Mental Health Evaluation During Internet Blackouts: A Machine Learning Approach

Md Tariqul Islam [1], Tahidul Islam [2], Mohammad Ariful Islam Rafi [3*], Tauhidur Rahman Sakib [1]

[1]*BRAC University, Dhaka-1212, Bangladesh*
[2]*Bangladesh University of Engineering and Technology, Dhaka-1000, Bangladesh*
[3]*University of Liberal Arts Bangladesh, Dhaka, 1207, Bangladesh*
** ariful.islam1.eee@ulab.edu.bd*

Keywords: Internet Blackout, Quota Movement, Mental Health, Emotional, Behavioural, Environment

Abstract

Internet has become essential for modern communication and access to services. However, blackouts during politically sensitive periods can disrupt daily life, causing anxiety and distress. This study examines the psychological effects of internet blackouts during the Bangladesh Quota Movement in July 2024, when internet access was shutdown to control information flow. The disruption significantly affected communication, financial transactions, and access to essential services, exacerbating anxiety, stress, tension, and feelings of isolation among citizens. A survey of 980 participants with 20 questions assessed behavioral, emotional, and psychological impacts. Results showed stress levels ranging from minimal to extreme, reflecting widespread distress. The study also used machine learning models to predict stress levels. The Decision Tree model showed limited predictive power, with around 55% accuracy, while the Random Forest model improved to 67%. XGBoost performed better than both, achieving over 94% in all metrics, demonstrating better accuracy. These findings highlight the potential of advanced algorithms to model mental health impacts, enabling policymakers to develop targeted interventions and allocate resources efficiently, ultimately minimizing the psychological toll of future internet disruptions and improving overall preparedness.

1. Introduction

The current global political landscape is witnessing an unprecedented increase in civil unrest and protests, urged by widespread dissatisfaction with government policies and actions across regions such as South America and Asia. These protests are often driven by economic disparities, social injustices, and a lack of political freedoms, resulting in financial instability, strained diplomatic relations, and security challenges for affected countries [1]. In Bangladesh, a significant example of such unrest is the Quota Movement, which has heightened national tensions. In response to this civil unrest, the Bangladeshi government implemented an internet shutdown to prevent the spread of information related to the protests. Starting on July 18, 2024, this “total shutdown” lasted for five days, effectively isolating the population from the rest of the world, while mobile internet services were additionally slowed down for 12 days [2-4]. During this period, Bangladeshi citizens faced severe limitations on communication, financial transactions, and access to essential services. This was one of the most extensive internet disruptions Bangladesh had experienced to date. Previous instances of internet slowdowns have also occurred during protests, such as the 2018 Road Safety Protest, where internet speed was reduced multiple times [5, 6]. Between 2009 and 2024, the Bangladeshi government frequently blocked or slowed down internet access in response to socio-political movements, affecting millions of people [7, 8].

Internet blackouts, such as those seen in Bangladesh, have profound implications for mental health. The sudden disconnection from digital communication and social support networks exacerbates 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 anxiety can lead to various health complications, including cardiovascular issues and the exacerbation of pre-existing mental health disorders [9, 10]. Mental health disorders are already a global concern, with depression being a leading cause of disability. Approximately 264 million people worldwide suffer from depression, which, in severe cases, can lead to suicide. Among individuals aged 15 to 29, suicide induced by depression ranks as the second leading cause of death, with nearly 800,000 people dying by suicide each year due to depression [11]. Mental health disorders also disrupt daily life, impacting personal relationships, work productivity, and overall quality of life [12]. The inability to access mental health support during crises, such as internet blackouts, exacerbates these issues. In regions like Bangladesh, where mental health infrastructure is underdeveloped, the impact of internet blackouts on mental health is particularly severe. In low- and middle-income countries (LMICs) like Bangladesh, more than 75% of individuals experiencing mental health disorders, such as depression, do not receive proper care, due to stigma, a lack of resources, and insufficient access to qualified specialists [13]. The fear of losing jobs, businesses, and social connections during these blackouts further compounds mental health challenges [14].

