Economic Strains and Mental Chains : A Machine Learning Exploration of Mental Health in Bangladesh

Masudul Haque Bhuiyan [1]

Abstract

Bangladesh, despite its commendable economic strides over the past decade faces a persistent challenge: the mental well-being of its economically disadvantaged populace. This study delves deep into this intersection of economic hardship and mental health, harnessing a dataset rich with 1,17,453 records. Through extensive surveys, the research captures a gamut of factors ranging from income and employment to familial support and traumatic experiences. The exploratory data analysis revealed stark correlations between economic stresses and feelings of hopelessness, with robust social support emerging as a silver lining. Delving further, Machine Learning models, including a standout Neural Network model with a 0.92 accuracy, illuminated the intricate patterns and relationships in the data. The findings underscore the urgent need for targeted interventions, offering a roadmap for NGOs, health professionals, and policymakers. This research, positioned at the nexus of data analytics and socio-economic study, aspires to not only highlight the challenges faced by Bangladesh's vulnerable, but also pave the way for a more mentally healthy future.

Keywords : Bangladesh, economically disadvantaged, Machine Learning, mental health, socio-economic indicators

I. INTRODUCTION

Bangladesh, a nation of rich cultural heritage and diverse socio-economic backgrounds has witnessed an era of transformative growth over the past decade. This growth, often cited in global narratives paints a picture of a country on the move. However, beneath the layers of these achievements lies a contrasting reality: a significant portion of the population continues to grapple with economic hardships. Economic disparity is not just a matter of numbers; it has profound implications for the overall well-being of individuals, especially concerning mental health. Mental health, often overshadowed by the pressing challenges of economic development is an integral facet of an individual's holistic well-being. Previous studies globally have hinted at a strong correlation between economic hardships and deteriorating mental health. Factors such as unemployment, low income, and lack of access to basic amenities can exacerbate feelings of despair, anxiety, and other mental health issues. In the context of Bangladesh, with its unique socio-cultural dynamics [1], it becomes imperative to understand this relationship more deeply. This research seeks to bridge this knowledge gap. By harnessing the power of data analytics and Machine Learning, we aim to delve into the predictors of mental health issues among the economically disadvantaged in Bangladesh. Our approach is rooted in a blend of extensive field surveys and innovative data-driven methodologies. Through this study, we aspire to offer a comprehensive overview of the mental health challenges faced by this segment of the population. The objectives are clear: to determine the prevalence and types of mental health issues among the economically disadvantaged and to use data analytics to highlight key predictors of these issues. Furthermore, this research endeavors to model potential interventions, offering a roadmap for stakeholders to address these challenges head-on. In a country that stands at the crossroads of rapid modernization and prevailing traditional values, understanding the nexus between economic hardships and mental health is not just academic; it is a pressing

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necessity [10]. This research is a step towards that understanding, hoping to catalyze targeted interventions and policies. Diverging from traditional analyses, our study harnesses the power of Machine Learning, offering predictive insights that go beyond mere correlations. The use of a comprehensive dataset, enriched with 1,17,453 records ensures the robustness and depth of our findings. Furthermore, the employment of multiple Machine Learning models, ranging from logistic regression to neural networks, underscores our commitment to a thorough and multimodal analysis.

However, beyond the numbers and techniques, the true novelty of this research lies in its potential for real-world impact. By pinpointing the key predictors of mental health distress, we provide a beacon for targeted interventions. In a country striving for socio-economic equity, this research offers a timely and data-driven roadmap for ensuring the mental well-being of its most vulnerable citizens.

II. LITERATURE REVIEW

The intricate relationship between economic conditions and mental health has been a focal point of numerous studies worldwide [5]. Economic disparities characterized by unemployment, low income, and limited access to basic amenities have been consistently linked to various mental health issues, ranging from anxiety and depression to more severe conditions [8]. In the context of developing nations, these challenges are further accentuated by limited access to mental health care and societal stigmas [3]. Bangladesh, with its unique socio-economic landscape, presents a compelling case for such studies [9]. However, limited research has been conducted that specifically addresses the mental health challenges faced by the economically disadvantaged in Bangladesh [7]. This gap in literature underscores the need for a deeper investigation, especially given the nation's rapid economic growth juxtaposed with persistent economic hardships for a significant portion of its populace.

