An Unconventional Tale on Sentiment Analysis over Anonymous Online Reporting by the People in Bangladesh during an Outburst Period

ANONYMOUS AUTHOR(S)

Our tale began several years back, when we designed and developed an anonymous online reporting system (uReporter) for the people of Bangladesh – the first of its kind to the best of our knowledge. It took years to catch attention of the people, until a student in the top engineering university of the country was brutally killed. This event ignited an outburst among the people, and our developed system (which remained mostly dormant before the event) became a sudden online hub for anonymous reporting of the outburst and checking the reports from different corners of the world. It became so popular with no time that it caught attention of regulatory authorities leading to a temporary suspension of the system, which quickly got widespread in national and international media.

This paper digs into the sentiments over the online anonymous reports submitted during the outburst period. Here, our findings highlight nuanced shifts in dominant emotions, thematic trends, and evolving public discourse over time. By revealing complex emotional responses and social patterns during periods of the societal distress and outbursts, this research perhaps newly contributes to CSCW by demonstrating the potential of sentiment analysis on large-scale platform-driven data. Moreover, our study paves the path to enable CSCW inferring community resilience and collective sentiment during outburst events in similar socio-political environment of the Global South.

CCS Concepts: • **Human-centered computing** → **User centered design**; • **Information systems** → *Information retrieval*; • **Computing methodologies** → Natural language processing; • **Applied computing** → Law, social and behavioral sciences; • **Security and privacy** → Privacy protections.

Additional Key Words and Phrases: Crowdsourcing, Sentiment Analysis, Emotion Detection, This, Code, Put, the, Correct, Terms, for, Public Reporting

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1 Introduction

The process of reporting social issues is critical in fostering transparency and responsiveness from authorities, especially in third-world countries, where challenges like corruption, human rights violations, and inadequate public services are prevalent. However, under-reporting often obstructs meaningful intervention, as many individuals are discouraged by concerns over anonymity, privacy, and a lack of confidence in the reporting system. To address these obstacles, we develop an anonymous, online reporting system designed to allow citizens to submit reports on social issues while safeguarding their identities. This platform, described in our first study, provides a secure environment where citizens can voice their concerns, and it systematically forwards reports to the appropriate authorities after a review process, aiming to bridge the gap between the public and policymakers.

Towards Making an Anonymous and One-Stop Online Reporting System for Third-World Countries [25] tried to build the pathway of this process. A system was established allowing individuals from all socioeconomic classes in Bangladesh to anonymously report any social concerns or public issues they have encountered. The system's creation initially garnered significant approval, evidenced by a boom in submitted reports. Nevertheless, the project had to be suspended due to unforeseen circumstances, precluding any further review of the supplied papers. Our research encompasses the integration of real-time emotion detecting capabilities into the reporting system.

Emotion detection allows for the continuous monitoring of public sentiment within submitted reports, capturing a nuanced understanding of emotional responses such as anger, fear, and hope. Drawing from recent advancements in Natural Language Processing (NLP) and machine learning, particularly the use of adaptive lexicons and support vector machines, as explored in previous studies like [11] and [3], this phase seeks to analyze the emotional intensity and type embedded in reports. Such insights enable authorities to recognize patterns in public sentiment, detect emerging issues, and prioritize responses more effectively. The integration of emotion detection in our reporting system allows for a responsive and adaptable approach to governance. Unlike traditional sentiment analysis, which often focuses on binary or polarized views [19], emotion detection captures a broad spectrum of psychological states, revealing more precise and context-sensitive insights. By continuously analyzing the emotional undertones in submitted reports, our system fosters a real-time, empathetic connection between citizens and authorities, ensuring that public grievances and expectations are met with appropriate action. This enables us to address the following concerns:

RQ1: How can we analyze an outburst of the people in the cyber domain - specifically in the case of Bengali-speaking people in the global south?

RQ2: What are the prevalent sentiments expressed by the Bengali-speaking people in the global south during an outburst in the cyber domain?

