Mental health evaluation during internet blackouts: a case study of Bangladesh Quota Movement

Mohammad Ariful Islam Rafi[1*], and *Tahidul* Islam[2]

[1] University of Liberal Arts Bangladesh, Dhaka, 1207, Bangladesh
[2] Bangladesh University of Engineering and Technology, Dhaka-1000, Bangladesh

Abstract. This study investigates the psychological effects of internet blackouts during the Bangladesh Quota Movement in July 2024, when the government shutdown internet access to control information flow. The disruption severely affected communication, financial transactions, and access to essential services, exacerbating stress, tension, and feelings of isolation. A survey of 980 participants using 20 questions assessed behavioural, emotional, and psychological impacts, particularly in academic, work, and social contexts. Results revealed varying stress levels, from minimal to extreme, reflecting widespread distress. Machine learning models were employed to classify the stress levels, with the Decision Tree model achieving 55% accuracy, the Random Forest model improving to 67%, and XGBoost performing better than both with over 94% accuracy. These findings highlight the utility of advanced algorithms in modelling mental health impacts, aiding policymakers in preparing targeted interventions and allocating resources to mitigate psychological effects during future disruptions.

1 Introduction

The current global political landscape is experiencing an unprecedented surge in civil unrest and protests, driven by widespread dissatisfaction with government policies and actions across various nations, from South America to Asia [1-7]. These persistent protests, often fueled by economic disparities, social injustices, and lack of political freedoms, have profound implications, leading to financial instability, strained diplomatic relations, and security challenges for affected countries [8]. One prominent example of such unrest is in Bangladesh, where the Quota Movement has significantly intensified national tensions. In response to growing civil unrest, the Bangladesh government imposed a state-sanctioned internet shutdown to control the spread of protests. Beginning on July 18, 2024, this "nationwide shutdown" lasted five days [9], which led to cutting off the country's population from the rest of the world [10] and Mobile internet services were also slowed down for following days [11]. During this period, Bangladeshi citizens faced severe restrictions on communication, financial transactions, and access to essential services, effectively isolating

*Corresponding author: ariful.islam1.eee@ulab.edu.bd

them from the outside world. This blackout, referred to by many as a “nationwide shutdown” of the country, was one of the most extensive internet disruptions Bangladesh has experienced to date [12-15]. A similar occurrence happened in previous years when the government slowed down the internet. For instance, in 2018, when a Road Safety Protest occurred where the internet was slowed down several times from July 29 to August 10 [16], the same types of incidents happened from 2009 to 2024 when the government slowed or blocked the internet multiple times [17-20]. Internet blackouts, such as the one in Bangladesh, have significant adverse effects on mental health. The sudden disconnection from digital communication and social support networks can exacerbate feelings of isolation, anxiety, and stress. The absence of reliable information sources during such blackouts creates uncertainty, leading to increased psychological distress among the population. This heightened state of anxiety often serves as a contributing factor to various psychological and physical health complications, including heart disease and diabetes, and can aggravate pre-existing mental health disorders [21, 22].

Globally, mental health disorders, particularly depression, are a leading cause of disability, affecting approximately 264 million people. Depression can severely disrupt daily life, relationships, and productivity, and in extreme cases, it contributes to nearly 800,000 suicides annually, making it the second leading cause of death among individuals aged 15 to 29 [23, 24]. The inability to access mental health support during critical periods, such as internet blackouts, worsens these outcomes, as individuals are left without the necessary resources to manage their conditions. In regions like Bangladesh, where mental health care infrastructure is already underdeveloped, the impact of internet blackouts on mental health is particularly severe. With 6.4 million people (4.10% of the population) experiencing various depressive disorders, over 75% of individuals in low- and middle-income countries (LMICs) like Bangladesh do not receive proper mental health care [25, 26]. The stigma surrounding mental health, combined with a lack of access to qualified specialists, prevents many from seeking necessary treatment, exacerbating the burden of mental health disorders in these communities. The situation is expected to worsen during internet blackouts as people fear losing jobs, businesses, and connections to their support networks. For many, the lack of access to information about their surroundings during these blackouts heightens fear and uncertainty, compounding their mental health challenges. Despite the availability of treatment, a significant proportion of those suffering from depression remain undiagnosed and untreated, highlighting the critical need for early recognition and intervention to manage mental health disorders effectively.

In recent years, the integration of machine learning (ML) into mental health research has led to significant advancements in predicting, classifying, and understanding psychological disorders. A variety of supervised learning methods, such as random forests (RF), decision trees (DT), support vector machines (SVM), Bayesian models, and neural networks, have been employed, along with unsupervised techniques like latent Dirichlet allocation (LDA) and clustering methods (K-means, hierarchical). These models utilize diverse features, including demographic, behavioral, and physiological data, to enhance mental health predictions [27, 28]. For instance, a study [29] used DT to predict future depression cases based on various data features, including behavioral and demographic information, achieving high classification accuracy. Similarly, another study [30] demonstrated the effectiveness of ensemble learning techniques for early diagnosis of anxiety and depression, leveraging electronic health records (EHRs) and self-reported survey data to improve predictive performance. Classification algorithms, such as RF and eXtreme Gradient Boosting (XGBoost), have been instrumental in distinguishing between mental health states like depression, anxiety, and stress. For example, research [31] utilized RF models to classify stress levels among students, using data on academic performance and physiological metrics like heart rate and skin conductance. Additionally, another study [32] applied big data analytics and machine learning techniques, including RF, to detect depression in real-time from social media platforms, such as Twitter. The system effectively monitored user sentiment and language patterns, providing real-time predictions of depression. Furthermore, a study [33] applied XGBoost to identify cases of post-traumatic stress disorder (PTSD) by analyzing survey responses and biometric data, showcasing the model's ability to manage complex variable interactions. Additionally, ML has facilitated emotion recognition and behavioral analysis through advancements in deep learning and natural language processing (NLP). For instance, [34] applied NLP techniques to predict depressive episodes by analyzing shifts in emotional tone and sentiment in social media posts. These examples highlight the transformative potential of ML in understanding and addressing mental health challenges.

The advancement of technology, particularly in data analytics and machine learning algorithms, has significantly improved the evaluation and detection of mental health risks and their after-effects. These innovations enable early identification of mental health disorders, paving the way for timely interventions. However, despite these advancements, there remains a considerable gap in research on the impact of internet blackouts on mental health, especially from the perspective of Bangladesh and worldwide. To date, no comprehensive studies have been conducted specifically evaluating mental health during internet blackouts despite numerous works on mental health in other contexts. Addressing the mental health impact of internet blackouts requires a multi-faceted approach that includes enhancing access to mental health care, reducing stigma, and ensuring continuous communication and information access during crises. Recognizing early signs of mental health disorders allows for timely interventions, which can save lives and improve overall well-being [35].

