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Research Article

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Investigating Public Sentiment on High-Profile Incidents in Pakistan: A Computational Approach for Forensic and Security Insights

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ABSTRACT

Twitter and other social apps have made it easy to stay on top of how people react to breaking news nationwide. The study seeks to mine public opinion associated with the five major events occurred in Pakistan based on a set of 248259 tweets retrieved through the Twitter v2 API. The use of emojis, emoticons and contemporary slang (e.g., TBH, OMG) constitute a new thing in this study to enhance interpretation of sentiment of tweets. A computational framework is applied in this study to research public reaction to the Sialkot lynching, Murree's snowfall disaster, TLP protests, Johar Town blast and the tragedy in Anarkali market in Pakistan. The tweets were classified based on the text2emotion Python package that uses five categories of emotions (Happy, Angry, Sad, Surprise, Fear) to label the dominant emotion. A sixth label Neutral was given when there were no emotion scores that were significant hence dealing with uncertainty in emotional tone. Six models of machine learning, including Logistic Regression, Naïve Bayes, Support Vector Machine (SVM), Decision Tree, Random Forest and K-Nearest Neighbors (KNN), were taught and tested on incident datasets. Among all methods, SVM achieved the best average results and reached 95.8% accuracy on all datasets. The findings reveal that making sense of microblogs with computational sentiment analysis

can strengthen digital forensics, crisis management and criminology related to public safety and widespread communication.

Keywords: Twitter, social media, sentiment analysis, public reaction, Pakistan incidents, Text2Emotion, machine learning, SVM, digital forensics, crisis management, criminology, microblogs, emotion detection, public safety, computational framework

1 INTRODUCTION

The rapid rise in internet usage and online activities has led to the generation, transformation, and analysis of vast amounts of structured and unstructured data, a phenomenon known as Big Data. With the recent expansion of social media, individuals are now able to share their perspectives on various people, organizations, issues, and events in both formal and informal contexts. Such data can be analyzed across a range of real-world applications using techniques from Web Mining, Data Mining, and Text Mining [1].

Microblogging, a practice where people share brief updates about daily experiences, thoughts, and activities, has become widespread [2]. Among microblogging platforms, Twitter stands out as both highly restrictive and incredibly popular, allowing users only 280 characters per post. As a result, users frequently incorporate GIFs and videos to enrich their content [3]. Over time, Twitter has evolved into a prominent social network for discussing global incidents. Analyzing these discussions provides valuable insights into public sentiment on various issues, particularly in developing countries. As of January 2022, Twitter reported 436 million active users worldwide, including 206 million daily active users, with 42% of its users holding a college degree. Notably, 71% of Twitter users obtain news updates from the platform, where an average of 500 million tweets are shared daily [4].

The computational task of analyzing sentiments and opinions within text, known as sentiment analysis or opinion mining, plays a crucial role in understanding user emotions, preferences, and dislikes. Opinion mining is just as similar to the natural language processing recommender systems in context, like text reviews; though opinion mining infers users' sentiments from text, a recommender system predicts users' preferences using numeric ratings [5].

Opinion mining can identify key issues of concern and provide valuable insights, which can be beneficial for government and media organizations. The government can better understand public opinion by measuring the public sentiment on certain incidents. This can lead to better decision-making and policymaking since it is based on facts. It can be responded to in a timely and effective manner, and ultimately, this can result in better policymaking in terms of public concerns [6].

Tweets have been accumulated about five major incidents which have occurred in Pakistan, among them are the following:

- Sialkot Incident

A tragic incident on December 3, 2021, took place in Sialkot, Punjab when a mob lynched a 49-year-old Sri Lankan man named Priyantha Kumara Diyawadana for alleged blasphemy.

- Murree Incident

A heavy snowstorm on January 7, 2022 swept through Murree in the Rawalpindi District of Punjab, Pakistan, and left almost 4 feet of snow burying the area, resulting in tragic loss of 23 locals who had come to enjoy the snowfall.

- TLP Protest

A nationwide protest movement was led by Tehreek-e-Labaik Pakistan between 11 to 20 April 2021. The protesting was against Prime Minister Imran Ahmad Khan Niazi and his cabinet based on the call to action after a controversial cartoon was released recently.

