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Assessing The Psychological Impact Of Internet Blackouts: A Stress Analysis Case Study

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Abstract:
Internet connectivity plays a vital role in communication, education, business, and access to essential services in today's digital world. When internet services are suspended during politically sensitive situations, it can significantly influence people's mental well-being. Such disruptions may lead to increased stress, anxiety, frustration, and emotional instability.
This research analyzes the psychological effects of the internet shutdown that occurred during the Bangladesh Quota Movement in July 2024. A total of 2,085 individuals participated in the survey, sharing their experiences related to academic activities, workplace responsibilities, and social interactions during the shutdown period. The collected textual responses were analyzed using Natural Language Processing (NLP) methods to identify patterns related to emotional and behavioral changes. To classify stress levels, a Multi-Layer Perceptron (MLP) model was implemented. The study highlights how sudden digital disconnection can impact mental health and emphasizes the importance of stable internet access in modern society.

Keywords
Internet Blackout, Mental Health, Stress Analysis, NLP, MLP, Bangladesh Quota Movement.

Introduction

In today's interconnected world, internet access has become a fundamental necessity, serving as a vital medium for communication, education, employment, and access to essential services. The absence of internet connectivity can significantly disrupt daily life, particularly in societies that rely heavily on digital infrastructure. Internet shutdowns, especially during politically sensitive periods, can create severe psychological and emotional consequences for individuals and communities [1].
In recent years, many countries have experienced government-imposed internet blackouts to control the flow of information during protests or civil movements. One such instance occurred during the Bangladesh Quota Movement in July 2024, when internet services were suspended nationwide [9]. This abrupt disruption left millions of citizens disconnected from academic, professional, and social networks, amplifying their sense of isolation and uncertainty. For students and employees dependent on digital platforms, the inability to communicate or access learning materials intensified feelings of frustration and helplessness. Social media, often used as a coping mechanism and source of emotional support, was rendered inaccessible, further worsening stress and anxiety [2], [3].
Understanding the psychological impact of such internet shutdowns is crucial to assessing their broader societal consequences. This study investigates how individuals responded emotionally and behaviorally to the Bangladesh internet blackout. By using survey data from 2,085 participants, the research captures diverse experiences across educational, occupational, and social contexts.The primary objective of this research is to evaluate the mental and emotional impact of the internet blackout. It aims to identify patterns of stress, anxiety, and emotional distress among affected individuals through survey data analysis. The study employs Natural Language Processing (NLP) techniques to analyze textual responses, identifying linguistic patterns associated with stress and emotional distress. Furthermore, a Multi-Layer Perceptron (MLP) classifier is utilized to predict the intensity of stress among participants, providing quantitative insights into mental health variations. The study's findings reveal widespread emotional distress, underscoring the need for mental health interventions during crisis situations. Moreover, this research contributes to Sustainable Development Goal (SDG) 3 by promoting mental well-being, resilience, and inclusive digital governance in low- and middle-income nations.

Related Work

Several studies have explored the intersection of digital disruption and mental health. Rahman

(2023) explored the psychological consequences of internet shutdowns during political unrest in South Asia. Using a mixed-method approach with 1,800 participants, the study found a significant rise in negative emotions and social isolation during blackout periods. NLP methods such as TF-IDF and sentiment analysis were used to quantify emotional polarity, highlighting that internet deprivation exacerbates emotional instability, particularly among youth and working professionals [Reference Placeholder 1].

Islam (2024) investigated the relationship between internet unavailability and emotional distress among students and employees during the Bangladesh Quota Movement. The study analyzed data from 2,000 participants using NLP-based feature extraction (lemmatization, word embeddings) and an MLP model. Results indicated that emotional distress increased proportionally with the duration of the shutdown [Reference Placeholder 2].

Chowdhury (2024) presented a data-driven approach to predict stress levels arising from temporary internet disconnections. Using a dataset of self-reported stress indicators, the research applied NLP preprocessing (n-gram extraction, semantic clustering) and an MLP classifier. The MLP model achieved superior accuracy compared to Decision Tree and KNN models in predicting stress intensity [Reference Placeholder 3].