This research outlines the methodologies adopted in integrating and testing emotion detection within our reporting system, followed by an evaluation of its impact on public engagement and authority responsiveness. We present a discussion on the technical framework, challenges in emotion detection, and the implications of emotion-driven analytics for enhancing public service systems in underrepresented regions

2 Related Work

The anonymous reporting mechanism facilitates the collection of sensitive social information and public concerns related to social issues. Anonymous systems promote user engagement by mitigating the dangers of exposure; yet, analyzing the feelings or emotions linked to reported situations provides valuable insights into public opinion and prevailing trends in public sentiment. This section examines the approaches that were employed to create an anonymous reporting system for social issues, along with the analyses conducted to assess feelings associated with these topics.

2.1 Anonymous Reporting System

Anonymous reporting systems have been investigated in multiple fields to promote user participation while safeguarding privacy. Toha et al. presented a secure, comprehensive internet platform designed for developing nations such as Bangladesh, enabling users to anonymously report issues like corruption and public safety concerns, while sending these reports to authorities and preserving anonymity. This approach is foundational in mitigating under-reporting due to fear of exposure [25].

Messman et al. conducted a comprehensive assessment of anonymous reporting systems utilized for the prevention of school-based violence in the United States. The research indicated that these systems, albeit beneficial, necessitated more empirical assessment to enhance their efficacy [15]. Payne et al. investigated anonymous reporting in educational institutions, revealing that supportive school climates markedly increase students' propensity to report threats, hence highlighting the impact of institutional environments on reporting frequencies [21].

Zou et al. advanced anonymous reporting by introducing ReportCoin, a blockchain-based platform that incentivized such reporting through token payments. This system protected privacy and encouraged involvement through incentives, demonstrating a secure and transparent method for anonymous reporting [28].

Burden et al. applied a similar framework to healthcare with their characterization of anonymous physician perspectives on COVID-19 using social media data. They explored how anonymous posts by healthcare professionals on social media during the pandemic could provide valuable insights into their experiences. This study used sentiment analysis to extract emotions such as frustration, fear, and hope from anonymous online reports, demonstrating the potential of these tools in highly sensitive environments like healthcare [5].

Khare et al. expanded the discussion into medical error reporting with their anonymous web-based system, which captured more reports of emergency department errors by removing the fear of exposure. Their findings underscored the effectiveness of anonymous reporting in high-stakes environments, such as healthcare, where privacy concerns often inhibit transparency [13].

2.2 Sentiment Analysis for Social Issue Detection

Sentiment analysis techniques have become essential for understanding public sentiment in reponse to social issues. Arslan et al. presented Political-RAG, a generative AI framework that retrieved political event information from media, utilizing sentiment analysis to offer insights into societal trends and attitudes [1]. This method demonstrated the capability of sentiment analysis in identifying subtle social patterns.

Jahin et al. introduced the TRABSA model in robust sentiment classification, integrating transformer-based architecture with attention mechanisms for efficient sentiment analysis on extensive datasets, including tweets. This model proficiently identified positive, negative, and neutral attitudes while providing interpretability, an advantageous attribute for assessing extensive amounts of user-generated content in reporting platforms [12].

Paul et al. contributed to this field with AnonyMine: mining anonymous social media posts using psycho-lingual and crowd-sourced dictionaries, which focused on extracting emotional cues from anonymous social media posts. By leveraging sentiment analysis and psycho-lingual dictionaries, AnonyMine demonstrated how emotional insights could be drawn from anonymized user data, making it relevant to systems designed to process anonymous reports [20].

Gagandeep and Verma demonstrated the use of NLP-based sentiment analysis to detect suspicious activities in social media, such as hate speech and disinformation. By flagging content with negative sentiment profiles, their model provided a valuable early warning mechanism that could be adapted for social reporting platforms [9].

In healthcare, Darzi et al. conducted a sentiment analysis of health care tweets, which highlighted how sentiment analysis could be used to interpret public opinion on healthcare-related issues. Their findings revealed that sentiment analysis tools could effectively categorize emotional responses in sensitive areas like healthcare, which could be adapted to anonymous reporting platforms [6].

Prichard et al. expanded sentiment analysis into crime prevention with their study, social media sentiment analysis: a new empirical tool for assessing public opinion on crime. They explored how sentiment analysis could be applied to anonymous social media reports to assess public sentiment on crime, highlighting the relevance of such tools in enhancing crime reporting systems [22].

Oliveira Júnior et al. offered another innovative approach with their anonymous real-time analytics monitoring solution. This system integrated sentiment analysis to support decision-making in real-time anonymous reporting platforms, providing a comprehensive solution for monitoring public sentiment as reports were submitted [7].