To overcome this gap, this paper studied an XGBoost model [36-39] to evaluate mental health during the internet shutdown following the Quota Movement protests in Bangladesh. The study surveyed 980 individuals using a 20-question questionnaire to assess levels of depression, anxiety, stress, and overall mental well-being during the blackout. The findings highlight the impact of the internet blackout on mental health, revealing that every aspect of life was affected, particularly in sectors already vulnerable to resource constraints, such as academia. The academic sector, already struggling with resource shortages, was further destabilized, exacerbating stress and anxiety among students. Survey and results are processed comprehensively, and the model is trained with the XGBoost approach. The efficacy of the method is validated by evaluating Decision Tree (DT), and Random Forest (RF) for stress level classification and comparing them with the XGBoost model. The study evaluates several performance metrics for both the XGBoost method and other algorithms.

2 Theoretical background

2.1 Mental health

A mental health illness is a condition that affects a person's wellbeing, emotions, thoughts, behaviour, and communication with others [40-42]. According to the American Psychiatric Association (APA), mental health illness refers to emotional, behavioural, or a combination of both types of health conditions that are linked to family, social, or work-related problems. It can be further explained that mental health illness is a condition that impacts a person's emotional and behavioural wellbeing, leading to physiological effects.

2.2 Anxiety

According to the APA, anxiety involves feelings of nervousness, anxiousness, and excessive fear [43, 44]. These feelings are often accompanied by physiological symptoms that persist and appear cyclically when anxiety is triggered [45]. Anxiety disorders are commonly classified into three main types: Generalized Anxiety Disorder (GAD), panic disorder, and social anxiety disorder. GAD leads individuals to either avoid or seek reassurance about unpredictable circumstances and to be excessively concerned about unfavorable outcomes. Panic disorders are characterized by sudden onset of psychological and physiological reactions, such as an irregular pulse, sweating, shaking, and shortness of breath. Social anxiety disorder involves an extreme fear of social settings, where individuals become anxious about others' reactions or judgments. Those with social anxiety often avoid situations that may draw attention or cause embarrassment [46]. Anxiety disorders are particularly prevalent among students, affecting their daily activities and academic performance.

2.3 Depression

Depressive disorder, also known as clinical depression, is a mood disorder that causes severe symptoms affecting a person's feelings, thoughts, and daily activities. This disorder is typically characterized by sadness, loss of interest, guilt or low self-worth, disturbed sleep, low appetite, fatigue, and poor concentration. There are two types of depressive disorders: persistent depressive disorder and psychotic depression. Persistent depressive disorder, also known as dysthymia, is a state where a person experiences a depressed mood for at least two years [47]. A person diagnosed with persistent depressive disorder may have major depressive episodes along with periods of less severe symptoms, and this cycle of symptoms lasts for two years, making this disorder more chronic. Psychotic depression differs from persistent depressive disorder in that a person experiences severe depression accompanied by psychosis, where symptoms include disturbing false fixed beliefs and hallucinations of seeing or hearing things that others cannot.

2.4 Environmental

Surroundings and environmental stressors, particularly during movements or political events, significantly impact mental health. Exposure to such environments, including protests, increased crime rates, and unstable political conditions, can elevate stress, anxiety, and depression, especially among those directly involved or affected [48-53]. Events like the Black Lives Matter protests and the Hong Kong pro-democracy protests demonstrations highlight how external stressors such as crowding, noise, and police presence can worsen mental health conditions [54-57]. These patterns suggest that during crises like internet shutdowns, social media engagement is heavily disrupted, adding to environmental stressors that impact individuals' mental health, such as routine disruptions, unsafe surroundings, and pollution, such as noise [59]. This aligns with broader findings that these stressors exacerbate the psychological impact of social and political upheaval [60].

3 Methodology

3.1 Questionnaire design

A questionnaire was developed for this study, consisting of 20 questions in total. The survey was designed to be inclusive and was disseminated using a Google form to ensure accessibility across a diverse group of participants. Voluntary consent was obtained from all participants before they engaged in the survey, emphasizing the study's adherence to ethical standards. Two items in the questionnaire collected demographic information: gender and age. This demographic data allowed for a contextual analysis, offering insights into how different age groups and genders experienced and responded to environmental stressors during significant societal movements. The remaining survey questions were structured around four main categories: general, mental, emotional, and behavioural, each comprising five sub-questions. This organization allowed for a comprehensive examination of the psychological impact on participants. Stress levels were quantified by asking participants to rate their stress or anxiety on a scale from 1 to 5, where 1 indicated no stress and 5 indicated extreme stress. This rating system provided a straightforward way to gauge the intensity of stress experienced. Specific questions were designed to measure contributing factors to stress. For example, participants were asked how frequently they felt anxious about losing internet connectivity, whether they experienced social isolation, and the extent of emotional distress they faced due to being disconnected. By aggregating these responses, we could derive a comprehensive stress metric. This metric reflected the cumulative impact of various stressors, offering a structured and measurable analysis of psychological stress. It enabled the identification of significant stressors and their relative contributions to overall mental health, facilitating a deeper understanding of the emotional and behavioural consequences of internet disruptions.

3.2 Survey objective

The survey, with a primary object on the mental health impact of the internet blackout during the Bangladesh Quota Movement in July 2024, was designed to capture the invaluable experiences and perceptions of the participants. It aimed to understand how the lack of internet access affected their mental state, making their contributions crucial to the research. As a general guideline, participants were instructed to think about the questions to understand or visualize the scenario that occurred in the movement. The survey collected 980 responses, and the data was saved into an Excel file for in-depth analysis. The psychological and behavioral impact of the internet shutdown during a critical social movement enlightens about the potential mental health implications of such events.

3.3 Factors of Mental Health

Fig. 1 shows the factors influencing mental health during internet blackouts, specifically highlighting Internet Usage, Stress Level, Surroundings, and Emotional Well-being. Internet usage disruptions, such as for academic, social media, communication, entertainment, and work purposes, are primary contributors to stress, as they interrupt daily routines and create emotional challenges. Stress levels are categorized into No Stress, Stress, and Extreme Stress, quantifying the immediate psychological impact of these disruptions on mental stability.