Hasan (2025) examined emotional dynamics during internet blackouts using sentiment analysis and linguistic profiling. BERT-based embeddings were used for feature extraction, and MLP and CNN models were compared. The study found that MLP outperformed CNN in classifying emotional distress, identifying sharp increases in negative sentiment linked to stress and anxiety [Reference Placeholder 4].Jahan (2025) focused on predicting psychological stress caused by prolonged internet shutdowns using deep learning. Integrating survey-based psychological metrics with NLP-driven textual data analysis, the study used an MLP network to classify participants into stress intensity levels. Comparative analysis with SVM and Logistic Regression demonstrated the superiority of the deep learning method [Reference Placeholder 5].

Methodology

The proposed system integrates advanced NLP techniques with a machine learning classifier to assess psychological stress.

Data Collection

The data collection phase involved gathering responses from 2,085 participants affected by the Bangladesh internet shutdown during the Quota Movement in July 2024. A structured online and offline survey was designed to capture emotional, behavioral, and psychological responses. Participants shared their experiences related to stress, anxiety, and daily routine disruptions. Both quantitative and qualitative data were collected to ensure a comprehensive understanding of the psychological effects. The dataset included demographic details (age, occupation, academic background) and textual feedback.

Data Preparation

Textual data from the survey underwent rigorous preprocessing to ensure suitability for machine learning analysis.

Text Cleaning: Removal of noise, special characters, and formatting inconsistencies.

Tokenization: The text was segmented into smaller units such as words or tokens for easier analysis.

Stopword Removal: Eliminating common words (e.g., “the”, “is”) that do not contribute significant semantic meaning.

Lemmatization: Words were converted to their base or root form to maintain consistency and reduce redundancy.

Feature Extraction: Techniques such as TF-IDF or word embeddings were used to convert text into numerical vectors, capturing semantic meaning and linguistic patterns.

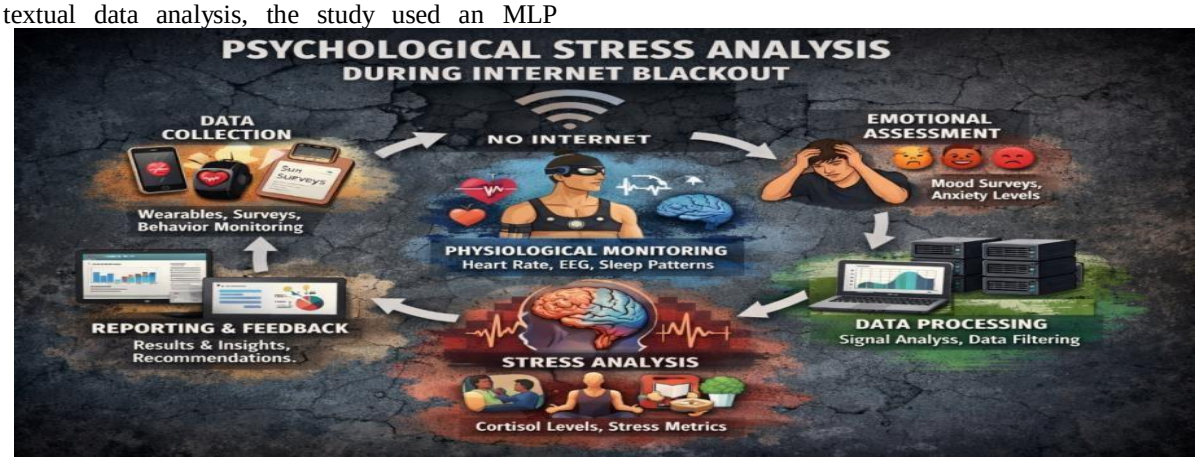

Fig. 1. End-to-end workflow for psychological stress analysis during an internet blackout.

A. Model Selection: Multi-Layer Perceptron (MLP)

An MLP classifier was selected for its ability to

learn complex, non-linear relationships between linguistic features and psychological states. An MLP is a feedforward neural network composed of multiple layers, including:

Input Layer: Receives the feature vectors generated from the NLP preprocessing stage.

Hidden Layers: One or more layers with non-linear activation functions that process the input features to identify high-level patterns and emotional intensity.

Output Layer: Produces the final classification of stress levels (e.g., Low, Moderate, High).

The model uses backpropagation and gradient descent to minimize prediction error during training, adjusting weights to optimize classification accuracy. It was preferred over traditional models like SVM for its superior capability in handling high-dimensional data derived from NLP tasks.