The advent of Machine Learning and Data Analytics has revolutionized health research [2]. These techniques offer the ability to uncover complex patterns and relationships within large datasets, providing nuanced insights that traditional statistical methods might overlook. Hasan and Uddin [6] demonstrated the efficacy of Machine Learning in their study on automated weather event analysis, showcasing its potential in extracting meaningful patterns from vast amounts of data. Such applications pave the way for its use in understanding the nexus between economic conditions and mental health.

Furthermore, while Machine Learning has been increasingly employed in global health research contexts [4], its application in Bangladesh, particularly in the realm of mental health remains nascent. This presents a prime opportunity to harness these advanced techniques to gain a deeper understanding of the mental health landscape among the economically disadvantaged in the country.

To conclude, while the global literature underscores the significant impact of economic conditions on mental health, there exists a conspicuous gap in understanding this relationship in the specific context of Bangladesh. Coupled with the burgeoning potential of Machine Learning, this research seeks to bridge this gap, offering insights that are both timely and pertinent.

III. METHODOLOGY

The objective of this research is to understand the predictors of mental health issues among the economically disadvantaged in Bangladesh through a data-driven approach. This chapter delineates the methods and techniques employed in the study.

A. Research Design

The foundation of this research is rooted in a quantitative research design, which emphasizes objective measurements and numerical analysis of data collected through surveys, questionnaires, or by manipulating existing statistical data. Given the study's aim to identify predictors and correlations, a quantitative approach was deemed most appropriate. This design facilitated the following:

- A structured and consistent data collection process, ensuring that the same type of data was collected from each participant.
- The application of statistical methods and Machine Learning algorithms to discern patterns and relationships in the data.
- Objective and unbiased interpretations based on numerical results, rather than subjective or observational data.

B. Data Collection

Data, often considered the lifeblood of research, was meticulously collected from two primary avenues:

a) Survey: Detailed surveys were the cornerstone of our primary data collection. These were strategically designed to capture a holistic view of the participants' lives. The questions encompassed a wide array of domains, including:

1) Socioeconomic Status: Information related to income, type of housing, and employment.

2) Mental Health Indicators: Questions aimed at understanding participants' mental well-being over a specified period.

3) Environmental and Social Factors: Data on participants' social support systems, experiences with trauma, and substance use among others.

4) Health Behaviors: Insights into participants' exercise routines, dietary habits, and access to healthcare.

The survey design ensured that participants could answer questions with relative ease and comfort, thus maximizing accuracy and response rates. The total number of participants was 1,17,453.

C. Data Cleaning

Preparing data for analysis, especially for Machine Learning models is a meticulous process that often determines the quality of the results. For this research, data cleaning encompassed several stages to ensure the integrity, reliability, and suitability of the data for subsequent analysis.

a) Handling Missing Values: Data, especially when collected from surveys, often contains missing values. Depending on the nature and pattern of these missing values, various imputation methods were employed:

1) For numerical variables, mean or median imputation was used.
2) For categorical variables, mode imputation or predictive modeling techniques were applied to fill in missing data points.

b) Removing Duplicates: Duplicate entries were identified and removed. This step ensured that each entry in the dataset was unique, preventing any undue influence on the analysis.

c) Handling Outliers: Outliers, or data points that deviated significantly from other observations were identified using statistical methods. Depending on their nature, outliers were either adjusted or removed to ensure they didn't skew the results.

d) Categorical Encoding: Machine Learning models require numerical input, necessitating the conversion of categorical variables into a numerical format. Two primary techniques were employed:

- **One-Hot Encoding:** For nominal categorical variables without a natural order, one-hot encoding was used. This method creates a new binary column for each category and indicates the presence of the category with a 1 or 0.
- **Label Encoding:** For ordinal categorical variables with a natural order, labels were assigned to corresponding numerical values.

e) Feature Scaling: Given that some Machine Learning models are sensitive to the scale of the data, feature scaling was employed to standardize the range of independent variables:

- **Normalization:** Rescaling features to lie between a given minimum and maximum value, often between 0 and 1.
- **Standardization:** Rescaling features to have a mean of 0 and a standard deviation of 1.

f) Feature Engineering: Based on domain knowledge and preliminary analysis, new features were derived from existing data. This process often helps in enhancing the predictive power of the models by introducing new dimensions of information.