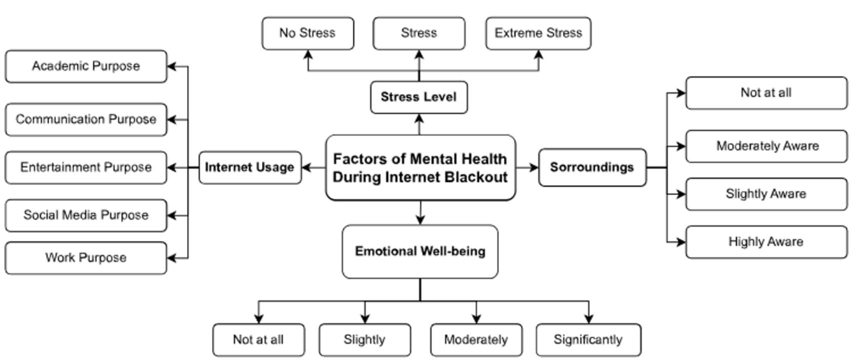

Fig. 1. Factors Influencing Mental Health During the Internet Blackout.

Emotional Well-being is assessed by how significantly individuals feel affected, from ‘Not at all’ to ‘Significantly,’ reflecting emotional disturbances like anxiety, depression, or feelings of isolation. Surroundings measure the level of environmental awareness during the blackout, showing how internet disconnection affects interactions with one’s immediate physical and social environments. These factors reveal how the lack of internet access during critical moments like social motions can severely disrupt daily life, contribute to heightened stress, and impact long-term emotional and mental well-being, affecting social behaviors and coping mechanisms.

4 Machine learning approach

4.1 Data overview and visualization

Our dataset consists of various features collected from survey responses aimed at evaluating the psychological impact of internet blackouts. The features include demographic information (such as 'Gender' and 'Age'), alongside detailed survey questions that measure emotional and behavioral impacts. The target variable captures the overall stress levels of participants, rated on a scale from 1 to 5, during the blackout period.

4.1.1 Data overview

We began by exploring the distribution of key demographic and response features. The 'Gender' variable is categorical and was represented using one-hot encoding to highlight the proportion of male, female, and other respondents. The 'Age' variable, a continuous feature, was standardized to understand age distribution and its relation to stress levels. We also examined the frequency of various responses to survey questions, such as the primary uses of the internet, the impact on daily routines, and emotional responses to the blackout.

4.1.2 Data visualization

A variable in text analysis, such as frequently mentioned A variable in text analysis, such as frequently mentioned terms in survey responses, represents an attribute that reflects recurring themes and concerns in participants' experiences. Table 1 illustrates the frequency of specific words appearing in the dataset, highlighting dominant concepts within the data. The size of each word is determined by a weighting scheme, typically based on Term Frequency (TF), which is mathematically expressed in (1)

$$TF(t) = \frac{\text{Total number of terms in the text}}{\text{Number of times term } t \text{ appears}} \tag{1}$$

here t represents a specific term in the text. Words with higher frequencies have a larger significance, drawing attention to their importance.

For example, Table 1 displays terms like "Stress," "Affected," "Frustrated," and "Worried," which are prominent due to their high term frequencies.

Table 1. Performance On Multiple Evaluation Metrics

Words	Counts
Extreme Stress	198
Stress	506
Frustrated	246
Concerned	360
Severely Affected	360
Moderately Affected	330
Affected	360
Negative Thoughts	105
Felt Down	310

These terms underscore the psychological toll and emotional responses linked to the dataset, emphasizing the mental health impact of the reported events. The mathematical importance of these terms can also be examined using probability distribution, where the probability P_i of a word w_i appearing prominently is given in (2)

$$P_i = \frac{\mathrm{TF}(w_i)}{\sum_{j=1}^{n} \mathrm{TF}(w_j)} \tag{2}$$

Here n is the total number of unique words.

The table not only highlights the emotional and behavioral effects but also provides insight into recurring patterns within the text corpus. Terms such as “Extreme Stress,” “Negative Thoughts,” and “Addictive Behaviors” prominently reflect participants’ struggles, while words like “Tried to Stay Positive” indicate attempts at resilience amidst challenging circumstances.

4.2 Preprocessing

To prepare the dataset for analysis, we conducted several preprocessing steps to ensure data quality and compatibility with machine learning models. First, we addressed missing values by removing any rows containing null entries, transforming the original dataset D into a cleaned dataset

$$D' = D \backslash \{\text{rows with missing values}\} \tag{3}$$

Here D' denotes the cleaned dataset and text data were standardized by removing leading and trailing spaces and converting all text to lowercase to minimize inconsistencies. Further, we standardized text data by stripping extra spaces and converting all text to lowercase to maintain uniformity and reduce noise.

For categorical variables, we applied Label Encoding to transform the target variable y into numerical values

$$P_i = Encoded\ value\ of\ category\ i \tag{4}$$

For the ‘Gender’ variable, we utilized One-Hot Encoding, which transformed the categorical data into a binary vector representation **v** of length n, with n representing the number of unique categories.

To bring numerical features, such as ‘Age,’ onto a uniform scale, we applied Standard Scaling. The transformation of each data point x is given in (5)

$$x' = \frac{x - \mu}{\sigma} \tag{5}$$

Here μ is the mean and σ is the standard deviation. This scaling ensured all features had a mean of zero and unit variance, critical for algorithms sensitive to feature magnitude.

For survey responses expressed as text, we employed Term Frequency-Inverse Document Frequency (TF-IDF) to convert text data into numerical features. The $TF - IDF$ value for a term t in a document d is calculated as

$$TF - IDF(t, d) = TF(t, d) \log\left(\frac{N}{DF(t)}\right) \tag{6}$$

In (6), $TF(t, d)$ represents the frequency of term t in document d, N is the total number of documents, and $DF(t)$ denotes the number of documents containing term t. This vectorization technique captures the importance of terms within the context of the entire dataset.

Also to address class imbalances in our target variable, we implemented Random Over-Sampling. This method generates additional samples from the minority classes to balance the dataset. Mathematically, the resampling process ensures in (7)

$$\left|C_{majority}\right| = \left|C_{minority}\right| \tag{7}$$

Here $\left|C_{majority}\right|$ and $\left|C_{minority}\right|$ denote the sizes of the majority and minority classes, respectively. By equalizing class distributions, the model training process becomes unbiased and more effective at classifying all categories.

