A Data-Driven Insight to Enhancing Stress Management Through Chatbot Interaction Among Undergraduate Students.

Abstract—**Student stress management at the undergraduate level is a significant issue in the educational world. Therefore, this stress is a challenging issue that needs to be dealt with. As higher educational requirements stack up and their challenges grow, most students struggle to keep the required balance between their studies and preparation. This study establishes a deeper investigation of stress management among undergraduate students using machine-learning algorithms to identify factors contributing to stress and provide solutions. The research aims to illuminate the fundamental causes and health implications of stress for students. Through surveys and questionnaires, the study categorizes stress stages, identifying patterns and enabling the use of new stress management strategies. The findings are used to address concerns shared by undergraduate students and determine interventions to help them cope effectively which aim to provide students with the strength, knowledge, resources, and support needed to manage stress effectively and live a fulfilling life during their university years and future years. The findings will be used to develop policies and programs backed by science to ensure emotional and academic success for students.**

Index Terms—**Stress Management, Undergraduate Students, Mental Health, Chatbot Interaction, Machine Learning Algorithms, Emotional Well-being, Human-Computer Interaction (HCI)**

I. Introduction

IN the modern age, Undergraduate students face numerous challenges in their academic journey, including academic pressure, financial strain, and social pressures [1], [2]. These pressures, driven by the competitive nature of the education system and societal expectations for achievement, can significantly impact their mental health and overall well-being [3]. Financial tension, tuition fees, living expenses, and education debt contribute to the complexities of student well-being, often leading to heightened stress and anxiety [4]. Additionally, students face social pressures to balance academic responsibilities with social activities and relationships, resulting in feelings of isolation and loneliness [5], [6]. Mental health issues like depression, anxiety, and stress are prevalent among students, emphasizing the need for accessible and destigmatized mental health resources on college campuses [4]. Maintaining a healthy work-life is crucial for undergraduate students to overcome these challenges [7].

Human-computer interaction is crucial in addressing the digital divide in mental health treatment, fostering interdisciplinary cooperation, and developing AI-driven solutions [8]. Innovative methodologies like virtual reality and immersive video games are being explored to enhance therapeutic results. Bangladesh is a leading participant in this movement, where technology is essential for complex health needs and mental health issues [9]. Integrating a social model framework with medical interventions can enhance personal agency and prioritize patients' needs within technical advancements [10]. The key to a more promising future lies in the collaboration of specialists in Human-Computer Interaction (HCI) and professionals in the field of mental health [11].

Within this context, this study investigates stress management among undergraduate students in Bangladesh, examining the impact of academic pressure, social needs, and personal issues on mental health and academic performance. Through an interdisciplinary approach integrating psychology, technology, and machine learning, we aim to identify interventions to promote student resilience and mental well-being.

Based on that, our research addresses 3 research questions:
RQ1: How effective are HCI and ML algorithms in predicting stress levels among undergraduate students based on their interaction with a stress management chatbot?
RQ2: What is the efficacy of chatbot interactions in delivering immediate support and guidance for stress management among undergraduate students?
RQ3: How does the personalization of chatbot interactions, based on individual user data and preferences, find the effectiveness of stress management interventions?

We use machine learning algorithms to classify undergraduate students' stress levels into five stages, enabling the development of personalized interventions. The personalized chatbot, designed using HCI principles, uses survey questionnaires and qualitative data analysis to understand stress contexts and promote resilience.

A. Research Contribution

- Research suitable machine learning methods to achieve higher and more precise accuracy for classification.
- Utilize data-driven insights to develop personalized interventions that offer students real-time support, guidance, and resources.
- Explore the potential of chatbot technology as a scalable and accessible tool for addressing stress management challenges among undergraduate students.