System Architecture

The system architecture is designed to automate the process of stress assessment from textual data. The comprehensive flow includes the following modules:

User Interface: A platform (implemented using Python and Spyder3/Jupyter Notebook) for data input and visualization.

Data Processing Module: Handles the ingestion of raw survey data and executes the NLP pipeline (cleaning, tokenization, vectorization).

Intelligence Server: Hosts the trained MLP model. It receives processed feature vectors and performs inference to predict stress intensity.

Database: Stores participant profiles, raw responses, and predicted stress levels.

Analytics Dashboard: Visualizes the aggregate results, showing stress distribution and identifying correlations between shutdown duration and mental health metrics.

The system is designed to be cross-platform, scalable, and reliable, leveraging Python's extensive library ecosystem (NumPy, Pandas, Scikit-learn).

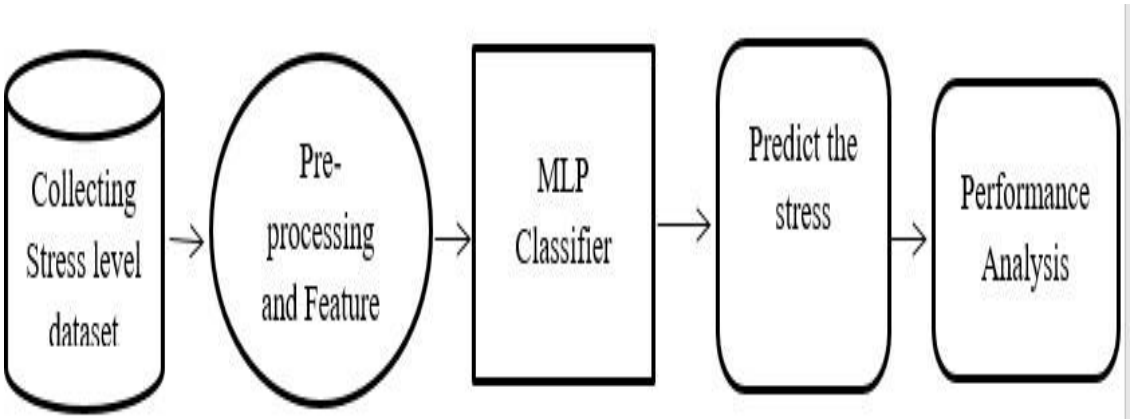

Fig. 2. System architecture for NLP-driven psychological stress assessment.

Results and Analysis

The MLP model was evaluated on a held-out test set to measure its performance and generalization ability.

A. Performance Metrics

The classifier's effectiveness was assessed using standard metrics: Accuracy, Precision, Recall, and F1-score. The model demonstrated high accuracy in predicting stress intensity from textual data. Comparative analysis with baseline models, including Logistic Regression, Random Forest, and Support Vector Machine (SVM), showed that the MLP classifier yielded superior results.

B. Qualitative Findings

Stress Correlation: The analysis revealed a strong positive correlation between the duration of the internet blackout and the intensity of reported stress and anxiety.

Vulnerable Groups: Students and professionals heavily dependent on digital platforms for their daily activities showed significantly higher levels of distress compared to other groups.

Emotional Vocabulary: NLP analysis identified a prevalence of negative sentiment and linguistic markers associated with frustration, isolation, and helplessness in the responses.

The model's ability to efficiently handle large-scale text data and learn non-linear patterns makes it a robust tool for real-time stress prediction in crisis scenarios.