4.3 Machine Learning

4.3.1 Decision Tree (DT)

DT is an intuitive supervised learning algorithm used for both classification and regression tasks. It operates by constructing a tree-like model of decisions, where each internal node represents a test on a feature, each branch corresponds to the outcome of the test, and each leaf node represents the final prediction or class. The hyperparameters of a Decision Tree include the maximum depth of the tree, the minimum number of samples required to split a node, and the criterion used for splitting, such as Gini impurity or information gain. The primary advantages of DT are its interpretability, simplicity, and the ability to handle both categorical and numerical data.

4.3.2 Random Forest (RF)

RF is an ensemble learning algorithm that combines multiple decision trees to improve classification accuracy. It determines the final class by taking a majority vote across all the trees. Key hyperparameters include the number of trees and their depth, which influence model performance. RF uses cross-entropy as the loss function to measure the difference between predicted and actual class probabilities. It is favored for its speed, robustness to noise, and ability to capture complex, nonlinear patterns in data. These advantages make RF a powerful tool for handling diverse datasets in various machine learning applications.

4.3.3 eXtreme Gradient Boosting (XGBoost)

XGBoost is a powerful and widely-used ensemble learning algorithm that builds multiple decision trees sequentially to optimize performance. It determines the final prediction by combining the outputs of all trees, using a weighted approach to minimize errors. XGBoost's hyperparameters include the learning rate, the number of trees, the maximum depth of each tree, and regularization terms to prevent overfitting. The algorithm uses a custom loss function, often a combination of logistic loss for classification and regularization terms, to improve model generalization. XGBoost is favored for its high efficiency, scalability, and ability to capture complex, nonlinear relationships in data, making it highly effective for structured and tabular datasets.

$$obj = \sum_{i=1}^{n} l(y_i,\ \hat{y}_i) + \sum_{k=1}^{n} \Omega(f_k) \tag{8}$$

Here, $l(y_i,\ \hat{y}_i)$ is the loss function that measures the difference between the true label y_i and the predicted label $\hat{y}_i$ and $\Omega(f_k)$ the Regularizationterm that penalizes the complexity of the model, defined as

$$\Omega(f) = \gamma T + \left(\frac{1}{2}\right)\lambda \|w\|^2 \tag{9}$$

Here, T is the number of leaves in the tree, λ is the regularization parameter for the weights, γ is the penalty for each additional leaf in the tree, and $\|w\|^2$ is the squared sum of the leaf weights.

XGBoost builds trees one at a time, adding a new tree f_t at each iteration t to minimize the residuals from the previous iterations and the updated prediction is given in (10)

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{10}$$

Here, $\hat{y}_i^{(t-1)}$ is the prediction from the previous iteration and $f_t(x_i)$ is the output of the new tree.

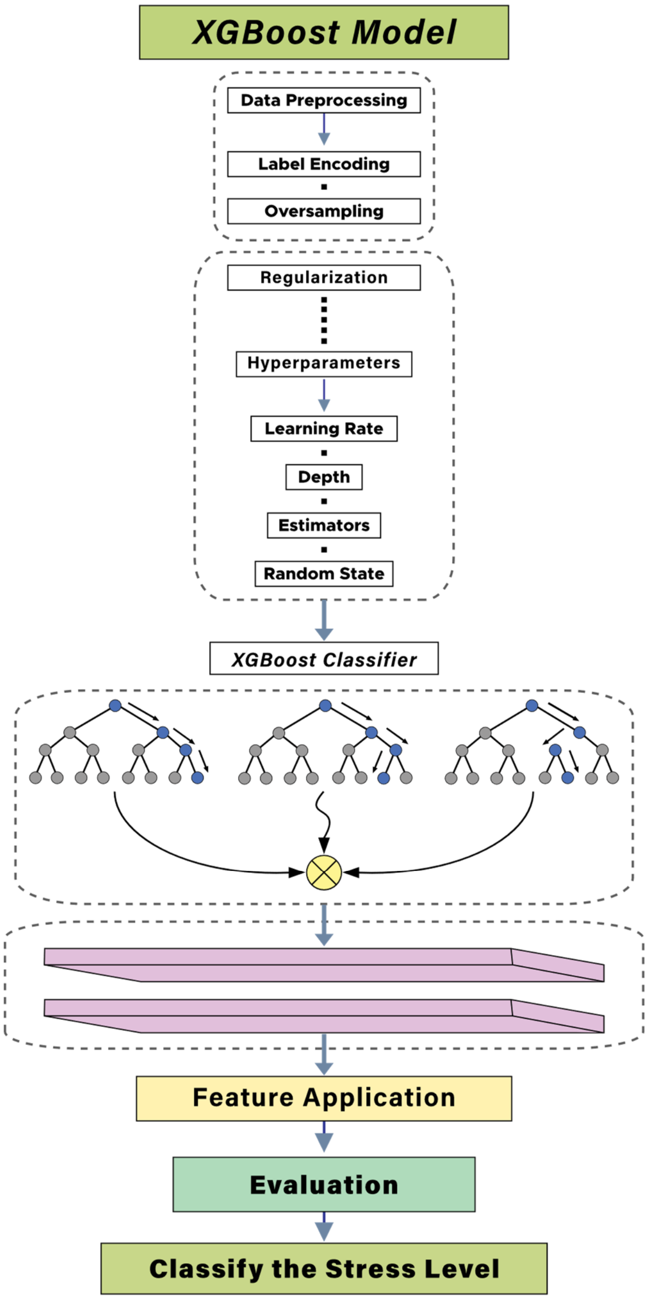

Fig. 2. XGBoost Model Arichitecture.

$$\sum_{i=1}^{n}\left[g_i f_t(x_i) + \left(\frac{1}{2}\right) h_i {f_t}^2(x_i)\right] + \Omega(f_t) \quad (11)$$

Here, g_i is the first-order gradient of the loss function and h_i is the second-order gradient (Hessian) of the loss function.

The algorithm splits the data to minimize the loss function using the best split found through a scoring function, which considers both the gradient and the regularization terms. The gain from a split is given in (12)

$$Gain = \frac{1}{2}\left[\frac{{G_L}^2}{H_L + \lambda} + \frac{{G_R}^2}{H_R + \lambda} + \frac{(G_L+G_R)^2}{H_L+H_R + \lambda}\right] - \gamma \quad (12)$$

Here, G_L and G_R is the sum of gradients for the left and right splits, H_L and H_R is the sum of Hessians for the left and right splits.