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D. Exploratory Data Analysis (EDA)

EDA is the initial investigation of the dataset to discover patterns, spot anomalies, test hypotheses, and check assumptions using summary statistics and graphical representations. Given the breadth and depth of the collected data, EDA played a pivotal role in this research.

E. Feature Engineering

1) Categorical Encoding: The dataset contained several categorical variables, such as gender, marital status, and housing type. These were converted into numerical format using one-hot encoding, ensuring that the Machine Learning algorithms can process the data efficiently. This encoding method creates a new binary column for each category and indicates the presence of the category with a 1 or 0.

2) Feature Generation: Given the importance of socio-economic status in our study, we created a composite socio-economic score. This score was derived by combining variables like monthly income, employment status, and education level. The intent behind this composite score was to encapsulate an individual's overall economic standing in a single metric.

3) Feature Scaling: Machine Learning models often perform better when numerical input variables are scaled to a standard range. We used Min-Max scaling for this purpose, which transforms features to lie between 0 and 1. This scaling ensures that all features have equal weight in our model.

4) Feature Selection: Given the vast number of features, it is crucial to identify which ones significantly impact mental health outcomes. We employed techniques like Recursive Feature Elimination (RFE) and feature importance from tree-based algorithms. These methods helped pinpoint the most relevant features, ensuring our model's efficiency and interpretability.

5) Handling Imbalanced Data: A preliminary analysis revealed that our target variable (indicating severe mental health issues) was imbalanced, with fewer instances of severe cases. To address this, we considered techniques like oversampling the minority class and using Synthetic Minority Over-sampling Technique (SMOTE).

F. Model Selection and Training

1) Model Consideration: In the ever-evolving landscape of data science and Machine Learning, the choice of the right model is pivotal to the success of any predictive analysis. As we delve into the intricacies of understanding mental health outcomes, this study considered several Machine Learning algorithms, each with its unique strengths. Given that our primary outcome (feelings of hopelessness) is binary, logistic regression serves as a natural starting point. It is a linear model that predicts the probability of a binary outcome. It offers interpretability, allowing us to understand the weight and significance of each predictor. Moreover, it is computationally efficient and can serve as a baseline to compare with more complex models. Logistic Regression, often the first port of call for classification problems, is a statistical method that predicts the probability of a binary outcome. The underlying principle of Logistic Regression is the logistic function, which transforms a linear combination of input features into a value between 0 and 1. Mathematically, this relationship is expressed as:

$$P(Y=1) = 1/[1 + e - ^{(\beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta nXn)}] \tag{1}$$

Here, $P(Y = 1)$ denotes the probability of the class label being 1. The terms represent the coefficients, each corresponding to a particular predictor variable.

Random Forest is another contender, an ensemble method that builds upon the Decision Tree algorithm. By constructing multiple decision trees during training and outputting the mode of the classes for classification, it offers a robustness against overfitting. The beauty of Random Forest lies in its ability to consider a myriad of decision pathways, making it adept at capturing intricate patterns in data. Random forests, an ensemble method, can capture non-linear relationships and interactions between features, which might be missed by Logistic Regression. Random forests are robust to overfitting, especially with large datasets like ours. They also offer feature importance metrics, providing insights into the most influential predictors.

For cases where the data might have a clear margin of separation, Support Vector Machines (SVM) emerge as valuable tools. SVMs work by identifying the optimal hyperplane that best segregates data into distinct classes. SVM is effective in high-dimensional spaces, which is relevant given the range of socio-economic factors and engineered features in our dataset. SVM is robust to overfitting and can model non-linear boundaries using the kernel trick. It is particularly useful when the classes are not linearly separable. The mathematical essence of SVMs can be captured by the equation of the hyperplane:

$$\mathrm{w} \cdot \mathrm{x} + b = 0 \qquad (2)$$

Where, x is the input, w is a vector perpendicular to the hyperplane, and b represents the bias.