II. Background Study

In exploring stress management tools, Park et al. (2019) [12] and Potts et al. (2023) [13] conducted studies in this area, emphasizing the importance of interactive questioning and personalized assistance in mental health initiatives. Consequently, they observed modest improvements in well-being, particularly among younger users, indicating the potential value of integrating tools like ChatPal into conventional mental health services. Investigating stress management dynamics, Meng et al. (2021) [14] found that both chatbot and human interactions contribute to stress reduction, with emotional support from humans playing a crucial role. Meanwhile, Abbas et al. (2022) [15] explored mature students' transition to higher education, highlighting the impact of online chat platforms and chatbots on their adjustment, despite challenges such as students' preference for familiar messaging services. Klos et al. (2021) [16] conducted a study using the AI-based chatbot Tess to deliver psychological interventions to college students in Argentina. He found a significant reduction in anxiety symptoms. Lin et al. (2021) [17] introduced the Virtual Reality Group Chatbot Counseling (VRGC) system, integrating various modules for tailored support, including chatbot and VR-enabled group therapy sessions. In order to assist undergraduates in managing stress and anxiety, Silvia Gabrielli (2021) [18] and Patel et al. (2019) [19] developed chatbots. Eight sessions concentrating on cognitive behavioral therapy, positive psychology, and mindfulness techniques were conducted with 71 female first-year university students as part of Gabrielli's study. Conversely, Patel's chatbot utilized emotion recognition to offer personalized advice, effectively reducing symptoms of tension and anxiety. Fitzpatrick et al. (2017) [20] found that a conversational bot delivering self-help programs significantly reduced depression symptoms in college students with anxiety and depression. Additionally, Hegde S. [21] identified severe depression, anxiety, and suicidal thoughts among US college students, highlighting the urgent need for research and interventions. Chancellor S. [22] and Bone D. [23] explore machine learning and social media data for mental health state prediction, highlighting its potential for early disorder detection and treatment. Pendse (2021) [24] investigates the Indian mental health helpline system's impact on distress and offers suggestions for technology-mediated care. Daher K. [25] uses blue light to reduce stress, yielding promising results. Rachel Kornfield et al. [26] study young adults' preference for online mental health self-screeners, Ng et al. [27] explore Fitbit's potential for PTSD patients, Pretorius et al. focus on enhancing online help-seeking for youth mental health, and Doherty [28] investigates the effectiveness of mobile applications in supporting pregnant women's mental well-being and addressing depression. Smith et al. [29] developed Flip*Doubt, a web application that helps users manage negative thoughts related to mental health, addressing depression among university students in developing nations like Bangladesh. Sen et al. [30] employed machine learning models to identify early signs of depression among Bangladeshi university students, aiming to improve their quality of life through early intervention. Suresh (2022) [31] highlights the growing specialized use of Natural Language Processing (NLP) chatbots in mental health services. Pendse et al. (2019) [32], utilizing Appadurai's paradigm, highlight the necessity of incorporating mental health factors into research on Human-Computer Interaction Design for Development (HCI4D).

III. Dataset

A. Dataset Exploration and Analysis

As a part of our research, we found existing public datasets insufficient for our study goals. Consequently, we developed a customized 30-question survey informed by dataset analysis and HCI. This bespoke questionnaire covers topics including mental health disorders, academic stressors, coping strategies, and perspectives on technology-driven interventions. Our aim is to gather comprehensive data on the unique challenges faced by undergraduate students in Bangladesh regarding stress management and mental well-being.

B. Data Collection

To ensure accurate data, we consulted with BRACU Counseling Unit psychiatrists to verify our survey and classify stress and depression levels. Collaborating with mental health experts, we developed a comprehensive approach to studying stress management among Bangladeshi undergraduate students. We created a 30-question on mental health, academic pressures, coping strategies, and technology-based interventions, plus a 15-question stress and depression assessment. Using snowball sampling on platforms like Discord and Facebook, we gathered 473 responses, ensuring confidentiality and anonymity through Google Forms' secure interface.

C. Data preprocessing

A heatmap is used to visualize the correlation between features and target variables, identifying factors affecting student mental health. A threshold value of 0.12 filters out strongly correlated features. The dataset is divided into training and testing subsets, with 80% used for training and 20% reserved for testing. The model deployment marks the transition from development to practical application, converting trained models for real-time or batch processing and integrating with existing systems.

D. Survey Questions

For constructing the dataset, the survey was conducted based on the questions mentioned in the table I

IV. Methodology

The diagram 1 outlines a methodology for developing a machine learning-based application for classifying depression patterns and offering suggestions. It details a comprehensive data preprocessing workflow, including data collection, cleaning, normalization, and transformation, preparing the data for model training. The data is then divided into training 80% and testing sets 20%. The model is trained with the training data and used to classify depression levels in the test data. The classification results are analyzed to evaluate the model's performance. The Flask framework is utilized for application development. This involves integrating the trained model, managing user data and sessions, and implementing features to display results and handle errors effectively.