4.4 Model training

To build a machine learning model, the chosen technique in this case is eXtreme Gradient Boosting (XGBoost), a powerful and efficient algorithm well-suited for handling complex classification tasks such as stress level prediction. The XGBoost model was trained on 80% of the preprocessed dataset, with the remaining 20% set aside for validation to ensure the model's performance and ability to generalize effectively to new, unseen data. The model was configured with key hyperparameters optimized to achieve a balance between performance and computational efficiency. The learning rate was set to 0.2 to control the step size during optimization, preventing the model from overfitting while enabling it to converge faster. The maximum depth of each decision tree was configured at 7, which allows the model to capture intricate patterns in the data without becoming overly complex. Additionally, the model used 500 boosting rounds (trees) to iteratively learn and minimize errors from previous iterations. Regularization terms were also incorporated to penalize model complexity and reduce the risk of overfitting: λ (L2 regularization) was adjusted to stabilize the weights of the trees, and γ was used to enforce a minimum loss reduction required for further partitioning, ensuring that only meaningful splits were made. The objective function included logistic loss for binary classification, along with these regularization components to maintain a well-generalized model. Moreover, to handle the issue of class imbalance, the class weights were adjusted based on the inverse frequency of each class, ensuring that minority classes were adequately represented during the learning process. The comprehensive evaluation of the XGBoost model included the use of performance metrics to assess accuracy, precision, recall, and F1-score. These metrics helped validate the model's ability to classify stress levels effectively and demonstrated its robustness in handling non-linear relationships in the data, as depicted in Fig. 2. The combination of hyperparameter tuning and regularization made XGBoost an ideal choice for this stress classification task, providing high predictive accuracy and resilience against overfitting.

5 Result and Discussion

5.1 Metrics evaluation

The XGBoost model, proposed in this research, utilized a series of decision trees built sequentially to optimize performance for multi-class classification. The model applies gradient boosting, where each tree learns from the residual errors of the previous trees, effectively capturing complex, non-linear relationships in the data. Key components of XGBoost include regularization techniques that penalize model complexity, reducing overfitting and improving generalization. Evaluation metrics were defined through (13) to (16): Precision, Recall, F1-score, and Accuracy.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives+False Positives}} \tag{13}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives+False Negatives}} \tag{14}$$

$$\text{F1} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{15}$$

$$\text{Accuracy} = \frac{\text{Total Number of Predictions}}{\text{Number of Correct Predictions}} \tag{16}$$

Precision measures the proportion of true positive predictions to the total number of positive predictions made by the model, providing insight into the model's ability to avoid false positives. Recall evaluates the proportion of true positive predictions to the total number of actual positive cases, indicating how well the model identifies all relevant instances. The F1-score is the harmonic mean of Precision and Recall, offering a balanced metric that accounts for both false positives and false negatives. Lastly, Accuracy reflects the overall correctness of the model, measuring the ratio of accurate predictions to the total number of predictions. These metrics comprehensively assess the performance and effectiveness of the XGBoost model in classifying multiple stress levels.

5.2 Performance validation

In this study, three machine learning models DT, RF, and XGBoost were evaluated for their effectiveness in classifying stress levels. The performance of the DT model was notably limited, with significant misclassifications across all stress categories. As shown in Fig. 3(a), the model accurately identified only 23 cases of "Extreme Stress" but misclassified 18 cases of "Stress" as "No Stress." This resulted in lower performance metrics: a weighted precision of 55.67%, recall of 55.10%, F1-score of 55.12%, and an overall accuracy of 55.10%. RF model, depicted in Fig. 3(b), performed moderately better but still exhibited a considerable number of misclassifications. For instance, 16 cases of "Extreme Stress" were incorrectly labeled as "Stress," and 25 instances of "No Stress" were misclassified. This led to a weighted precision of 70.31%, recall of 67.35%, and an F1-score of 67.21%, culminating in an overall accuracy of 67.35%. Despite the improvement over DT, RF's performance remained moderate compared to XGBoost.

Fig. 3. Confusion matrix for Model DT (a) and Model RF (b) on actual and predicted label.

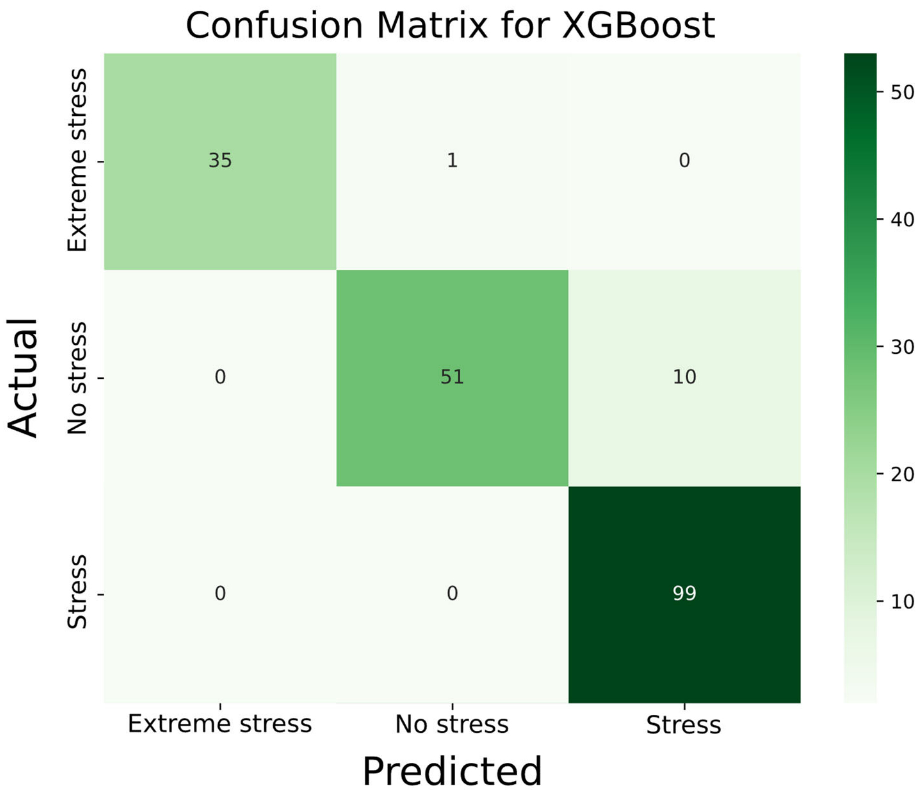

Fig. 4. Confusion matrix for XGBoost Model on actual and predicted label.

