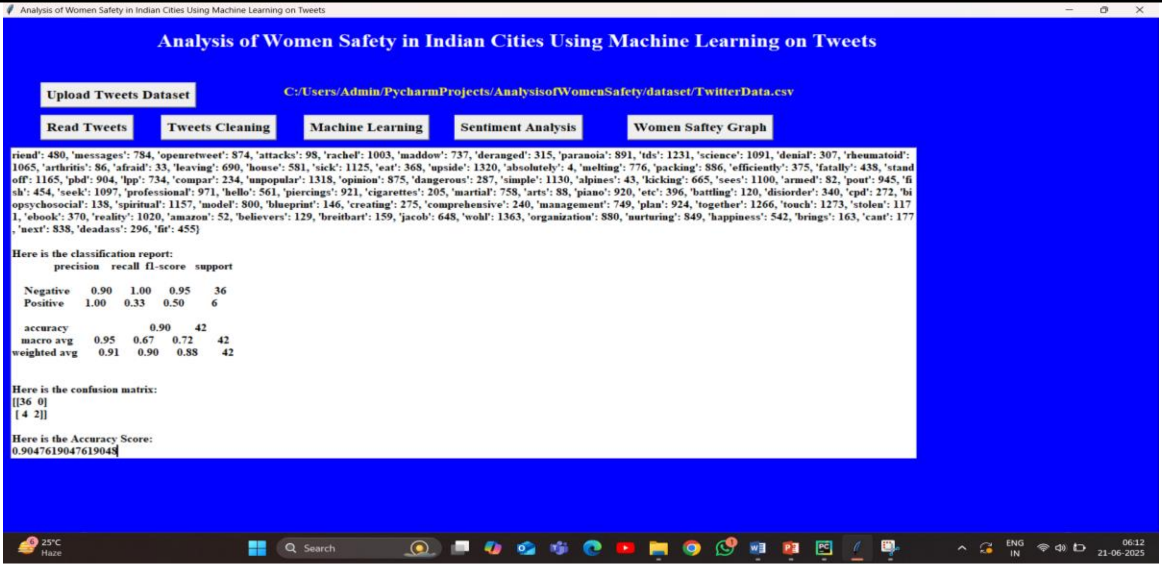


Figure 12: Sentiment Classification

5.1.5. *Women Safety and Sentiment Graph*

A **Women Safety and Sentiment Graph** visually represents the public's emotional response to women's safety issues over time or across different cities. It is generated by classifying tweets into **positive**, **negative**, and **neutral** sentiments and plotting them using line graphs, bar charts, or pie charts.

Purpose

- To track how public sentiment changes over time (e.g., after an incident or policy announcement).
- To identify cities or areas with a higher percentage of negative sentiment, indicating safety concerns.
- To visualize the impact of safety initiatives based on sentiment trends.

This graph helps authorities, researchers, and policymakers understand public concerns and respond effectively to emerging safety issues.

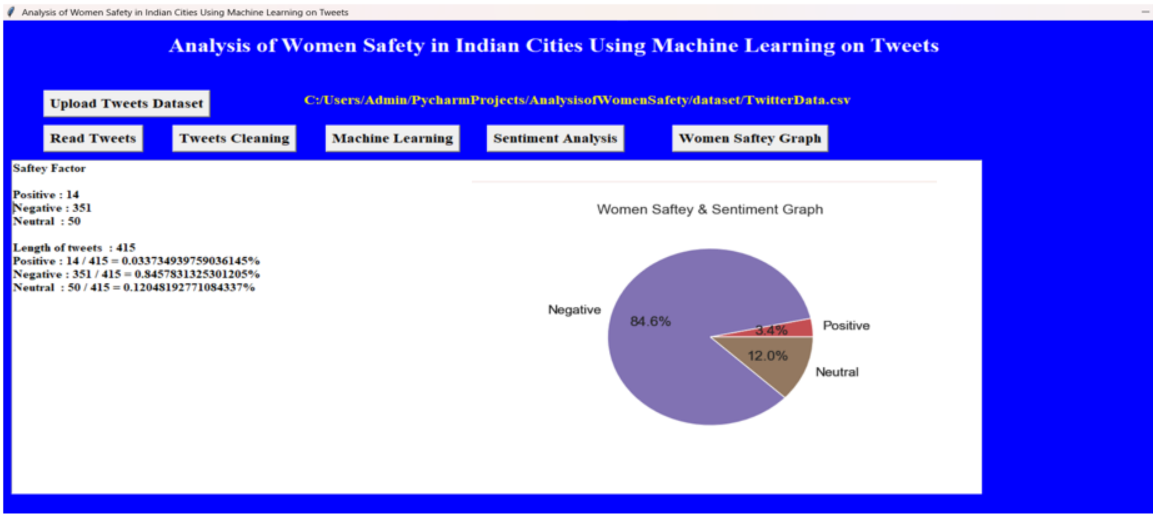


Figure 13: Women Safety and Sentiment Graph

6. CONCLUSION AND FUTURE SCOPE

6.1. Conclusion

This study analyzed women's safety in Indian cities using machine learning on tweets. By leveraging natural language processing (NLP) and sentiment analysis, we extracted public sentiment and identified trends in safety concerns. The key findings highlight that social media data can serve as an effective tool for monitoring public perceptions of women's safety, offering real-time insights into areas with heightened risks.