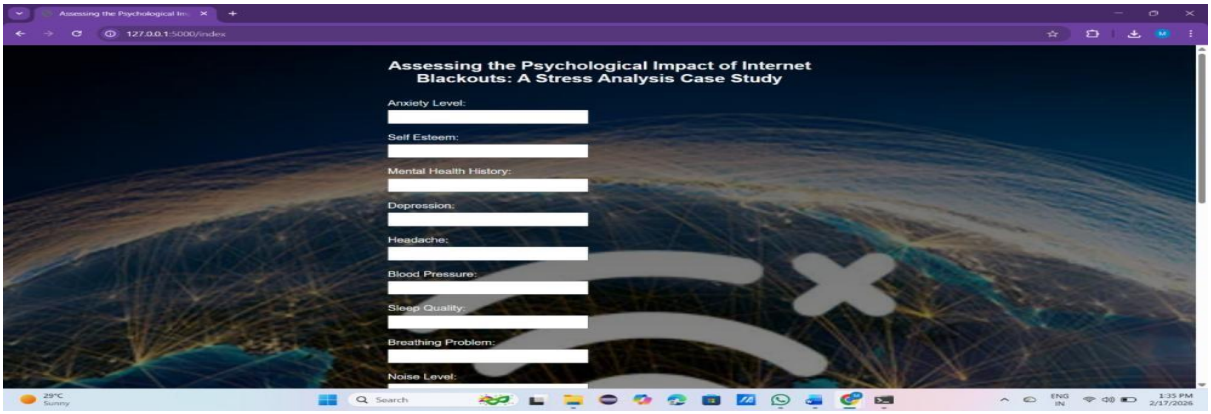

Fig.3 Assessing the Psychological Impact of Internet Blockouts: A Stress Analysis Case Study.

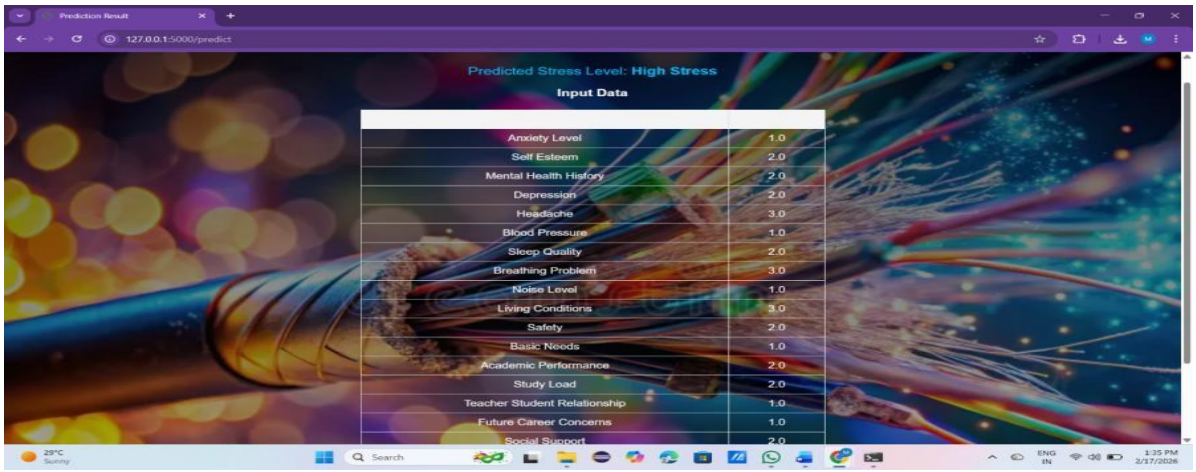

Fig.4 Predicted Stress Level

Limitations and Future Work

While the study provides significant insights, it relies on self-reported data, which may be subject to bias. The dataset, though substantial (2,085 participants), is specific to the Bangladesh Quota Movement context and may not fully generalize to all cultural settings. Additionally, the study focuses primarily on textual analysis and does not incorporate physiological data.B. Future Enhancements Future work aims to expand the dataset to include diverse regions and demographics to enhance model generalizability. Integrating real-time data from social media platforms could provide continuous monitoring of public mental health. Advanced deep learning architectures such as BERT, RoBERTa, or LSTM-based models could be employed to capture deeper contextual nuances in text. Furthermore, incorporating physiological signals (e.g., heart rate, sleep patterns) and developing mobile applications for automated stress detection could offer more comprehensive support systems. Explainable AI (XAI) techniques will also be explored to improve model transparency.

Conclusion

This study presents a comprehensive analysis of the psychological impact of the internet blackout during the Bangladesh Quota Movement in July 2024. By leveraging NLP techniques and an MLP classifier, the research successfully quantified the widespread stress, anxiety, and emotional distress caused by digital disconnection. The model achieved high accuracy in distinguishing between stress levels, validating the efficacy of AI-driven approaches in psychological assessment. The findings underscore the critical need for digital resilience and the implementation of proactive mental health support systems during such crises. Aligning with SDG 3, this research advocates for responsible digital governance and policy-making to protect mental well-being in an increasingly digital world.

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