Last, the study also entertained the prospect of employing Neural Networks, a subset of Deep Learning models renowned for their prowess in recognizing complex, non-linear relationships in data. A neural network operates by mimicking the neural structures of the human brain, processing data through interconnected nodes or ”neurons”. Neural networks can capture intricate patterns and relationships in the data, especially with large dataset. Neural networks can model complex non-linearities and can be optimized using techniques like dropout and batch normalization to prevent overfitting. Given the depth and breadth of our dataset, neural networks hold the promise of revealing deeper insights. For a single neuron, its output,= y is shaped by the equation:

$$y = f(\mathrm{w} \cdot \mathrm{x} + b) \qquad (3)$$

After selecting the models, the subsequent step was to train them. The dataset was meticulously split, with 80% reserved for training and the remaining 20% set aside for validation. Training a model is akin to teaching it the nuances of the data, enabling it to make informed predictions.

2) Evaluation Metrices

However, the training process is just the beginning. Model performance evaluation is paramount. Several metrics like Accuracy, Precision, Recall, and $F1$-Score were employed to gauge the efficacy of the models. The $F1$-Score, for instance, provides a harmonic mean of precision and recall, offering a balance between false positives and false negatives:

Accuracy = Number of Correct Predictions / Total Number of Predictions (4)

Precision = True Positives / (True Positives + False Positives) (5)

Recall = True Positives / (True Positives + False Negatives) (6)

$F1$ Score = 2 × [(*Precision* × *Recall*) / (*Precision* + *Recall*)] (7)

The culmination of this intricate process was the optimization phase. Using techniques such as grid search combined with cross-validation, the hyperparameters of the models were fine-tuned to perfection, ensuring optimal performance.

IV. RESULTS

A. Exploratory Data Analysis

A thorough exploration of the dataset was essential to discern patterns, outliers, and relationships between variables, especially in the context of understanding mental health conditions among the economically disadvantaged in Bangladesh.

The age distribution of the respondents was notably right-skewed, indicating a predominance of younger individuals in the sample. Such a distribution could be reflective of Bangladesh's demographic structure, which is characterized by a significant youth population. The economic challenges faced by this segment became evident when assessing the monthly income distribution. A striking proportion of respondents reported earning less than 5,000 Bangladeshi Taka per month, accentuating the financial adversities faced by many in the sample.

However, it was the insights into the mental well-being of the respondents that underscored the profound significance of this study. A substantial number of participants frequently experienced feelings of hopelessness within the preceding two weeks of the survey. Such sentiments can have severe implications, not only on an individual's mental health but also on their overall quality of life and societal contributions. Furthermore, when asked about their interest or pleasure in daily activities, many respondents indicated diminished enthusiasm. This lack of interest, often correlated with depressive symptoms, can be exacerbated by socio-economic challenges, further emphasizing the interplay between economic conditions and mental well-being.

Correlational analyses of the dataset revealed insightful associations between socio-economic