2. Literature Review

The use of machine learning (ML) in mental health research has advanced significantly, offering new methods for predicting, classifying, and understanding psychological disorders. Machine learning models, such as Decision Trees, Support Vector Machines (SVM), and neural networks, have proven effective in mental health applications, using a variety of features like demographic, behavioral, and physiological data. For instance, one study demonstrated the effectiveness of ensemble learning techniques, including data from electronic health records (EHRs) and self-reported surveys, to improve early diagnoses of anxiety and depression [15]. Classification algorithms such as Random Forest and XGBoost have also been instrumental in differentiating mental health conditions. For example, Random Forest models have been used to classify stress levels among students, utilizing academic performance data and physiological metrics like heart rate and skin conductance [16]. Another study applied XGBoost to identify post-traumatic stress disorder (PTSD) cases by analyzing survey responses and biometric data, showcasing the model's ability to manage complex interactions between variables [17]. These examples illustrate the value of machine learning in mental health, with models effectively handling complex, multi-dimensional data to predict mental health conditions. NLP techniques, meanwhile, have proven useful in detecting shifts in emotional tone and sentiment in social media posts, providing early warning signs of depressive episodes [18]. These techniques emphasize the transformative potential of ML in advancing our understanding and treatment of mental health challenges.

Despite these advancements, there remains a gap in research on the impact of internet blackouts on mental health, particularly in low- and middle-income countries like Bangladesh. The loss of reliable information sources during these blackouts creates uncertainty, increasing psychological distress. For individuals already experiencing mental health disorders, the lack of access to resources further worsens outcomes. Studies show that mental health disorders are often exacerbated by such disruptions, which can hinder support networks and amplify existing mental health conditions [19, 20]. Approximately 6.4 million people in Bangladesh (4.1% of the population) experience various depressive disorders, yet mental health care remains scarce and stigmatized. This lack of support is further aggravated during internet blackouts, when individuals may feel a heightened sense of isolation and vulnerability. The stigma surrounding mental health, combined with the limited availability of qualified mental health specialists, prevents many from seeking the treatment they need [21].

Addressing the impact of internet blackouts on mental health requires a multi-faceted approach, including improved access to mental health care, efforts to reduce stigma, and the establishment of mechanisms for continuous communication and information access during crises. Recognizing early signs of mental health disorders allows for timely intervention, potentially saving lives and improving quality of life. Our study contributes to this field by applying XGBoost to evaluate mental health during the internet shutdown in Bangladesh. By surveying 980 individuals with a 20-question questionnaire covering depression, anxiety, and stress, we provide a comprehensive understanding of the mental health impacts of the blackout. The findings emphasize the need for accessible mental health resources and policy interventions to mitigate the negative effects of digital disruptions [22].

3. Theoretical Background

3.1. Mental Health

A mental health illness is a condition that affects a person's overall well-being, emotions, thoughts, behavior, and communication with others [23]. According to the American Psychiatric Association (APA), mental health illnesses encompass emotional, behavioral, or a combination of both types of health conditions that are often linked to problems in family, social, or work environments [24]. In simpler terms, a mental health illness impacts a person's emotional and behavioral well-being, which can also lead to physical health effects.

3.2. Anxiety

According to the APA, anxiety is characterized by feelings of nervousness, uneasiness, and excessive fear [25]. These feelings often come with physiological symptoms that can persist and appear cyclically when anxiety is triggered [26]. Anxiety disorders are generally classified into three main types: Generalized Anxiety Disorder (GAD), panic disorder, and social anxiety disorder. GAD leads individuals to either avoid situations or seek reassurance about unpredictable circumstances, often resulting in excessive concern about unfavorable outcomes. Panic disorders are marked by sudden psychological and physical reactions, such as an irregular pulse, sweating, shaking, and shortness of breath. Social anxiety disorder involves an extreme fear of social situations, where individuals worry about others' reactions or judgments. Those with social anxiety often avoid situations that might draw attention or lead to embarrassment [27]. Anxiety disorders are particularly prevalent among students, significantly affecting their daily activities and academic performance. To understand and quantify the psychological impact of internet blackouts, we propose a conceptual model to measure stress levels influenced by various factors.