Table 2. Performance on Multiple Evaluation Metrics

Models	Weighted Precision	Weighted Recall	F1-score	Accuracy
Decision Tree (DT)	55.67%	55.10%	55.12%	55.10%
Random Forest (RF)	70.31%	67.35%	67.21%	67.35%
eXtreme Gradient Boosting (XGBoost)	**94.77%**	**94.39%**	**94.28%**	**94.39%**

On the other hand, the XGBoost model, shown in Fig. 4, demonstrated exceptional performance in classifying stress levels. It achieved high accuracy in distinguishing between "Extreme Stress," "No Stress," and "Stress" categories. Specifically, the model correctly classified 35 cases of "Extreme Stress" with only 1 misclassification and flawlessly identified 99 cases of "Stress," showcasing its precision and capability to handle complex, non-linear relationships in the data. Minor misclassifications, such as 10 instances of "No Stress" incorrectly classified as "Stress," indicate areas for potential refinement. A comprehensive comparison in Table 2 highlights that XGBoost outperformed both the Random Forest and Decision Tree models, achieving a weighted precision of 94.77%, recall of 94.39%, and an F1-score of 94.28%, with an overall accuracy of 94.39%. These results highlight XGBoost's performance better and reliability for stress level classification, establishing it as the most effective model in this study in Fig. 4.

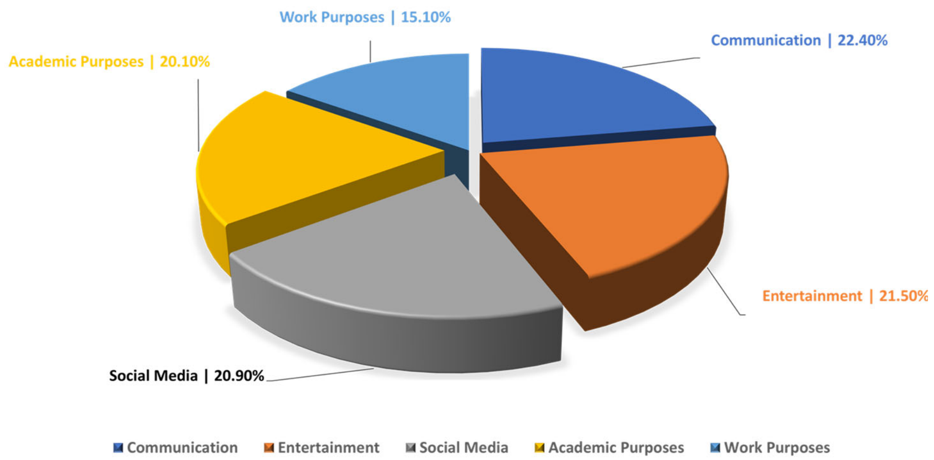

Fig. 5. Internet Usage For Daily Activities.

5.3 Various impacts

5.3.1 Impact on daily activities

Daily work is closely linked to mental health, as the nature and conditions of work significantly impact an individual's psychological well-being. Work provides structure, purpose, and social interaction, essential for maintaining mental health. Fig. 5 presents an overview of Internet usage across various age groups in Bangladesh, highlighting how individuals use the Internet for academic, social media, entertainment, communication, and work purposes. The highest internet usage is observed among younger age groups, particularly those aged 19 to 27, with the peak at 24 years, where 820 individuals are actively engaged online, mainly using the Internet for social media, entertainment, and academic purposes. A noticeable shift occurs as users age; internet usage for social media and entertainment decreases, while work-related and communication purposes become more prominent among those aged 30 and above. The age group of 23 to 25 shows the most diverse internet activity across all categories, with significant contributions from work and communication. The lowest number of users is at age 27; however, above this age, the graph indicates an increasing trend of using social media for work and communication. This pattern suggests that internet usage in Bangladesh reflects age-related shifts in priorities, with younger individuals focusing more on social, entertainment, and academic needs, while older users prioritize professional and communication purposes. Internet shutdowns can severely disrupt these patterns, affecting mental health by limiting access to social, academic, work-related, and communication activities, thereby increasing stress, isolation, and anxiety.

5.3.2 Stress levels

During internet blackouts, stress levels vary widely. Fig. 6 shows that near 54% of participants reported moderate stress, while 20% experienced extreme stress, reflecting severe psychological strain. Only 26.3% felt no stress, showing resilience. These results indicate that while some individuals cope better, many are vulnerable to moderate or extreme stress, manifested as anxiety, frustration, and isolation.

5.3.3 Emotional impact

Emotionally, internet disruptions also have significant impacts. Fig. 6 reveals that 35% of respondents felt “worried but hopeful” about potential job losses, blending anxiety with cautious optimism. Meanwhile, 30% were “frustrated,” feeling helpless about losing work opportunities. On the other hand, 20% expressed no concerns, feeling confident in their job security, while 10% felt secure, showing minimal anxiety. Overall, 65% of respondents experienced notable emotional distress, emphasizing the blackout's effect on remote workers’ stability and confidence.

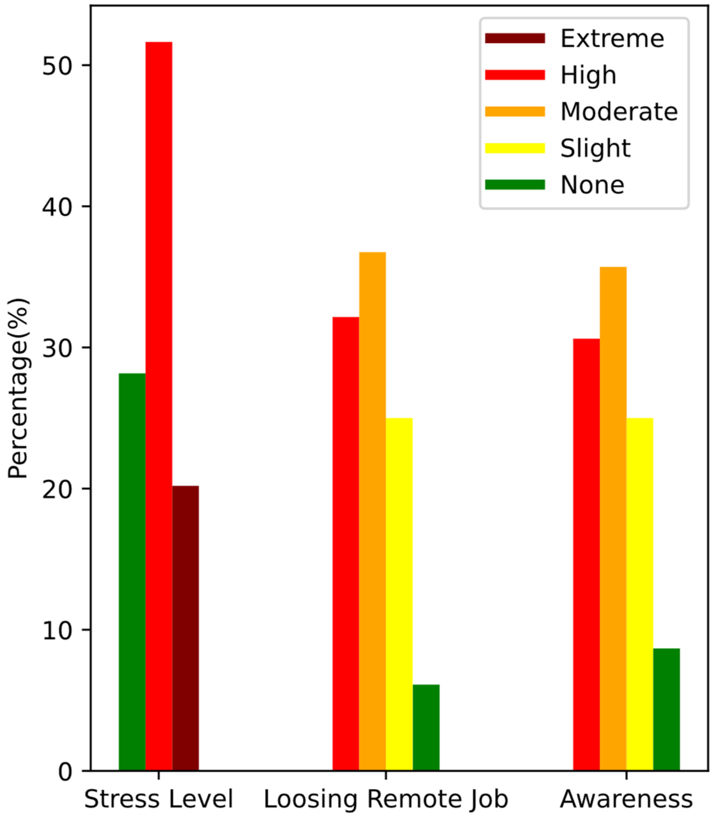

Fig. 6. The overall scenario of the impacts of mental health during an Internet blackout.