Trupthi et al. introduced detection of inappropriate anonymous comments using NLP and sentiment analysis, which focuses on filtering inappropriate anonymous comments through NLP and sentiment analysis. This method could be adapted to enhance anonymous reporting platforms by ensuring only relevant and appropriate content was flagged for further review [26].

Lastly, Watkins et al. introduced the SENSE system, which quantifies student performance through sentiment analysis, effectively translating textual feedback into quantitative insights. This study underscored the applicability of sentiment analysis for actionable feedback, which could also be extended to analyzing public sentiment in anonymous reporting systems [27].

3 Methodology

Our approach followed a structured three-stage process designed to facilitate emotion detection and visualization of public sentiment from submitted reports. A flowchart of the process can be found in Figure 1. The process started with the collection of reports submitted by the users, allowing them to raise their concerns or complaints anonymously. In the next stage, the raw data underwent several transformation and structuring, to make it suitable for emotion detection. Finally, several language models were used on the data to identify the sentiments expressed in each report.

Fig. 1. An overview of our three-step analysis

3.1 Collection of Reports

We built upon the work of Toha et al.[25]. The reporting system mentioned in the paper which can be accessed in https://ureporter.cse.buet.ac.bd was publicized. The system was made accessible by anyone to submit reports on the "Submit a Report" page. In addition to being a registered user of the system, anyone could also submit by being anonymous without registering. We retained both of the options for users. Registered users also had the option to choose to submit reports anonymously. To submit a report, users needed to add a short description in a text box. In addition to the textual description of a report, anyone could use the optional field to add any evidence file(s) associated with the report.

Subsequent to the submission of a report, it was sent for evaluation. Any registered reviewer of the system could review the reports and chose to publish the report to the public if the report was deemed eligible for publishing. While publishing, the reviewer would add the responsible authority name who could handle the situation in the report. After a report was published, anyone, whether a registered user or not could view the report in the "Explore Published Reports" page.

The page for published reports featured a tabular display of all reports and included a search option for responsible authorities. The table view comprised of the following columns:

- Report_ID
- Submission_Time
- Short_Description
- Responsible_Authority
- Action

A published report, accessible via the "Full View" button in the "Action" column, contained a section titled "Public Opinion". Individuals were permitted to express their opinions upon the report. This comment may also be made anonymously if any registered user were logged in. The comment was inherently anonymous if the user was not logged in. Additionally, the commenter may include supplementary evidence with the comment.

3.2 Pre-processing the Reports

We extracted the submitted reports to analyze the sentiment or emotion expressed by the users. Before the emotion detection process, some of the reports were excluded from our analysis which were not actual reports (e.g. test reports).

As the main target of the system was people in Bangladesh, the reports submitted to the system were composed in English, Bengali, and a mixture of Bengali written in Latin script (commonly referred to as "Romanized Bengali"). We employed OpenAI's GPT-4 model [18] to translate the non-English reports (Bengali written in both Bengali and Latin scripts) into English.

3.3 Emotion Detection

Several trained language models and a lexicon-based analyzer for emotion detection were explored. We ran these on our report texts and generated the detected emotions. We also generated charts showing the distribution of emotions detected by each model. The models we tried are described below.

3.3.1 Lexicon Based Analyzer. We tested a lexicon based analyzer for emotion detection. We scanned each word of a text and checked if the word corresponded to any emotion in the lexicon list. After scanning the whole text, the emotion value with the highest number was set as the emotion of the full text. The analyzer is able to detect from 8 emotions (anger, fear, anticipation, trust, surprise, sadness, joy and disgust) and 2 sentiments (positive and negative) using the NRC Emotion Lexicon [16, 17]. We ignored the 2 sentiments for our case.

3.3.2 Language Models. The explored language models are presented in Table 1.

Finally, we generated visualization for each model output to illustrate the distribution of emotions within the reports.