3.3. Depression

Depressive disorder, commonly referred to as clinical depression, is a mood disorder that severely impacts a person's emotions, thoughts, and daily activities. It is typically characterized by symptoms such as sadness, loss of interest in previously enjoyed activities, feelings of guilt or low self-worth, disrupted sleep, decreased appetite, fatigue, and difficulty concentrating [23]. There are two main types of depressive disorders: persistent depressive disorder and psychotic depression. Persistent depressive disorder, also known as dysthymia, is a condition in which a person experiences a depressed mood for at least two years. Individuals diagnosed with persistent depressive disorder may endure episodes of major depression alongside periods of less severe symptoms. This cycle of symptoms persists for two years, making the disorder more chronic [23]. In contrast, psychotic depression involves experiencing severe depression combined with psychosis. This can include disturbing fixed beliefs and hallucinations, such as seeing or hearing things that others do not.

3.4. 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 [28]. Events like the Black Lives Matter protests and the Hong Kong pro-democracy demonstrations highlight how external stressors such as crowding, noise, and police presence can worsen mental health conditions [29]. These incident 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 [30, 31] and air. This aligns with broader findings that these stressors exacerbate the psychological impact of social and political upheaval [32].

4. Methodology

4.1. 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 behavioral, 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 behavioral consequences of internet disruptions.

4.2. 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.

4.3. 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. 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.

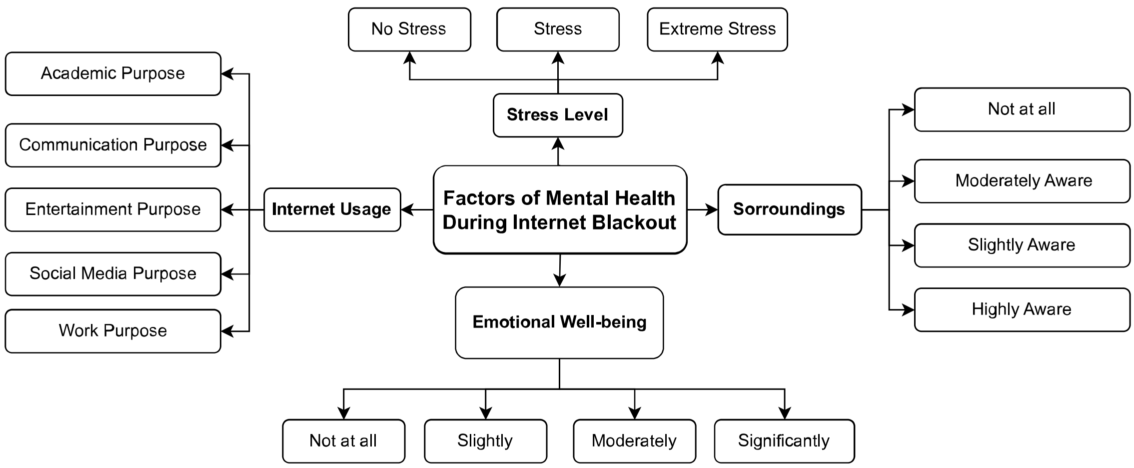

Fig. 1. Factors Influencing Mental Health During the Internet Blackout

5. Machine Learning Approach

5.1. 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. 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.

5.2. *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

$$D' = D \backslash \{\text{rows with missing values}\} \tag{1}$$

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

$$P_i = Encoded\ value\ of\ category\ i \tag{2}$$

For the 'Gender' variable, we utilized One-Hot Encoding, which transformed the categorical data into a binary vector representation $\mathbf{v}$ of length n, with n representing the number of unique categories.