- Johar Town Blast

On 23 June 2021, at 11 AM local time, a car bombing occurred in the Johar Town region of Punjab in Pakistan. The attack killed three and left over twenty people injured.

- Anarkali Blast

An explosion occurred at Anarkali in Lahore, Punjab, on January 20, 2022, killing at least three people and injuring more than 20. The blast, caused by a 1.5 kg improvised explosive device planted on a motorbike, occurred outside a bank around 1:40 PM.

2 LITERATURE REVIEW

Opinion mining is also known as sentiment analysis. It mainly deals with the computationally automatic classification of written text into either positive or negative sentiments. Since people comment on whatever is happening around them, social media analysis is important for determining the public mood. Social media analysts mine user-generated content to extract useful information about the views and opinions of the users. Due to this reason, social network analysis becomes a strong tool for gathering data from the social media and interpreting such data to make more informed decisions in light of the public sentiments [7].

Researchers of this study utilized the PyPI Twitter API to gather a set of tweets for analysis. They fine-tuned the hyperparameters of the neural network before training a Recurrent Neural Network model using the election data of the 2013 year. With this method, an accuracy of 87% was reported with the RNN model. As far as further validation of model performance is concerned, it had applied the model on to all those tweets that occurred around 2018 elections so did perfectly predict Pakistan Tehreek-e-Insaf was to be the biggest player while these predictions quite akin and followed what happened around that elections year with PTI actually, ending up being that mainstream of a political party right after an election was held into motion [7].

This paper applies machine learning models for analyzing microblogging in detecting public sentiment concerning the China-Pakistan Economic Corridor (CPEC) at national as well as at the international level. In the classifiers used, K-Nearest Neighbors, logistic regression, and Support Vector Machines are involved. The three classifiers that were applied had it revealed that Pakistan amongst all other relevant countries came up with the most positive tweets. India was observed to give the most negative sentiments. To note, tweet negativity in Baluchistan was significantly reflected by negative tweets, which formed the largest share of all the negative feelings noted in the analysis [8].

For this research work, the authors have used the Twitter API in fetching those tweets that are linked with IPL 2016 hashtags: #IPL2016 and #IPL9. The Random Forest algorithm has then been used to classify them. For the classification task, the proposed model achieved an accuracy of 81.69% [9].

The authors of this paper synthesized the data set of tweets related to the 2017 election of the 14th Gujarat Legislative Assembly to make use of public opinion in calculating probability for winning a party. They extracted about 1,000 tweets from the two verified accounts @vijayrupanibjp and @BharatSolankee by using the Streaming API from Twitter between 9 November 2017 to 7 January 2018. They applied NRC Emotion Lexicon that has eight different emotions to analyze the general mood of the tweets and ParallelDots AI API that could classify the sentiments as neutral, negative, or positive. The study obtained an accuracy of 88% using the ParallelDots AI API [4].

The Data Miner Scraper was used for pulling the comments and posts from the Facebook pages of all news channels, such as PTV News, ARY News, The News, Dawn, Express, Samaa, Geo, and Dunya News. Categorizations on four classes of neutrality-based, low extremism level, moderate extremism level, and high extremism level-based analysis of the level of expressed extremism were assigned to the provided textual views. To make this possible, intensity weights were established using a multilingual lexicon that, according to domain experts, was accurate at 88% in the validation steps. After the establishment of intensity weights, data classification was carried out using the Linear Support Vector Classifier and Naïve Bayes algorithms. It was noted that the accuracy of the Linear Support Vector Classifier was at 82% for the multilingual dataset used in this experiment [6].

This article conferred special status to Jammu and Kashmir; that too was revoked by Article 370 of Indian law on August 5, 2019. On this pretext, this paper calculates neutrality, negativity, and positivity of tweets across the world. A total of 2,200 tweets was retrieved between August 5 and August 30 using Tweepy, a Python client for the official Twitter API. The author classified the sentiments in the retrieved tweets using the TextBlob library. The author also utilized Python packages Matplotlib and Pandas for better visualization and data analysis purposes. Overall, the results indicate that the public opinion on this matter is found to be positive largely. It is worth mentioning that Pakistanis are concerned about trade effects, while Indians are worried about implications of terrorism [10].