[1] https://huggingface.co/SamLowe/roberta-base-go_emotions
[2] https://huggingface.co/arpanghoshal/EmoRoBERTa
[3] https://huggingface.co/j-hartmann/emotion-english-distilroberta-base
[4] https://huggingface.co/bhadresh-savani/distilbert-base-uncased-emotion
[5] https://huggingface.co/michellejieli/emotion_text_classifier
[6] https://huggingface.co/MilaNLProc/xlm-emo-t

Table 1. Language Models Used

No.	Model Name	Description
1	SamLowe/roberta-base-go_emotions[1]	This model is trained by fine-tuning RoBERTA Base [14] using the GoEmotions [8] dataset. The model can be used for multi label classification for emotion detection where the total number of emotions is 28 including a neutral label.
2	arpanghoshal/EmoRoBERTa[2]	This model is also trained using the GoEmotions dataset by fine-tuning the RoBERTA Base model.
3	j-hartmann/emotion-english-distilroberta-base[3]	This model [10] is fine-tuned from DistilRoBERTa Base [23] using six datasets for emotion detection. This model can detect 7 types of emotions (anger, disgust, fear, joy, sadness, surprise and neutral).
4	bhadresh-savani/distilbert-base-uncased-emotion[4]	This model is a fine-tuned version of DistilBERT Base Uncased [23] using the dataset from [24]. The model can detect the emotions mentioned in the previous model except the neutral label.
5	michellejieli/emotion_text_classifier[5]	This is fine-tuned from model 3 to detect those 7 classes of emotions using a dataset of the transcript of the television show, F.R.I.E.N.D.S.
6	MilaNLProc/xlm-emo-t[6]	This is a multi-lingual model fine-tuned from XLM-T model [2] using the XLM-EMO dataset [4] containing data from 19 languages. The model can detect four emotions (anger, fear, joy and sadness).

4 Results

Table 2. Amount of Detected Emotions Per Model

Emotion	Lexicon Based	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
anger	13	1	1	15	62	18	44
disgust	4	1	1	28	-	21	-
fear	9	3	7	22	10	9	17
joy	7	0	1	2	25	3	21
sadness	11	7	14	14	24	1	39
surprise	5	0	1	4	0	1	-
anticipation	16	-	-	-	-	-	-
trust	45	-	-	-	-	-	-
disappointment	-	12	9	-	-	-	-
annoyance	-	6	7	-	-	-	-
curiosity	-	4	3	-	-	-	-
optimism	-	3	3	-	-	-	-
admiration	-	2	2	-	-	-	-
approval	-	2	1	-	-	-	-
caring	-	2	4	-	-	-	-
confusion	-	1	1	-	-	-	-
desire	-	1	3	-	-	-	-
realization	-	1	12	-	-	-	-
gratitude	-	1	2	-	-	-	-
remorse	-	1	1	-	-	-	-
embarrassment	-	0	2	-	-	-	-
disapproval	-	0	2	-	-	-	-
nervousness	-	0	1	-	-	-	-
neutral	-	73	43	36	-	68	-
undetectable	11	-	-	-	-	-	-