5.3. *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.

$$obj = \sum_{i=1}^{n} l(y_i,\ \hat{y}_i) + \sum_{k=1}^{n} \Omega(f_k) \tag{3}$$

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 Regularization term that penalizes the complexity of the model, defined as

$$\Omega(f) = \gamma T + \left(\frac{1}{2}\right) \lambda \|w\|^2 \tag{4}$$

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 (5)

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{5}$$

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.

$$\sum_{i=1}^{n} [g_i f_t(x_i) + \left(\frac{1}{2}\right) h_i {f_t}^2(x_i)] + \Omega(f_t) \tag{6}$$

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 (7)

$$Gain = \frac{1}{2}\left[\frac{{G_L}^2}{H_L + \lambda} + \frac{{G_R}^2}{H_R + \lambda} + \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}\right] - \gamma \tag{7}$$

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.

5.4. *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

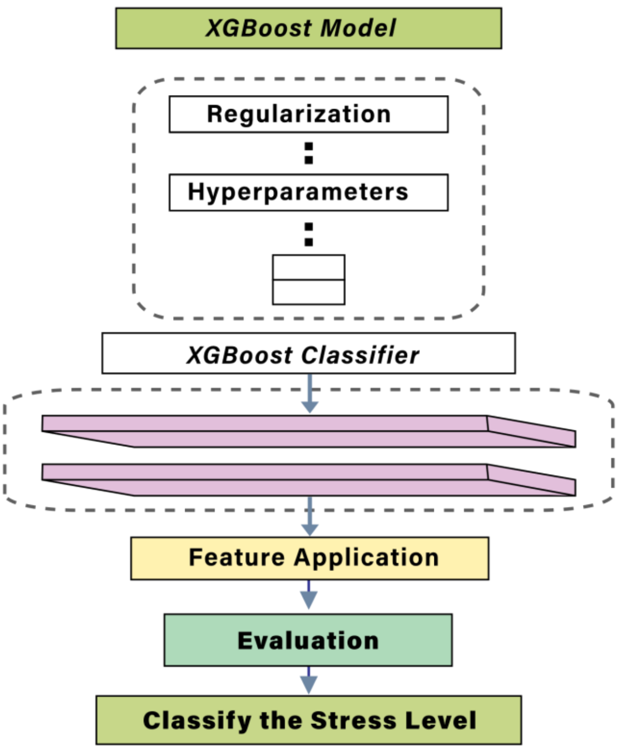

Fig. 2. XGBoost Model Arichitecture

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.

6. Result and Discussion

6.1. 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 (8) to (11): Precision, Recall, F1-score, and Accuracy.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}} \tag{8}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}} \tag{9}$$

$$\text{F1} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{10}$$

$$\text{Accuracy} = \frac{\text{Total Number of Predictions}}{\text{Number of Correct Predictions}} \tag{11}$$

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.

6.2. 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, 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. 4, 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. On the other hand, the XGBoost model, shown in Fig. 5, 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 I 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.