This paper used machine learning algorithms to study the 2018 general election in Pakistan. It harvested a dataset of 2,090 tweets via Tweepy API. Pakistan's election campaign significantly hinged on the use of social media applications. Here, the authors provide a five-step framework to estimate the fairness of election results using machine learning methods. They obtained an average accuracy of 71% using the Naïve Bayes, SVM, and deep learning classifier on positive, negative, and neutral emotions concerning the outcome of the election [11].

This research targets identifying the best way of collecting tweets related to different political parties and developing a predictive model that can decode the feelings and opinions of people from these tweets. Compared with the previous method, for example, by the Election Commission of Pakistan (ECP) that has used it in association with the traditional survey, this proposed technique under the current study delivers excellent performance and almost achieves the 95% accuracy level [12].

The authors collected 120,000 tweets based on the 2016 U.S. presidential election; in other words, they targeted all the tweets that contained the words "Hillary" and "Trump." They used the Naïve Bayes classifier for the classification of tweets and used the Google Cloud Prediction API in combination with this classifier. The accuracies were 90.21% when using the Naïve Bayes classifier and 89.98% with the Google Cloud Prediction API [13].

The author used the Twitter API to collect the tweets related to the Budget 2017. She used the keyword "Budget 2017" for retrieval. A number of preprocessing techniques were applied to clean the data suitably. The data was subsequently classified into eight distinct types of emotions using R programming. Sentiment analysis was conducted at the sentence level on the tweets related to the 2017 Budget. To present the results of the analysis, the author employed various types of graphs. Notably, no machine learning algorithms were utilized in this study [14].

The authors conducted an emotive assessment of public sentiment using a Twitter dataset in anticipation of Pakistan's upcoming general election in 2018. They focused on three major political parties: the Pakistan Tehreek-e-Insaf (PTI), Pakistan Muslim League-Nawaz (PML-N), and Pakistan Peoples Party (PPP), collecting a total of 30,000 tweets related to these parties. Utilizing R-Studio and its integrated libraries, they generated various analytical insights. The findings indicated a strong competitive landscape between PTI and PPP based on favorable sentiment, while PML-N was projected to remain the ruling party due to a predominance of negative sentiment towards it [15].

The author utilized Easy Web Extractor to collect comments from a blog discussing the topic "Effect of Facebook Usage." A total of 150 negative and 150 positive comments were gathered for analysis. To conduct pre-processing, classification, model development, and polarity prediction on the training dataset, the WEKA tool was employed. Text Classification was used with three types of classification models: Decision Tree, K-Nearest Neighbors (KNN), and Naïve Bayes. From the results, it is clear that the Naïve Bayes classifier had a great accuracy of 97.5%, while KNN and Decision Tree classifiers resulted in 95% and 92.5%, respectively, on the test dataset. It has been seen that the Naïve Bayes classifier provides better precision, recall, F-measure, and overall accuracy than both KNN and Decision Tree [16].

This research conducted a systematic review to produce a holistic view of current landscape research on the use of Twitter in emergency management: specifying challenges and possible directions for further research. Authors performed a systematic search on digital libraries, such as Scopus, IEEE Xplore, ISI Web of Science, and

Science Direct, for relevant literature. Their results reflect the fact that data mining and machine learning techniques are the most widely used strategies in these studies. Moreover, the NLP techniques have also been highly used in other proposals. The literature focuses particularly on weather-related emergencies; hence it is an excellent scope of research in this domain [17].

The authors of study [18] conducted a comparative analysis of SVM and Random Forest classifiers for malware detection in Android devices, emphasizing the role of classification performance and ROC-AUC metrics in cyber threat identification. These studies support the growing relevance of machine learning for both security and forensic applications.

The authors introduced a Deep Q-Network (DQN)-based intrusion detection system that bypasses the need for labeled data. By integrating adversarial learning, the model adapts dynamically to evolving cyber threats. Results show superior accuracy and lower false positives compared to CNN and MLP approaches [19].