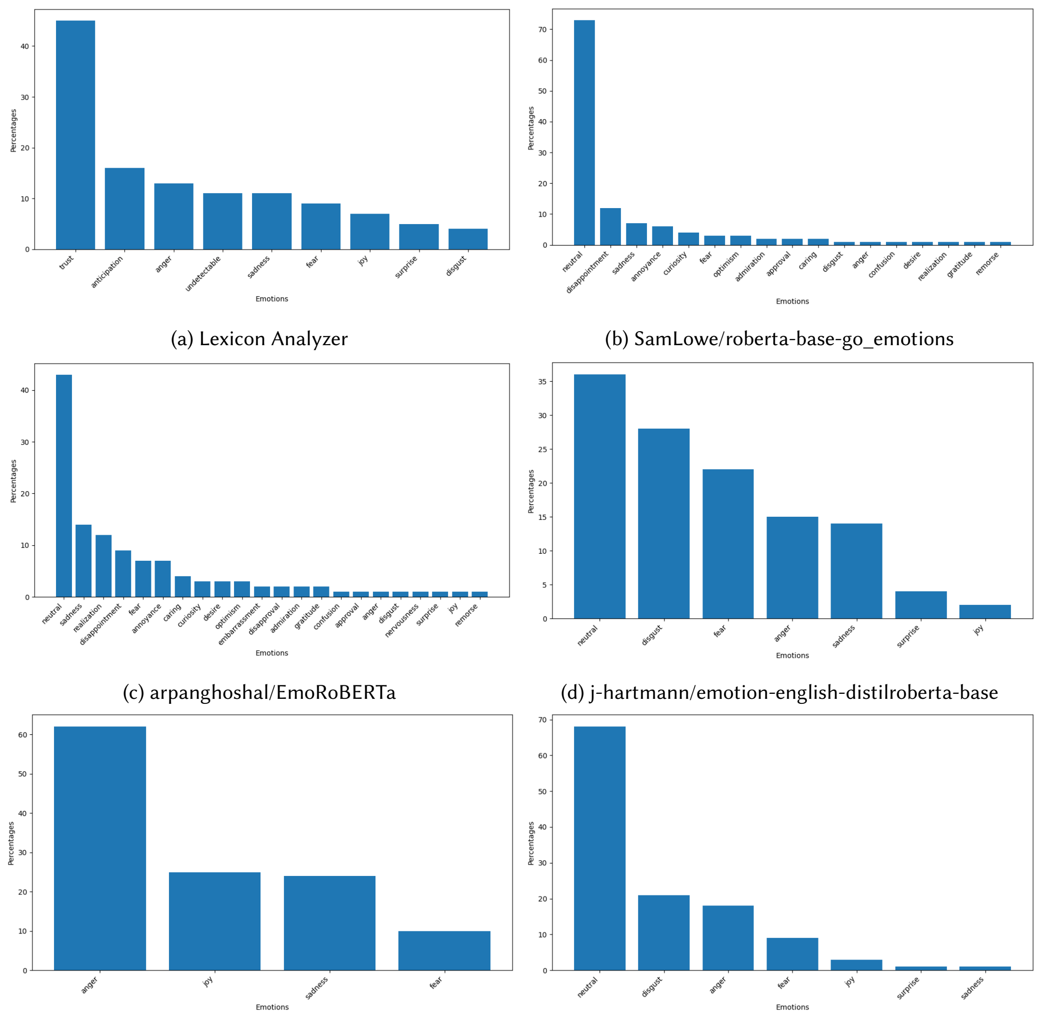
124 report submissions are made by several users. Among these reports, 74 of them are published. 3 reports are removed from the submissions after the pre-processing step.

Table 2 shows the amount of each detected emotion in all of the reports for each model. In the table, each column refers to the corresponding model and each row corresponds to the emotion. The numerical values represent the amount of the specific emotion found in all of the reports for the model. A value of '-' means that the model lacks the ability to detect that type of emotion due to its absence in the training data. For example, Model 1 can detect 6 emotions in all of the reports which corresponds to 'annoyance'. But Model 1 can not detect anything which may correspond to 'anticipation' since it is missing in its training data. Also, Model 1 can detect emotions with label 'surprise', but there is no report which could be labeled as such. So, the value is 0 in this case, not '-'.

There is a row for 'undetectable' emotion where 11 cases are present for only the Lexicon analyzer. This can be caused due to the lack of association of words found in the reports with any emotion. This may also happen because of the lack of vocabulary. This is a limitation of Lexicon based analysis.

We can further see that the rows for emotions 'anger', 'fear' and 'sadness' have non zero values in every column. All of the three are negative emotions.

In the following figures, we show the charts (bar and pie) generated using the detected emotion outputs from each model.



(a) Lexicon Analyzer

(b) SamLowe/roberta-base-go_emotions

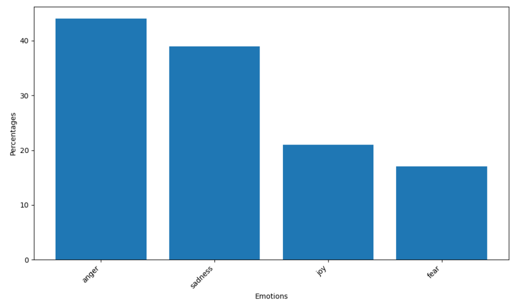
(c) arpanghoshal/EmoRoBERTa

(d) j-hartmann/emotion-english-distilroberta-base

(e) bhadresh-savani/distilbert-base-uncased-emotion

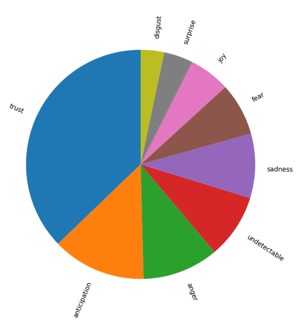
(f) michellejieli/emotion_text_classifier

Fig. 2. Bar Charts Showing the Distribution of Emotions.