6.3. Various Impacts

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

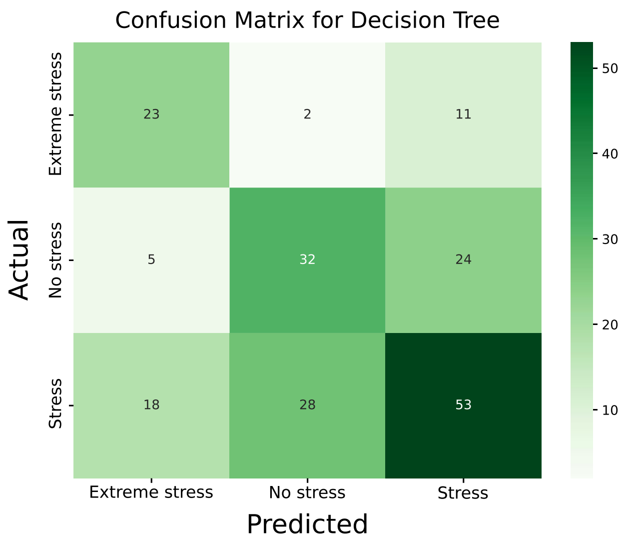

Fig. 3. Confusion matrix for DT on actual and predicted label

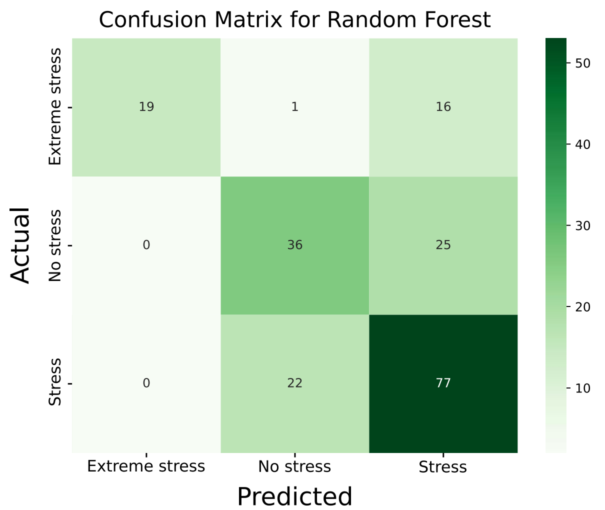

Fig. 4. Confusion matrix for RF on actual and predicted label

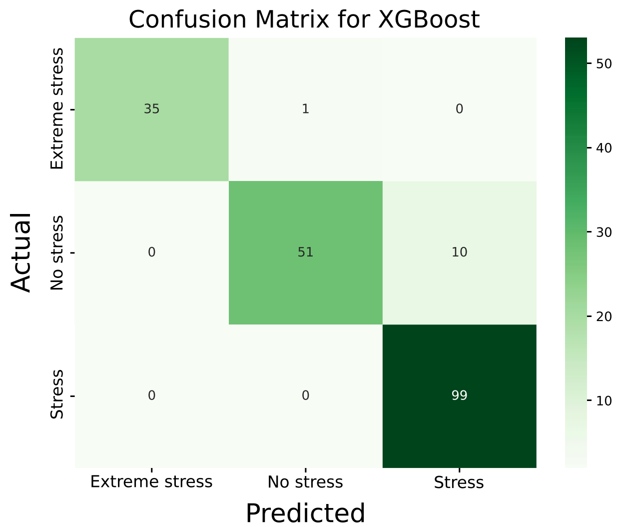

Fig. 5. Confusion matrix for XGBoost on actual and predicted label

TABLE I. PERFORMANCE ON MULTIPLE EVALUATION METRICS

Models	Weighted Precision	Weighted Recall	F1-score	Accuracy
DT	55.67%	55.10%	55.12%	55.10%
RF	70.31%	67.35%	67.21%	67.35%
XGBoost	**94.77%**	**94.39%**	**94.28%**	**94.39%**

or extreme stress, manifested as anxiety, frustration, and isolation.

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.

Behavioral Impact: Behaviorally, 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

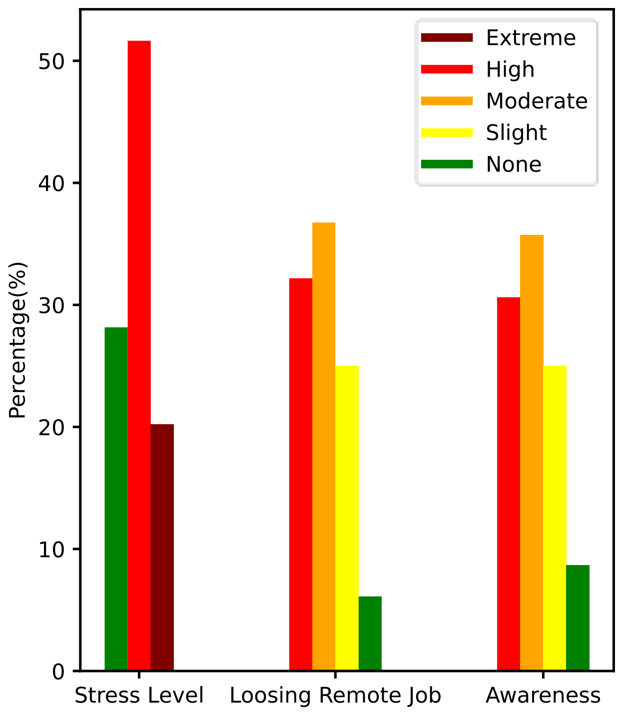

Fig. 6. The overall scenario of the impacts of mental health during an Internet blackout

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, behavioural, and psychological responses. Understanding these impacts is essential for developing strategies to mitigate the adverse effects on mental health and promote resilience in the face of such disruptions.