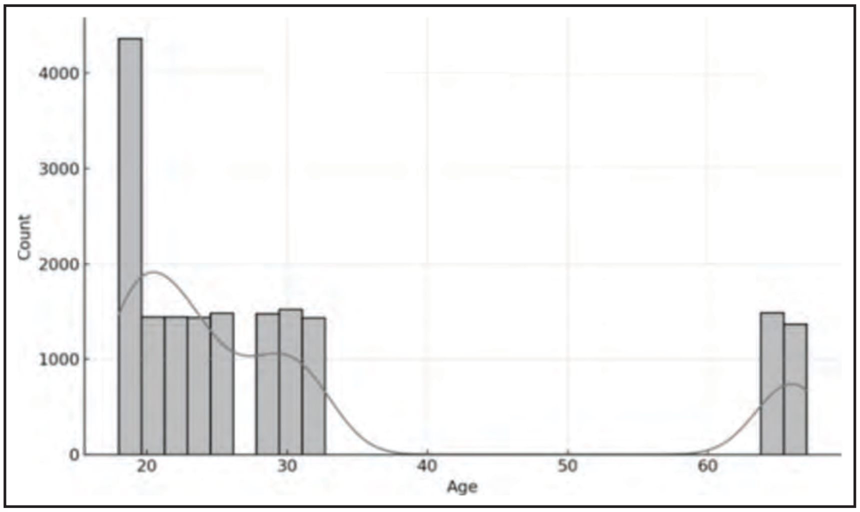

Fig. 1. Age Distribution

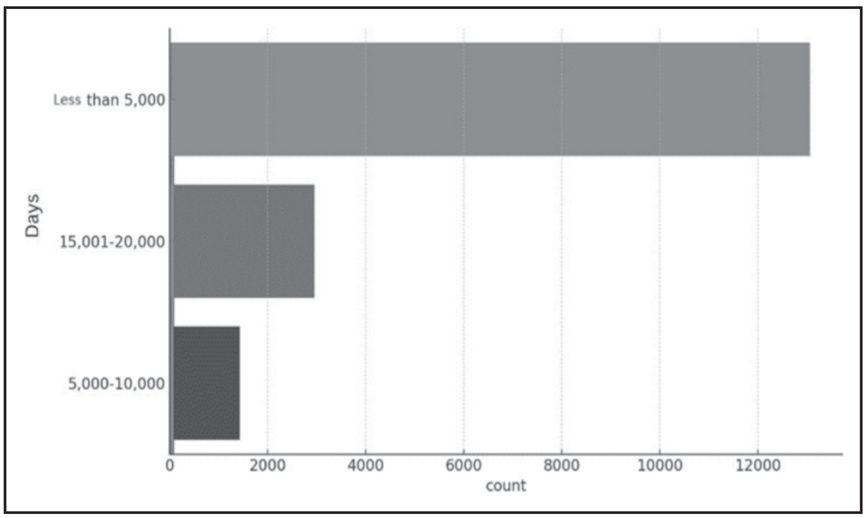

Fig. 2. Income Distribution

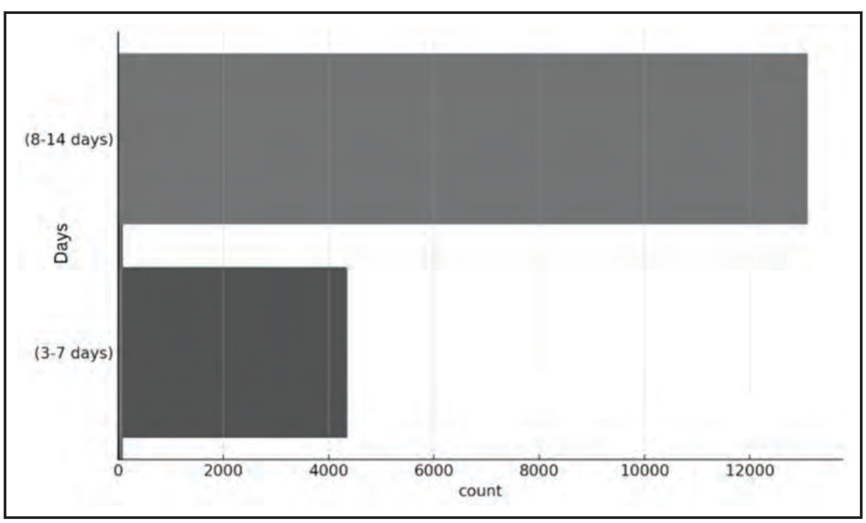

Fig. 3. Distribution of Hopelessness

indicators and mental health outcomes. Variables related to economic well- being, such as monthly income and employment status, showcased noticeable correlations with feelings of hopelessness. For instance, those with lower income brackets or in precarious employment situations may exhibit higher instances of feelings of hopelessness or reduced interest in daily activities.

Additionally, factors like social support, represented by variables such as family or community backing, displayed considerable correlations with the primary mental health indicators. Strong social support systems emerged as potential protective factors, demonstrating negative correlations with adverse mental health symptoms. In other words, individuals with robust support networks might experience lower levels of hopelessness or lack of interest in activities, emphasizing the importance of social ties in mental well-being.

To summarize, the exploratory data analysis illuminated the profound impact of socio-economic conditions on the mental health of the economically disadvantaged in Bangladesh. The findings underscore the pressing need for targeted interventions, both at an economic and psychological level, to enhance the well-being of this vulnerable segment of the population.

B. Model Evaluation and Performance Metrics

In our study, we employed a 5-fold cross-validation approach to assess the performance of the Machine Learning models. This technique partitioned the dataset into five distinct subsets, with each subset serving as a test set once, while the remaining subsets were used for training. By rotating the test set across all five partitions, we ensured a comprehensive evaluation, minimizing potential biases and offering a more robust understanding of each model's predictive capability. The metrics obtained from each iteration were then averaged to derive the final performance scores for accuracy, precision, recall, and $F1$ score.