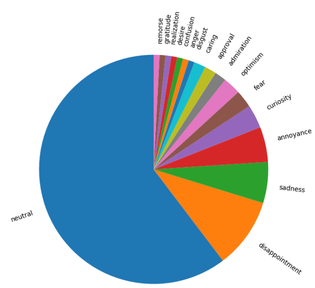


(g) MilaNLProc/xlm-emo-t

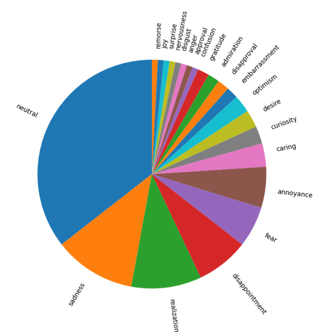
Fig. 2. Bar Charts Showing the Distribution of Emotions.



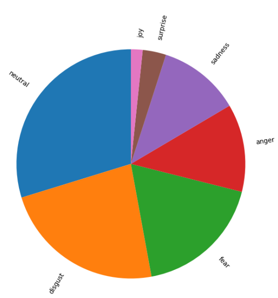
(a) Lexicon Analyzer



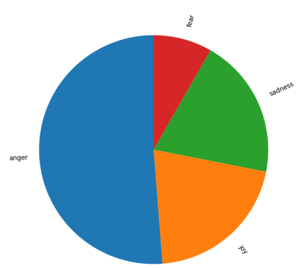
(b) SamLowe/roberta-base-go_emotions



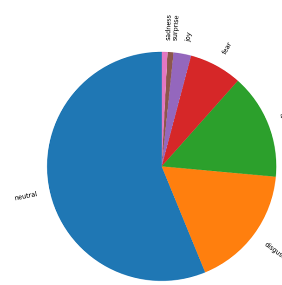
(c) arpanghoshal/EmoRoBERTa



(d) j-hartmann/
emotion-english-distilroberta-base

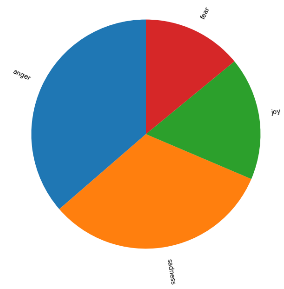


(e) bhadresh-savani/
distilbert-base-uncased-emotion



(f) michellejieli/emotion_text_classifier

Fig. 3. Pie Charts Showing the Distribution of Emotions.



(g) MilaNLProc/xlm-emo-t

Fig. 3. Pie Charts Showing the Distribution of Emotions.

5 Discussion

By adding real-time emotion detection to our anonymous reporting system, we have gained significant insights into how people feel about social issues in third-world countries. When we have analyzed the reports, we have found that negative emotions like anger, fear, and sadness are dominant across various models. This trend highlights the severity and urgency of the issues being reported, revealing a widespread sense of dissatisfaction and concern among the people.

The utilization of various language models, including both lexicon-based analyzers and advanced transformer-based models, allows for a comprehensive assessment of the emotional content within the reports. The lexicon-based analyzer provides a straightforward approach but is limited by its vocabulary and inability to capture context, leading to instances where emotions are undetectable or misclassified. In contrast, transformer-based models like RoBERTa and DistilBERT variants demonstrate a heightened ability to discern nuanced emotions due to their sophisticated understanding of language patterns. Models such as SamLowe/roberta-base-go_emotions and arpanghoshal/EmoRoBERTa, trained on the GoEmotions dataset, are particularly effective in identifying a wider range of emotions, including less frequently expressed ones like anticipation and trust.

However, in the study we also have faced several challenges. One big issue is handling reports in multiple languages and scripts, especially those written in Bangla and Romanized Bangla. Even though we have used OpenAI's GPT-4o model to translate these into English, some of the original language's nuances might have been lost, possibly affecting how accurately we have detected emotions. This limitation shows that we need multilingual models that can process emotions in native languages without relying only on translation, so we can preserve the original emotional context.