7. Conclusions

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.

8. References

[1] L. W. Ford and R. Hass, “Democracy in Asia,” Brookings, Jan. 22, 2021. [Online]. Available: https://shorturl.at/JpJcB

[2] K. Deininger, “Causes and Consequences of Civil Strife: Micro-Level Evidence from Uganda,” Oxford Economic Papers, vol. 55, no. 4, pp. 579–606, Oct. 2003, doi: 10.1093/oep/55.4.579.

[3] Cloudflare Radar [@CloudflareRadar], “The 5-day Shutdown was in Response to Student Protests.,” X/Twitter, Jul. 24, 2024. https://rb.gy/5vlaja (accessed Jul. 24, 2024).

[4] 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

[5] J. Tanner, “Mobile Internet Returns to Bangladesh, but Not Social Media,” Developing Telecoms, Jul. 31, 2024. https://rb.gy/ngp0yp

[6] A. Jazeera, “Bangladesh Restores Mobile Internet After 11-Day Blackout to Quell Protests,” Al Jazeera, Jul. 28, 2024. [Online]. Available: https://rb.gy/iva9r6

[7] G. S. Reporter, “Unrest in Bangladesh as Student Road Safety Protests Turn Violent,” The Guardian, Aug. 05, 2018. [Online]. Available: https://rb.gy/ffpcss

[8] A. Jazeera, “Dhaka Bans Youtube Over Mutiny Tape,” Al Jazeera, Mar. 10, 2009. [Online]. Available: https://shorturl.at/pgLmp

[9] 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

[10] M. Z. Islam, “Sudden Shutdown Follows Verdict,” The Daily Star, Nov. 20, 2015. [Online]. Available: https://shorturl.at/bOvgJ

[11] Access Now, “Internet Throttling in Bangladesh: Government, Telcos Must #KeepItOn - Access Now,” Access Now, Nov. 01, 2023. https://shorturl.at/vboH6

[12] M. A. Whooley and J. M. Wong, “Depression and Cardiovascular Disorders,” Annual Review of Clinical Psychology, vol. 9, no. 1, pp. 327–354, Mar. 2013, doi: 10.1146/annurev-clinpsy-050212-185526.

[13] C. Otte et al., “Major depressive disorder,” Nature Reviews Disease Primers, vol. 2, no. 1, Sep. 2016, doi: 10.1038/nrdp.2016.65.

[14] S. L. James et al., “Global, Regional, and National Incidence, Prevalence, and Years Lived With Disability for 354 Diseases and Injuries for 195 Countries and Territories, 1990–2017: A Systematic Analysis for the Global Burden of Disease Study 2017,” The Lancet, vol. 392, no. 10159, pp. 1789–1858, Nov. 2018, doi: 10.1016/s0140-6736(18)32279-7.

[15] A. R. Arusha and R. K. Biswas, “Prevalence of Stress, Anxiety and Depression Due to Examination in Bangladeshi Youths: A Pilot Study,” Children and Youth Services Review, vol. 116, p. 105254, Sep. 2020, doi: 10.1016/j.childyouth.2020.105254.

[16] P. S. Wang et al., “Use of Mental Health Services for Anxiety, Mood, and Substance Disorders in 17 Countries in the WHO World Mental Health Surveys,” The Lancet, vol. 370, no. 9590, pp. 841–850, Sep. 2007, doi: 10.1016/s0140-6736(07)61414-7.

[17] D. Liu, X. L. Feng, F. Ahmed, M. Shahid, and J. Guo, “Detecting and Measuring Depression on Social Media Using a Machine Learning Approach: Systematic Review,” JMIR Mental Health, vol. 9, no. 3, p. e27244, Dec. 2021, doi: 10.2196/27244.