5.3.4 Behavioral Impact

Behaviourally, internet blackouts affect how individuals engage with their communities. Fig. 6 also shows that 35.43% were moderately aware of their surroundings, maintaining community involvement. Another 29.14% were highly aware, proactively engaging with their environment, while 26.86% were only slightly aware, possibly limited by personal circumstances. A small 8.57% were unaware, reflecting isolation and a lack of engagement. Despite these challenges, most people showed resilience, staying moderately or highly connected to their communities, adapting to maintain social bonds even amidst disruptions. Internet blackouts disrupt crucial daily activities and evoke a spectrum of emotional, behavioral, and psychological responses.

6 Conclusion

The findings of this study highlight the impact of internet blackouts on mental health, particularly during socio-political movements like the Bangladesh Quota Movement. The enforced internet shutdown disconnected people from crucial communication and social networks, intensifying anxiety, stress, and feelings of isolation, all of which can worsen existing mental health conditions. Survey results showed that most participants experienced moderate to severe stress, reflecting the psychological toll of losing access to educational, professional, and social resources. This disruption heightened depression and anxiety levels, emphasizing the need for accessible mental health support during such crises, particularly in regions with limited mental health infrastructure. The study also applied machine learning models to predict the mental health consequences of internet blackouts, finding that advanced models like Extreme Gradient Boosting (XGBoost) performed exceptionally well, achieving over 94% in precision, recall, F1-score, and accuracy. Simpler models like Decision Trees and Random Forests had lower performance, around 55% and 67% respectively. These findings demonstrate the effectiveness of sophisticated algorithms in understanding and forecasting mental health impacts. The research highlights the need for policies to mitigate these effects, enhance public awareness, reduce stigma, and ensure ongoing access to mental health services, ultimately protecting social stability and quality of life

References

1. L. W. Ford and R. Hass, Democracy in Asia, Brookings, Jan. 22, 2021. [Online]. Available: https://www.brookings.edu/articles/democracy-in-asia/
2. Freedom House, A Leaderless Struggle for Democracy. [Online]. Available: https://freedomhouse.org/report/freedom-world/2020/leaderless-struggle-democracy
3. The power of protest, Jun 13th 2020, The Economist, The Economist, Jun. 13, 2020. [Online]. Available: https://www.economist.com/weeklyedition/2020-06-13
4. World Report 2021, Human Rights Watch, Oct. 31, 2024. [Online]. Available: https://www.hrw.org/world-report/2021
5. D. Braha, PLoS ONE, **7(10),** e48596 (2012) doi: 10.1371/journal.pone.0048596.
6. D. Braha, Phase Transitions of Civil Unrest across Countries and Time, arXiv (Cornell University), Jan. 2023, doi: 10.48550/arxiv.2306.08698.
7. C. Abi-Nassif, A. M. Islam, and D. Lederman, Perceptions, Contagion, and Civil Unrest. 2020. doi: 10.1596/1813-9450-9416.
8. K. Deininger, Oxford Economic Papers **55(4),** 579–606 (2003) doi: 10.1093/oep/55.4.579.
9. C. Radar, Internet traffic trends in Bangladesh, Shutdown of Mobile Networks in Response to Student Protests, [Online]. Available: https://shorturl.at/3zzZN [Accessed: Nov. 19, 2024].
10. J. Tanner, Mobile Internet Returns to Bangladesh, but Not Social Media, Developing Telecoms, Jul. 31, 2024. https://rb.gy/ngp0yp
11. T. Record, Bangladesh is Coming Back Online After Five Days of Near-Total Internet Blackout, The Record, Jul. 24, 2024. Accessed: Jul. 24, 2024. [Online]. Available: https://rb.gy/701ydp
12. A. Jazeera, Bangladesh Restores Mobile Internet After 11-Day Blackout to Quell Protests, Al Jazeera, Jul. 28, 2024. [Online]. Available: https://rb.gy/iva9r6

13. D. P. F. De Derecho Pucp PE, Bangladesh Authorities Announce End to 11-Day Internet Shutdown, JURIST - News, Jul. 29, 2024. [Online]. Available: https://shorturl.at/QJLCj
14. RTÉ News, 32 Dead, 'Near-Total' Internet Shutdown in Bangladesh, RTE.ie, Jul. 18, 2024. [Online]. Available: https://shorturl.at/mfnn1
15. N. Koswanage, Bangladesh Internet Goes Dark as Widening Job Protests Kill 25, The Star, Jul. 19, 2024. [Online]. Available: https://shorturl.at/5qzUx
16. G. S. Reporter, Unrest in Bangladesh as Student Road Safety Protests Turn Violent, The Guardian, Aug. 05, 2018. [Online]. Available: https://rb.gy/ffpcss
17. A. Jazeera, Dhaka Bans Youtube Over Mutiny Tape, Al Jazeera, Mar. 10, 2009. [Online]. Available: https://shorturl.at/pgLmp
18. Reuters, Bangladesh Lifts Ban on YouTube, Blocked After Anti-Islam Film, Reuters, Jun. 05, 2013. Accessed: Jun. 05, 2013. [Online]. Available: https://shorturl.at/FEqu3
19. M. Z. Islam, Sudden Shutdown Follows Verdict, The Daily Star, Nov. 20, 2015. [Online]. Available: https://shorturl.at/bOvgJ
20. Access Now, Internet Throttling in Bangladesh: Government, Telcos Must #KeepItOn - Access Now, Access Now, Nov. 01, 2023. https://shorturl.at/vboH6
21. M. A. Whooley and J. M. Wong, Annual Review of Clinical Psychology **9(1),** 327–354 (2013) doi: 10.1146/annurev-clinpsy-050212-185526.
22. C. Otte et al., Nature Reviews Disease Primers **15(2),** 16065 (2016), doi: 10.1038/nrdp.2016.65.
23. S. L. James et al., The Lancet **392(10159),** 1789–1858 (2018), doi: 10.1016/s0140-6736(18)32279-7.
24. A.-S. Uban, B. Chulvi, P. Rosso, Future Generation Computer Systems **124,** 480–494 (2021), doi: 10.1016/j.future.2021.05.032.
25. Guidelines Review Committee, "Mental Health Gap Action Programme (mhGAP) Guideline for Mental, Neurological and Substance Use Disorders," World Health Organization, Nov. 20, 2023. [Online]. Available: https://shorturl.at/30Qz4
26. World Bank Open Data, World Bank Open Data. [Online]. Available: https://shorturl.at/Jdzld
27. D. Liu, X. L. Feng, F. Ahmed, M. Shahid, J. Guo, JMIR Mental Health **9(3),** e27244 (2021), doi: 10.2196/27244.
28. A. B. R. Shatte, D. M. Hutchinson, S. J. Teague, Psychological Medicine **49(09),** 1426–1448 (2019), doi: 10.1017/s0033291719000151.
29. S. Banitaan and K. Daimi, International Journal of Public Health Science (IJPHS) **3(4),** (2014), doi: 10.11591/ijphs.v3i4.6920.
30. G. V. Benito et al., Artificial Intelligence in Medicine, **157,** 102991 (2024), doi: 10.1016/j.artmed.2024.102991.
31. W. L. Ku, H. Min, Healthcare **12,** 625 (2024). DOI: 10.3390/healthcare12060625
32. J. Angskun, S. Tipprasert, T. Angskun, Journal of Big Data **9,** 1 (2022). DOI: 10.1186/s40537-022-00622-2
33. S. Gupta, L. Goel, A. Singh, A. K. Agarwal, R. K. Singh, Cognitive Neurodynamics **16,** 833-846 (2022). DOI: 10.1007/s11571-021-09771-1
34. B. Silveira, H. S. Silva, F. Murai, A. P. C. Da Silva, Future Generation Computer Systems **125,** 641-651 (2021). DOI: 10.1016/j.future.2021.07.014