Another challenge we have faced was the imbalance in emotion detection. Negative emotions like anger and fear are overwhelmingly picked up by all the models. This may be because the reports focused on social issues and grievances. However, it can also be due to biases in the training data, which often includes more negative examples. As a result, the models are more tuned to detect negative sentiments and might underrepresent positive emotions like joy and trust. This is important because positive feelings are just as crucial for a balanced understanding of how the public feels.

We also have found that different models vary in how they detect specific emotions. Some models can identify feelings like disappointment, annoyance, and curiosity, while others miss them entirely. This inconsistency shows that the choice of model and its training data greatly affect emotion detection outcomes. It highlights how important it is to select models that align closely with the emotional expressions common to the people we're studying.

Also, relying on pre-trained models from different cultural backgrounds may not fully capture the unique linguistic and cultural nuances in our reports. Cultural expressions, idioms, and context are crucial for conveying and interpreting emotions. The models may misinterpret or overlook these subtleties, leading to less accurate emotion detection. This highlights the need for models trained on culturally relevant data or fine-tuned specifically for our domain.

Ethical issues arise when integrating emotion detection into an anonymous reporting system. While the goal is to help authorities respond better to public sentiment, it's crucial to ensure users' anonymity and privacy aren't compromised. We have to analyze emotional content carefully to prevent any chance of identifying individuals, especially when certain emotions could be linked back to specific users.

Despite these challenges, the incorporation of emotion detection has the potential to improve the effectiveness of anonymous reporting systems significantly. By providing authorities with deeper insights into the emotional landscape of the public, policies, and interventions can be better tailored to address the most pressing concerns. Monitoring shifts in public sentiment in real time allows for proactive engagement and resource allocation, fostering a more responsive and empathetic governance structure.

6 Future Work

Our future target is to refine the emotion detection system to identify better with multilingual capabilities. This hybrid model will handle Bengali in both Bengali text and Latin scripts. For the hybrid model to perform better, we will fine-tune the model for Bengali with Bengali text and Latin scripts. Additionally, we plan to create an automated report prioritization system based on emotion and urgency level. A temporal analysis system will also be constructed to monitor emotional patterns according to time and place. This system will be useful for tracking social issues before they escalate.

Table 3. Feature Comparison

Feature	Ureporter (2024)	Toha et al. (2016)
Anonymous Reporting System	✓	✓
Sentiment/Emotion Analysis	✓	×
Real-time Emotion Detection	✓	×
Evidence Attachment Support	✓	✓
Translation Capabilities	✓	×
Multilanguage Support	✓	×
Public Opinion Collection	✓	✓
Language Models Integration	✓	×
Initial Implementation/Testing	✓	✓
Rating System for Reports	×	✓

7 Conclusion

In conclusion, our story is resilient—a tale of an anonymous reporting system that lay in wait, silent and unnoticed, until a nation's voices have risen. When tragedy hits hard, the people of Bangladesh seek refuge in anonymity, venting their worries and frustrations and calling for quick action. Although it began its journey as a very little optimistic effort, it has quickly grown into a powerful forum for collective expression. Eventually, we have expanded this by adding something unique: emotion recognition and sentiment analysis.

Keeping that in mind, we have analyzed 124 anonymous reports using multiple detection models. While strong patterns of negative emotions such as anger, fear, and sorrow have been detected, indicating a distinct outpouring of distress, another emotion, trust, has risen to the surface. It is detected by our lexicon analyzer as the most frequent emotion. This is a surprising finding, suggesting a shared sense of hope or belief amid the turmoil. Another interesting finding is the emotion of realization, which is detected by the EmoRoBERTa model. It suggests a significant insight: in addition to the outpouring of emotions, individuals may also be gaining new insights or recognizing critical issues, contributing to the overall emotional landscape captured in our study. Furthermore, the adaptable nature of our approach, which incorporates six distinct language models and a lexicon-based analyzer, reveals the possibility of extracting extensive emotional insights from anonymous data.

This voyage establishes a connection between voices and authority, as well as communities and transformation. In the future, our research suggests that platforms such as these will be beneficial as they can offer valuable insights into collective emotion and community resilience, thereby, elucidating societal responses, adaptations, and eventual healing. Our system integrates sentiment analysis and anonymity to ensure correspondents' privacy and simultaneously provide authorities with a more profound understanding of public concerns.

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