The study categorizes existing approaches into rule-based, ML, and DL methods, highlighting their strengths, limitations, and application domains in clinical settings [20].

The authors developed a hybrid CNN-SVD and improved SVM-based model to detect vision-threatening diabetic retinopathy. Their approach integrates advanced attention mechanisms and multi-stage classification to achieve 99.18% accuracy on the IDRiD dataset [21].

In [22] authors introduced a partitioned multi-agent DRL framework that reduces observation complexity and boosts scalability in industrial IoT environments. Their model outperformed SAC and PPO in cumulative rewards, highlighting effective agent coordination.

The author [23] also indicated that recent advancements in intelligent systems, such as the integration of Grey Wolf Optimization with Deep Belief Neural Networks, have demonstrated high efficacy in detecting complex patterns, offering valuable insights for computational models used in security and forensic analysis.

The author of the study [24] used the application of supervised machine learning models which has shown significant promise in enhancing analytical systems, particularly in domains like anti-money laundering, where pattern recognition and classification are critical principles that are equally relevant in sentiment analysis for forensic and security insights.

Based on the preceding discussion, it can be concluded that various techniques for opinion mining exist, including dictionary-based or lexicon approaches and supervised or machine learning methods. While these strategies have demonstrated commendable results, their performance and accuracy tend to decline when faced with a high volume of concealed emotions or substantial content-based material in the analysis. Notably, there has been a lack of research focusing on incident-based opinion mining specific to events in Pakistan. Furthermore, no local datasets currently exist to effectively apply classification techniques in this context. Some researchers have made attempts to incorporate emoticons, emojis, and slang terms in their analyses, but comprehensive studies remain limited.

3 METHODOLOGY

Research methodology refers to the detailed explanation of the specific methods and procedures employed in a research project. This section outlines the technical steps involved in conducting the research, providing a comprehensive framework for the study's implementation

This section will detail the dataset collection and description, preprocessing, data labeling, and model development processes.

3.1 Dataset Collection and Description

A total of 248259 tweets data was gathered using the 2wttr tool from the v2 Twitter API, utilizing a bearer token associated with a Twitter developer account for academic research purposes. The tweets collected pertain to the following five significant incidents in Pakistan, with the following distribution:

a) Sialkot Incident 166371 tweets
b) Murree Incident 24978 tweets
c) TLP Protest 28497 tweets
d) Johar Town Blast 13937 tweets
e) Anarkali Blast 14476 tweets

The datasets include attributes such as the tweet text and the associated emotions. The emotion attribute serves as the class label, encompassing six distinct categories: Happy, Sad, Neutral, Fear, Surprise, and Angry.

3.2 Dataset Preprocessing

The data obtained from Twitter is mostly raw, full of unusual words, and symbols that need to be cleaned so that it could be understood by the machine learning model. Most of the tweets contain a combination of words, slangs, excessive punctuations, emojis, and emoticons.

In order to process the informal style of language that is common to Twitter, slang-type words, emoticons and emojis dictionaries were made. Frequently used slang words (e.g., "TBH", "OMG", "SMH") were obtained by using a combination of the publicly available online sources of slang glossaries together with domain-specific manual curation based on the frequent terms in the corpus. The emoji meaning was matched with the emoji Python library. This library translates Unicode emoji and gives a descriptive text. Usages of emoticons like ":)" and ":-(" were dealt with by using the standard emoticon-to-text mapping dictionaries available as open-access NLP preprocessing repos. The manual inspection of these mappings was used to provide contextual accuracy of the mappings prior to performing the transformations on the whole dataset.

All these slang words and emoticons along with their meanings were prepared. Then the same were translated using Python code to respective meaning in all the five datasets. A library of emoji was used in order to translate emojis to their meaning.

The preprocessing techniques applied include lowercasing, removal of URLs, @mentions, hashtags, punctuation, and non-English characters from the datasets. Additionally, tokenization and lemmatization were used to improve the quality of the data.