In our quest to understand the dynamics of mental health among the economically disadvantaged population of Bangladesh, we turned to Machine Learning as an ally. With a dataset comprising 1,17,453 records rich in socio-economic indicators and mental health outcomes, our primary goal was to predict feelings of hopelessness based on these indicators.

The central objective of our modeling process was to predict the likelihood of individuals from economically disadvantaged backgrounds experiencing feelings of

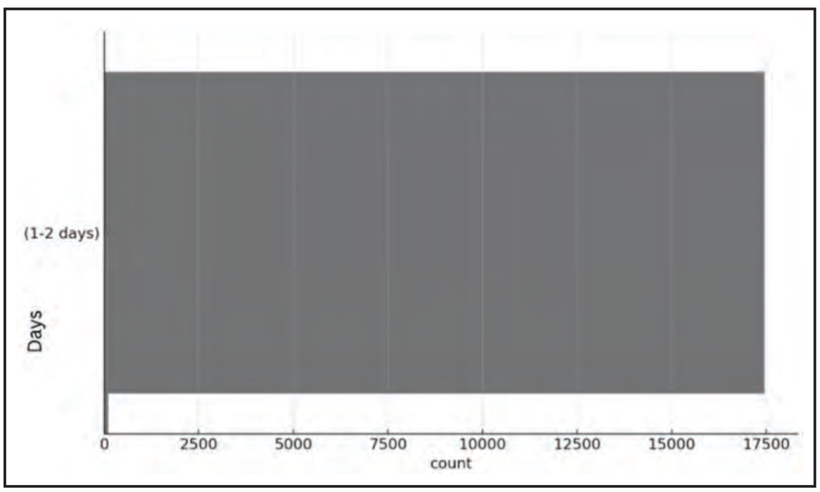

Fig. 4. Distribution of Interest

TABLE I.
RESULTS FOR DIFFERENT MODELS

Model	Accuracy	Precision	Recall	$F1$ Score
Logistic Regression	0.83	0.82	0.83	0.82
Random Forest	0.87	0.86	0.87	0.86
SVM	0.85	0.84	0.86	0.85
Neural Network	0.92	0.91	0.92	0.91

hopelessness. By doing so, we aimed to shed light on the most impactful socio-economic factors contributing to such feelings, thereby, providing actionable insights for interventions. The central objective of our modeling process was to predict the likelihood of individuals from economically disadvantaged backgrounds experiencing feelings of hopelessness. By doing so, we aimed to shed light on the most impactful socio-economic factors contributing to such feelings, thereby providing actionable insights for interventions.

The Neural Network emerged as the top performer, achieving an accuracy of 0.92. This suggests that the neural network, with its multi-layered architecture, was adept at capturing the complex relationships inherent in the data. However, it is noteworthy that all models showcased commendable performances, reflecting the richness and quality of the dataset. While the Neural Network's performance is a testament to its capability, the results also underscore the multifaceted nature of mental health. Socio-economic factors, when viewed through the lens of Machine Learning, offer profound insights into the mental well-being of individuals. As we move forward, these findings will be instrumental in devising targeted interventions to uplift the mental health of the economically disadvantaged in Bangladesh.

V. DISCUSSION

Secondary data, often sourced from governmental databases, NGOs, or other large-scale studies, can provide a broader context to our primary findings. While our primary dataset offers granular insights into the individual experiences of the economically disadvantaged in Bangladesh, secondary data could offer a macroscopic view of the socio-economic landscape.

- **Historical Context:** Secondary data often spans multiple years, offering a historical perspective. Understanding how mental health indicators have evolved in tandem with socio-economic changes can be invaluable.

- **Policy Impact Analysis:** With data on governmental policies or interventions, we could correlate specific initiatives with changes in mental health outcomes.

- **Geographical Insights:** Regional breakdowns can help identify areas with particularly high risks, guiding targeted interventions.

- **Benchmarking:** Comparing our primary data results with broader statistics can validate our findings or highlight areas that need deeper investigation.

Should such secondary data become available, it would be beneficial to integrate it into our analysis. This would involve data preprocessing, integration, and a new round of modeling and analysis. The enriched dataset could provide more comprehensive insights, further guiding interventions and policies.