The results indicate that cities with higher negative sentiment in tweets often correlate with regions experiencing frequent safety-related incidents. Sentiment classification models successfully categorized tweets into positive, negative, and neutral sentiments, providing a granular understanding of public discourse. Additionally, topic modeling revealed common themes, such as harassment, unsafe public transport, and inadequate law enforcement.

While this approach provides valuable insights, some limitations exist, such as potential biases in social media data, misinformation, and the challenge of distinguishing sarcasm in tweets. Future research can enhance accuracy by integrating multi-source data, improving classification models, and collaborating with law enforcement for better policy implementation.

Overall, this analysis underscores the potential of machine learning and social media analytics in enhancing public safety measures. Governments, policymakers, and law enforcement agencies can leverage such data-driven approaches to design more effective interventions, ultimately contributing to a safer environment for women in Indian cities.

6.2.Future Scope

The analysis of women's safety in Indian cities using machine learning on tweets presents significant opportunities for future research and improvements. Below are some key areas for future exploration:

1. **Enhanced Data Collection and Integration**
   Multi-Platform Data: Expanding the dataset beyond Twitter to include data from other social media platforms, such as Facebook, Instagram, and Reddit, can provide a more comprehensive understanding of public sentiment.
   Real-Time Analysis: Implementing real-time tweet monitoring can help authorities respond to safety concerns more proactively.
   Integration with Crime Records: Combining social media data with official crime statistics and geographic information system (GIS) data can enhance the accuracy of safety assessments.

2. **Improvement in Machine Learning Models**
   Advanced NLP Techniques: Incorporating transformer-based models (such as BERT and GPT-based architectures) can improve sentiment classification and sarcasm detection.
   Multilingual Support: Enhancing models to analyze tweets in multiple regional languages can help capture a broader and more diverse public perspective.
   Deep Learning for Pattern Recognition: Leveraging deep learning to detect complex patterns in sentiment shifts and safety trends can enhance predictive capabilities.

3. **Collaboration with Authorities and Policy Implementation**
   Public Safety Dashboards: Developing interactive dashboards for law enforcement agencies to track and analyze safety concerns in real time.
   Policy Recommendations: Using AI-driven insights to help policymakers design better safety measures, urban planning improvements, and legal reforms.

4. **Addressing Ethical and Data Privacy Challenges**
   Bias Reduction: Ensuring that data collection and model training mitigate biases in representation and reporting.
   Privacy Protection: Implementing secure and ethical data handling practices to protect user anonymity and prevent misuse of data.

   By incorporating these advancements, machine learning-based analysis of women's safety can become a powerful tool for fostering safer urban environments, enhancing policy-making, and ensuring real-time interventions in Indian cities

REFERENCES

[1] Agarwal, Apoorv, FadiBiadsy, 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.

[6] Apoorv Agarwal, 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.

[7] Luciano Barbosa 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.

[8] Adam Bermingham 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.

[9] Michael Gamon. "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.

[10] Soo-Min Kim and Eduard Hovy. "Determining the sentiment of opinions." Proceedings of the 20th international conference on Computational Linguistics. Association for Computational Linguistics, 2004.

[11] Dan Klein and Christopher D. Manning. "Accurate unlexicalized parsing." Proceedings of the 41st Annual Meeting on Association for Computational LinguisticsVolume 1. Association for Computational Linguistics, 2003

[12] Eugene Charniak and Mark Johnson. "Coarse-to-fine nbest parsing and MaxEnt discriminative reranking." Proceedings of the43rd annual meeting on association for computational linguistics. Association for Computational Linguistics, 2005.

[13] Gupta, B., Negi, M., Vishwakarma, K., Rawat, G., & Badhani, P. (2017). Study of Twitter sentiment analysis using machine learning algorithms on Python. International Journal of Computer Applications, 165(9), 0975-8887.

[14] Sahayak, V., Shete, V., & Pathan, A. (2015). Sentiment analysis on twitter data. International Journal of Innovative Research in Advanced Engineering (IJIRAE), 2(1), 178-183.

[15] Mamgain, N., Mehta, E., Mittal, A., & Bhatt, G. (2016, March). Sentiment analysis of top colleges in India using Twitter data. In Computational Techniques in Information and Communication Technologies (ICCTICT), 2016 International Conference on (pp. 525-530). IEEE.