3.3 Data Labeling

Emotion refers to a type of attitude that expresses personal significance or opinion regarding interactions with others or certain incidents and events. For data labeling, Text2emotion library has been used. This Python library is designed to find feelings and emotions in textual data; therefore, they are classified under the five most essential emotion categories: Happy, Angry, Sad, Surprise, and Fear. This newly introduced category, Neutral, further enhanced the classification process because a message labeled as Neutral in the sense that all the scores of emotion categories are zero. A notable strength of this library is its ability to recognize emotions conveyed through emojis, which represent human behavior.

Despite the fact that automatic emotion labeling was applied based on the use of Text2Emotion library, a manual validation procedure was performed on a random subset of 500 tweets per dataset of each incident (or 2,500 tweets in total). The consistency between the manifestation and predicted emotion was examined manually by two separate reviewers about these assigned labels. Conflicts were addressed and solved to enable better comprehension of borderline or fuzzy cases. The described process helped to make sure that the automatic labeling corresponded with the human understanding, particularly in the tweets with several emotions or indirect emotional coloring.

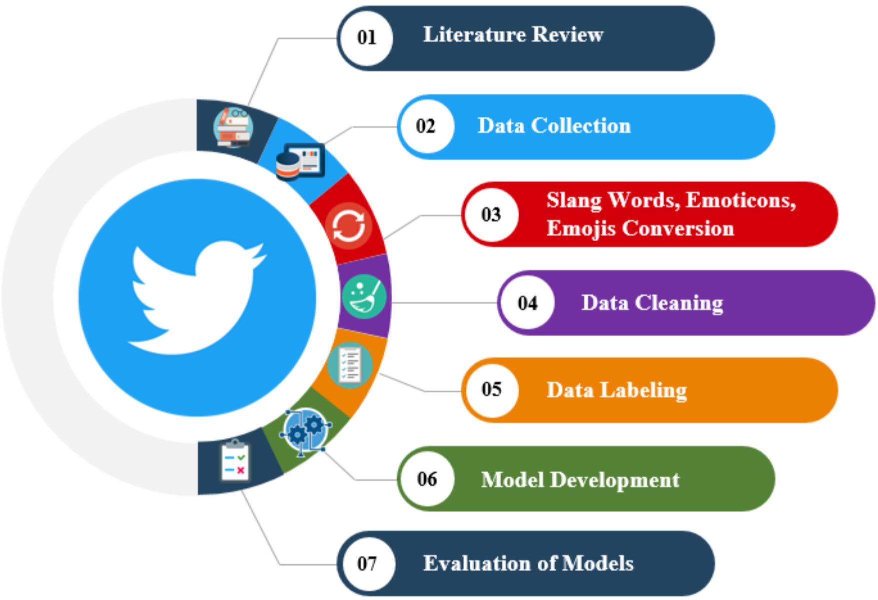

Figure 1. Research Methodology Overview

3.4 Model Development

A machine learning model serves as an algorithm that captures the underlying patterns within a dataset. The development of a machine learning model involves several key steps: collecting data from various reliable sources, preprocessing the data to ensure its suitability for model training, selecting appropriate algorithms, constructing the model, computing performance metrics, and identifying the best-performing model.

In this study, the data source for the prediction model was Twitter. As depicted in Figure 2, the process of building the prediction model comprises multiple stages, each critical to ensuring the model's effectiveness and accuracy.