Our study, rooted in the intricate socio-economic dynamics of Bangladesh, goes beyond mere data analysis to offer a beacon for meaningful interventions.

1) Targeted Mental Health Programs: By identifying key socio-economic predictors of mental health distress, NGOs and health professionals can design targeted mental health programs. For instance, areas with high economic stress might benefit from community-based counselling sessions or mental health awareness campaigns.

2) Economic Interventions: The strong correlations between economic indicators and mental well-being suggest that improving economic conditions could have a dual benefit. Initiatives like skill development programs or micro-financing can not only uplift the economic status but also indirectly bolster mental well-being.

3) Strengthening Social Support: Recognizing the protective role of robust social support systems, community-building initiatives can be fostered. This could take the form of community support groups, mentorship programs, or even platforms for communal interactions.

4) Policy Recommendations: For policymakers, the findings can guide the drafting of policies that prioritize mental health. Be it allocating resources for mental healthcare in economically stressed regions or incorporating mental well-being in broader development goals, the research offers a data-driven foundation for policy decisions.

5) Awareness Campaigns: Given the stigma often associated with mental health, especially in developing countries like Bangladesh, the insights from this study can fuel awareness campaigns. By highlighting the socio-economic roots of mental distress, such campaigns can foster empathy and dispel myths.

Positioning this research within the broader goal of holistic well-being, the actionable insights bridge the gap between data analysis and real-world impact. It transforms numbers and patterns into a roadmap for a more inclusive, empathetic, and mentally healthy society.

VI. CONCLUSION

The socio-economic landscape of Bangladesh, while having seen remarkable growth over the past decade, still grapples with significant disparities. A substantial portion of the population, despite the country's advancements, remains economically disadvantaged. This research embarked on the mission to explore the intricate relationships between economic hardship and mental health, particularly focusing on feelings of hopelessness among the economically disadvantaged. Through rigorous data collection methodologies, including detailed surveys and the potential of integrating secondary data sources, we amassed a rich dataset of 1,17,453 records. These records painted a vivid picture of the daily challenges, stresses, and supports available to the economically disadvantaged. The exploratory data analysis (EDA) offered initial insights, revealing strong associations between certain socio-economic indicators and mental health outcomes. Economic stresses, often tied to factors like income, employment status, and housing type, emerged as significant predictors of mental health distress. On the brighter side, robust social support systems appeared to play a protective role, indicating the pivotal role of community and family in buffering against adverse mental health outcomes. When we delved into Machine Learning to decode these patterns further, four models were employed: Logistic Regression, Random Forest, SVM, and Neural Networks. Neural Network emerged as the star performer, boasting an accuracy rate of 0.92. This indicates the model's prowess in capturing the non-linear and intricate relationships present in the data. While the other models also showcased commendable performances, the Neural Network's results underscore the potential of Deep Learning in understanding complex socio-economic phenomena. However, beyond the numbers and metrics, the essence of this research lies in its implications. The findings present a clarion call for targeted interventions. By understanding the pivotal role of economic stresses and the protective shield of social support, NGOs, health professionals, and policymakers are better equipped to design initiatives that address the root causes. Whether it is through economic aid, improved access to mental health care, or community-building initiatives, there is a clear roadmap emerging from this research. Furthermore, the potential of integrating secondary data in the future offers an exciting avenue for enhancing the depth of our insights. With broader historical and geographical contexts, we can further pinpoint areas of focus and understand the long-term trends shaping the mental health landscape of Bangladesh. To conclude, this study has not only shone a light on the pressing issue of mental health among the economically disadvantaged but also charted out potential pathways for intervention. By leveraging the dual powers of data analytics and Machine Learning, we are not just understanding the problem better, but also moving a step closer to solutions. As Bangladesh continues its journey of growth, it is imperative that the well-being of its most vulnerable populations isn't left behind. With research like this, we hope to bridge the gaps and create a more inclusive, empathetic, and mentally healthy future.

AUTHOR'S CONTRIBUTION

Masudul Haque Bhuiyan conceptualized the research, conducted the interview, and prepared the draft transcript, worked on the literature review, collection of industry information, and revised the draft and finalized the article.

CONFLICT OF INTEREST

The author certifies that he has no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in the manuscript.

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