[18] G. V. Benito et al., “Machine learning for anxiety and depression profiling and risk assessment in the aftermath of an emergency,” Artificial Intelligence in Medicine, vol. 157, p. 102991, Sep. 2024, doi: 10.1016/j.artmed.2024.102991.

[19] S. Gupta, L. Goel, A. Singh, A. K. Agarwal, and R. K. Singh, “TOXGB: Teamwork Optimization Based XGBoost model for early identification of post-traumatic stress disorder,” Cognitive Neurodynamics, vol. 16, no. 4, pp. 833–846, Jan. 2022, doi: 10.1007/s11571-021-09771-1.

[20] R. B. Jarros et al., “Anxiety disorders in adolescence are associated with impaired facial expression recognition to negative valence,” Journal of Psychiatric Research, vol. 46, no. 2, pp. 147–151, Oct. 2011, doi: 10.1016/j.jpsychires.2011.09.023.

[21] B. Silveira, H. S. Silva, F. Murai, and A. P. C. Da Silva, “Predicting user emotional tone in mental disorder online communities,” Future Generation Computer Systems, vol. 125, pp. 641–651, Jul. 2021, doi: 10.1016/j.future.2021.07.014.

[22] T. Zhang, A. M. Schoene, S. Ji, and S. Ananiadou, “Natural Language Processing Applied to Mental Illness Detection: A Narrative Review,” Npj Digital Medicine, vol. 5, no. 1, Apr. 2022, doi: 10.1038/s41746-022-00589-7.

[23] Healthdirect Australia, “Depression,” Symptoms, Types, Treatment, Healthdirect, April 2023. Accessed: April 2023. [Online]. Available: https://www.healthdirect.gov.au/depression

[24] D. P. Shenoy, C. Lee, and S. L. Trieu, “The Mental Health Status of Single-Parent Community College Students in California,” Journal of American College Health, vol. 64, no. 2, pp. 152–156, Jul. 2015, doi: 10.1080/07448481.2015.1057147.

[25] 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

[26] A. R. Teo, “Phobias,” in Elsevier eBooks, 2014, pp. 890–891. doi: 10.1016/b978-0-12-385157-4.01081-2.

[27] A. Heald et al., “Brexit, the Leave Campaign, and Mental Health of Ethnic Minority Communities,” The Lancet Psychiatry, vol. 5–5, Jan. 2018, [Online]. Available: http://www.thelancet.com/psychiatry

[28] M. E. Khoury-Malhame, S. B. Malhab, R. Chaaya, M. Sfeir, and S. E. Khoury, “Coping During Socio-political Uncertainty,” Frontiers in Psychiatry, vol. 14, Jan. 2024, doi: 10.3389/fpsyt.2023.1267603.

[29] StatCounter Global Stats, “Desktop Social Media Stats Bangladesh, Statcounter Global Stats,” StatCounter Global Stats, Available: https://gs.statcounter.com/social-media-stats/desktop/bangladesh

[30] M. A. Islam Rafi, M. Rahman Sohan, A. Jawad, H. R. Sourid and M. M. Hossain, “Sound Pollution Monitoring System and Awareness Creation in Modern Cities: A Case Study,” 2023 International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS), Bangalore, India, 2023, pp. 637-642, doi: 10.1109/ICAECIS58353.2023.10170378.

[31] M. A. Islam Rafi, M. R. Sohan, M. S. Hasan, T. S. Rafa and A. Jawad, “Exploring Classification of Vehicles Using Horn Sound Analysis: A Deep Learning-Based Approach,” 2024 23rd International Symposium INFOTEH-JAHORINA (INFOTEH), East Sarajevo, Bosnia and Herzegovina, 2024, pp. 1-6, Available: https://shorturl.at/VyVYD, doi: 10.1109/INFOTEH60418.2024.10496018.

[32] N. Selvaraj, “Psychological Acute Stress Measurement Using a Wireless Adhesive Biosensor,” 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, Italy, 2015, pp. 3137-3140, doi: 10.1109/EMBC.2015.7319057.