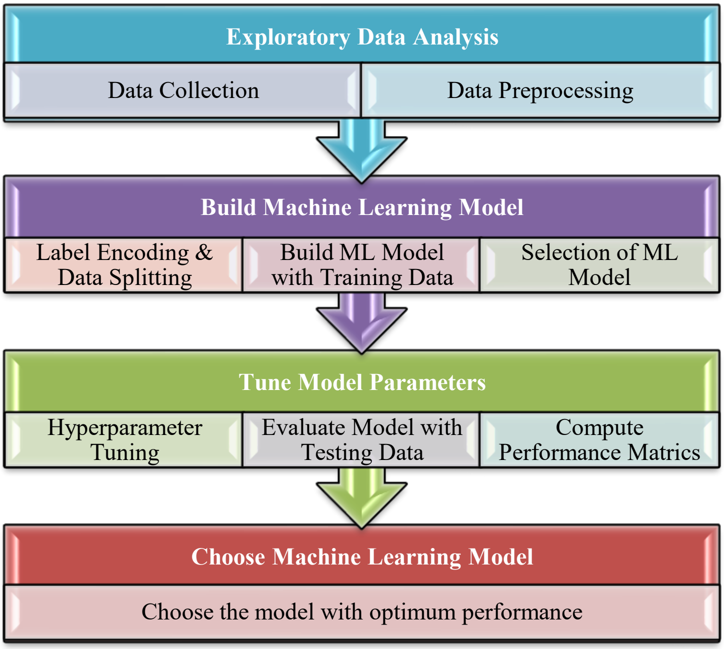

Figure 2. Model Development

Data for this study was collected using the 2wttr tool from the v2 Twitter API, leveraging a bearer token associated with a Twitter developer account for academic research purposes. Label encoding is employed to convert categorical labels into a numerical format, allowing them to be interpreted by machine learning algorithms. This technique assigns a unique numeric identifier (starting from 0) to each class in the dataset, which includes six categories: Happy, Sad, Neutral, Angry, Surprise, and Fear.

Subsequent to the label encoding process, the dataset is split into training and testing subsets, with 70% of the data designated for training the model and 30% allocated for testing its performance. As machines are not aware of any meaning that the words or the characters carry, CountVectorizer method is used to change textual data into numerical formats. This transformation will subsequently let proper application of the algorithm used for machine learning techniques into text classification and thus falls in the important category for preprocessing.

In our models, TF-IDF Transformer is applied to the training datasets in the training phase. CountVectorizer is used first in order to get the systematic word counts and then compute IDF values, which calculates the TF-IDF scores.

To further enhance our process of modeling we are using the n-gram function from NLTK so that we can create n-grams. This will help us develop the n-gram so that we can spot more complex words consisting of a group of more than one word by allowing a higher order value between 1 and 4.

Six supervised machine learning algorithms that include: Logistic Regression, Naive Bayes, Support Vector Machine (SVM), Decision Tree, Random Forest, and K-Nearest Neighbors (KNN) were chosen to offer a comparative analysis of the various algorithms families. These models were selected as their effectiveness in the tasks of text classification and sentiment analysis in detecting emotions was well established in the literature. Logistic Regression and SVM are strong linear models of classification that work well in high dimension spaces. Naive Bayes has the reputation of being easy and effective on short text. Decision Tree and Random Forest introduce interpretability, as well as ensemble learning features, and KNN has an instance-based approach. The wide range of the model set allows providing a competitive comparison and the most precise emotion-labeled tweets-classifier selection. The confusion matrix, accuracy, precision, recall, and F1 score of these models are thereafter determined as their performance metrics.

The K-Nearest Neighbors classifier has been configured with a hyperparameter k with value 3 as number of neighbors, and Random Forest classifier has been configured with n estimators = 200 as a hyperparameter value. Lastly, a range of 1 to 4 of n-grams is applied during the training of the models on the testing datasets to increase the accuracy of the models and their predictive capabilities. All these lead to overall impression of the effectiveness of the models in their classification outcome.

4 RESULTS

This section depicts the results for each incident which are derived by applying ML models to the respective datasets of the incidents.

4.1 Sialkot Incident

Figure 3 depicts the distribution of feelings expressed by people regarding the Sialkot incident. It can be seen that the most dominant feeling is sadness and holds 32.02%. Moreover, the portions of fear and surprise are also significantly increased as against the sentiments of neutrality, happiness, and anger. The SVM model exhibits a good performance on the Sialkot incident dataset, with an accuracy of 97%, recall and F1 score of 94% and 95%, respectively, and outperformance over all others.