35. T. Zhang, A. M. Schoene, S. Ji, S. Ananiadou, Npj Digital Medicine **5,** 1 (2022). DOI: 10.1038/s41746-022-00589-7
36. A. Sharma, W. J. M. I. Verbeke, Frontiers in Big Data **3** (2020). DOI: 10.3389/fdata.2020.00015
37. V. Arun, P. V, M. Krishna, A. BV, P. SK, S. V, 2021 IEEE Symposium Series on Computational Intelligence (SSCI) (2018). DOI: 10.1109/ssci.2018.8628945
38. B. Saylam, Ö. D. İncel, Diagnostics **14,** 501 (2024). DOI: 10.3390/diagnostics14050501
39. Z. Zheng, L. Liang, X. Luo, J. Chen, M. Lin, G. Wang, C. Xue, Frontiers in Psychiatry **15** 1280935 (2024). DOI: 10.3389/fpsyt.2024.1280935
40. Healthdirect Australia, Depression, Symptoms, Types, Treatment, Healthdirect, April 2023. Accessed: April 2023. [Online]. Available: https://shorturl.at/x79JB
41. World Health Organization: WHO, Mental health, Jun. 17, 2022. [Online]. Available: https://shorturl.at/DAhkk
42. NAMI, Mental Health Conditions, National Alliance on Mental Illness, Nov. 22, 2024. [Online]. Available: https://shorturl.at/jYFNC
43. Anxiety Disorders, National Institute of Mental Health (NIMH). [Online]. Available: https://shorturl.at/tHB7t
44. American Psychological Association, APA Dictionary of Psychology. [Online]. Available: https://dictionary.apa.org/anxiety
45. Substance Abuse and Mental Health Services Administration, Trauma-Informed Care in Behavioral Health Services. Substance Abuse and Mental Health Services Administration, 2014. [Online]. Available: https://shorturl.at/Mw5dq
46. A. R. Teo, in Elsevier eBooks (2014), pp. 890-891. DOI: 10.1016/b978-0-12-385157-4.01081-2
47. W. Coryell, Depressive Disorders, MSD Manual Professional Edition, Oct. 05, 2023. [Online]. Available: https://shorturl.at/Qq6lA
48. A. Heald et al., The Lancet Psychiatry, **5–5** (2018). [Online]. Available: http://www.thelancet.com/psychiatry
49. C. Wang, R. Pan, X. Wan, Y. Tan, L. Xu, C. S. Ho, R. C. Ho, International Journal of Environmental Research and Public Health **17,** 1729 (2020). DOI: 10.3390/ijerph17051729
50. C. Landwehr, C. Ojeda, and O. Tüscher, Too Sad to Vote? Mental Health's Impact on Political Participation during the Covid-19 Crisis, Items, Sep. 22, 2020. [Online]. Available: https://shorturl.at/0lbPE
51. S. L. MEd, How Does Your Environment Affect Your Mental Health?, Very well Mind, Mar. 23, 2023. [Online]. Available: https://shorturl.at/yAVdL
52. M. P. R. A and M. P. R. A, 'Living Under This Constant Threat': Environmental defenders face a mounting mental health crisis, Grist, Sep. 18, 2024. [Online]. Available: https://shorturl.at/cZmYj
53. P. Nie, K. Zhao, D. Ma, H. Liu, S. Amin, I. Yasin, Sustainability **16,** 8693 (2024). DOI: 10.3390/su16198693
54. M. E. Khoury-Malhame, S. B. Malhab, R. Chaaya, M. Sfeir, S. E. Khoury, Frontiers in Psychiatry **14** (2024). DOI: 10.3389/fpsyt.2023.1267603
55. C. Stott, L. Ho, M. Radburn, Y. T. Chan, A. Kyprianides, P. S. Morales, Policing a Journal of Policy and Practice **14,** 814-835 (2020). DOI: 10.1093/police/paaa073

56. D. A. Green, B. A. Williams, K. Park, Journal of Mental Health Counseling **43,** 198-211 (2021). DOI: 10.17744/mehc.43.3.03
57. L. Parsons and L. Parsons, How Unjust Police Killings Damage the Mental Health of Black Americans, Harvard Gazette, Jan. 12, 2024. [Online]. Available: https://shorturl.at/npyoT
58. StatCounter Global Stats, Desktop Social Media Stats Bangladesh, Statcounter Global Stats, StatCounter Global Stats, Available: https://gs.statcounter.com/social-media-stats/desktop/bangladesh
59. M. A. Islam Rafi, M. Rahman Sohan, A. Jawad, H. R. Sourid, M. M. Hossain, 2023 International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS), 637-642 (2023). DOI: 10.1109/ICAECIS58353.2023.10170378
60. N. Selvaraj, 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 3137-3140 (2015). DOI: 10.1109/EMBC.2015.7319057