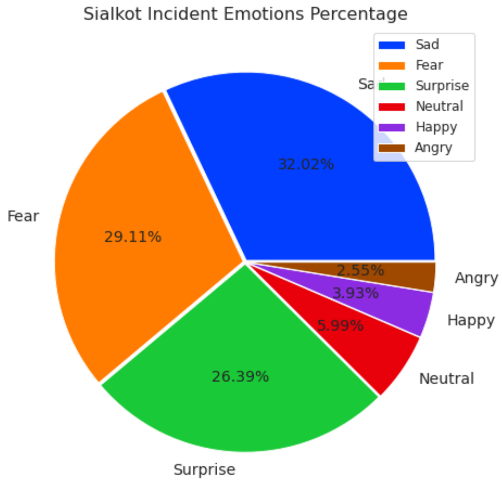

Figure 3. Sialkot Incident Emotions Percentage

4.2 Murree Incident

Figure 4 depicts the percentage share of people discussing about the Murree incident, which clearly shows that 32.64% percent of people are sharing fear. Apart from this, other percentages of sadness, surprise, and neutrality also increased in a considerable extent as compared to the feeling of happiness and anger. The SVM model also shows an optimal performance on the Murree incident dataset, bringing precision, recall, F1 score, and accuracy values of 95%, 84%, 88%, and 93%, respectively, that excel all other models.

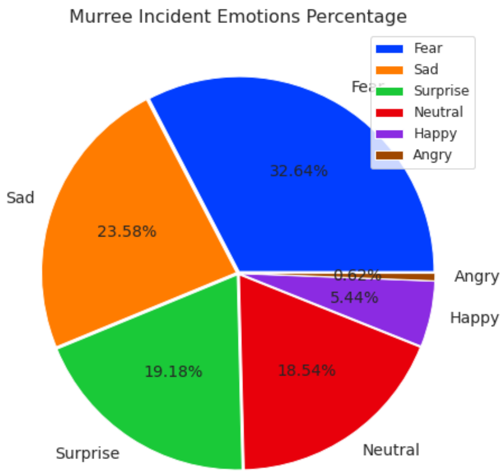

Figure 4. Murree Incident Emotions Percentage

4.3 TLP Protest

In Figure 5 the distribution of thoughts of people regarding the protest of TLP is shown. It has been observed that the share of sadness is the largest at 30.60%. Moreover, the proportion of fear, neutrality and surprise are also highly heightened as compared to the share of happiness and anger. The Random Forest model performs better on the TLP protest dataset since the precision, recall, F1 score, and accuracy rates have been set to 98%, 96%, 97%, and 97% respectively.

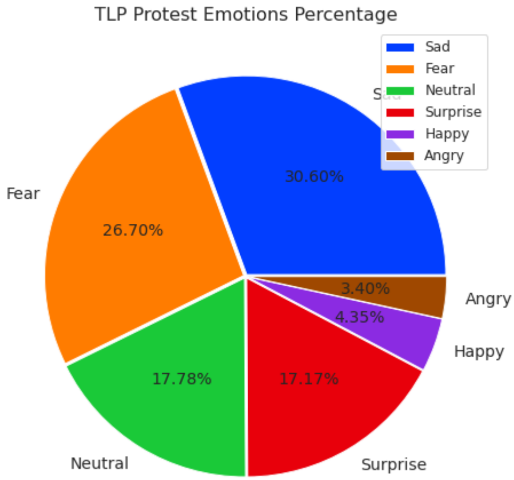

Figure 5. TLP Protest Emotions Percentage

4.4 Johar Town Blast

Figure 6 Distribution of Sentiments regarding the Johar Town Blast Figure 6. It can be seen that the most prominent percentage is by fear at 42.98%. Apart from this, the surprise and sad percentages are also highly increased in regard to neutral, happy, or angry sentiments. The Johar Town Blast dataset appears to give the best performance by an SVM model with 97%, 93%, 95%, and 95% for precision, recall, F1 score, and accuracy, respectively. These models have outperformed all others with the maximum difference.

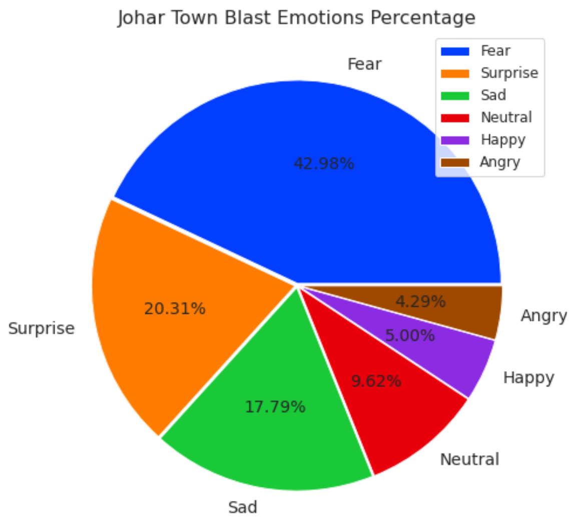

Figure 6. Johar Town Blast Emotions Percentage

4.5 Anarkali Blast

Figure 7 shows the people's feelings concerning the Anarkali Blast. The graph shows that fear is the most expressed sentiment at 36.96%. To my surprise, the next consecutive high percentages appear for surprise and sadness and come close to surpassing the percentages of neutrality, happiness, and anger.

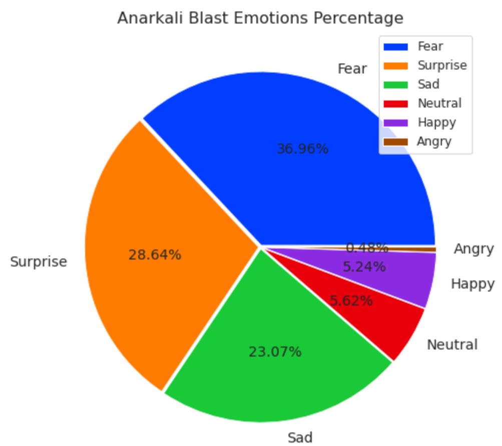

Figure 7. Anarkali Blast Emotions Percentage

The model with the best performance was achieved by SVM on the Anarkali Blast data set, yielding 92% precision, 83% recall, 87% F1 score, and 94% accuracy for the model, all the time outperforming the other models.
The average performance of the six models on all datasets is summarized in Table 1. Notably, the SVM model outperforms all other models in terms of average metrics across the five datasets. Specifically, the average precision, recall, F1 score, and accuracy of the SVM model are 96.6%, 92%, 94%, and 95.8%, respectively.

Table 1. Average Performance of all models

Model	Average Precision	Average Recall	Average F1 Score	Average Accuracy
Logistic Regression	94.4%	86.8%	89.2%	92.6%
Naïve Bayes	84.4%	63.8%	69.8%	79%
SVM	96.6%	92%	94%	95.8%
Decision Tree Classifier	91%	90.4%	90.6%	92.6%
Random Forest Classifier	96.2%	91.4%	93.6%	94.8%
KNN	90%	88.2%	89.2%	91.4%

5 CONCLUSION

Microblogging has emerged as a prominent platform for users to express their opinions, facilitating extensive discussions on various aspects of daily activities. This study focuses on extracting public sentiment from microblogs related to five significant incidents in Pakistan: the Sialkot Incident, Murree Incident, TLP Protest, Johar Town Blast, and Anarkali Blast. A total of 248259 tweets pertaining to these incidents were collected using the Twitter API. The Text2emotion library was employed for the labeling of these datasets. Six classification models—Logistic Regression, Naïve Bayes, Support Vector Machine (SVM), Decision Tree, Random Forest, and K-Nearest Neighbors (KNN)—were utilized for opinion mining. Techniques such as Label Encoding, CountVectorizer, TF-IDF, and n-gram modeling were applied for model training. The average performance of each model was assessed, concluding that the SVM model outperformed all others, establishing it as the most effective method for sentiment analysis in this context.
However, the present study incorporates some limitations. It is not very successful at sarcasm, irony or situation-specific sentiment which are prevalent in the context of microblogging. Also, the non-textual component of images, memes, and GIFs, which can be very emotionally expressive, were not considered. The

other weakness is that data collection is not real-time and hence lacks the dynamics of sentiment change.

Future work can focus on the real-time monitoring of opinions with streaming APIs and multimodal data analysis (e.g., text-image, text-metadata). Researchers can also explore a dual-layer processing framework using multi-queue adaptive priority scheduling as suggested by [25] to efficiently handle high-volume sentiment data streams, ensuring timely insights for forensic and security decision-making. Moreover, the addition of deep learning models such as transformers (e.g., BERT) and the optimization of sensitivity to the presence of sarcasm and mixed emotions may increase the reliability of sentiment classification in difficult social contexts several times.

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