TABLE I: Survey Questions

Section	Question	Response Format
Demographic	Please specify your gender identity.	Multiple choice
	Please select your age group.	Multiple choice
Inquiry about Potential Depression	Have you ever been diagnosed with depression?	Multiple choice
	On a scale of 1 to 5, how often do you experience symptoms of depression (e.g., sadness, loss of interest)?	Multiple choice
	Have you sought professional help or counseling for depression?	Binary choice
	Have you ever engaged in self-harming behaviors?	Binary choice
	Have you sought professional help or counseling for self-harm?	Binary choice
Inquiry about Potential Stress	How often do you feel stressed due to academic workload?	Multiple choice
	Do you engage in stress-relief activities (e.g., meditation, exercise)?	Binary choice
	On a scale of 1 to 5, how effective are your stress-management strategies?	Multiple choice
	Do you feel pressure to excel academically?	Binary choice
	On a scale of 1 to 5, how do you cope with academic pressure?	Multiple choice
	How frequently do you engage in activities or hobbies as a form of stress relief?	Multiple choice
	How much does a lack of proper sleep contribute to your overall stress levels?	Multiple choice
	What is your primary method of coping with academic or personal stress?	Multiple choice
Support and Services for Mental Well-being	Have you ever sought academic counseling or support?	Binary choice
	On a scale of 1 to 5, how comfortable are you discussing your mental health issues with others?	Multiple choice
	Do you believe that technology (e.g., NLP and HCI) can positively impact mental wellness?	Multiple choice
	Would you be open to using technology-based solutions to manage your mental health?	Multiple choice
	Are you comfortable discussing your mental health with friends or family?	Multiple choice
	Have you ever experienced stigma or discrimination related to your mental health issues?	Binary choice
	Would you be interested in participating in workshops or programs related to stress management and mental wellness?	Multiple choice
	How would you prefer to access mental health resources and information?	Multiple choice
	Please rate the importance of the following factors in promoting mental wellness at your educational institution (1 = Not Important, 5 = Extremely Important)	Multiple choice
	Accessible counseling services	Multiple choice
	Supportive academic environment	Multiple choice
	Peer support groups	Multiple choice
	Mental health awareness campaigns	Multiple choice
	Which stress-relief techniques or activities do you find most effective? (Select all that apply)	Checkboxes
	How effective do you find talking to someone (friend, family, counselor) about your stress and worries?	Multiple choice

A. *Data Preprocessing*

The data preprocessing process begins with data acquisition and analysis to understand its structure and quality. Pandas is used for efficient data manipulation and analysis, along with Seaborn, a library built on Matplotlib, for visualizations. Key attributes like shape, column names, data types, and summary statistics are displayed to gain insights into the dataset's structure. Custom functions are employed to calculate value counts and generate random ages, enriching the dataset's diversity. Seaborn's histplot function visualizes age distributions, aiding in pattern identification and potential outliers. Outliers in the 'Random Age' column are detected and handled using the interquartile range method. Categorical variables are converted into dummy variables for predictive models and statistical analyses. Columns are renamed, unnecessary columns are dropped, and textual responses are mapped to numerical values for quantitative analysis. Summaries of responses provide aggregated insights into the distribution and prevalence of responses.

B. *Model Description*

We examine the prediction models to help undergraduate students manage stress. Logistic regression is used to identify relationships between stressors and student outcomes, while decision trees assess stress decision-making processes. Support Vector Machines (SVM) determine stress thresholds and algorithms like Random Forest and AdaBoost are combined to uncover stress dynamics. Gradient Boosting highlights stress's impact on student's well-being and Naive Bayes provides explanations on stress probability. By integrating these algorithms, researchers can better understand and address student stress management issues.

V. Result Analysis

The evaluation results in table II show the performance of various machine learning models in the context of stress management. The Logistic Regression classifier performed well, accurately identifying 4 cases in class 1, 8 in class 2, 33 in class 3, 40 in class 4 with over 90% accuracy, and 4 in class 5. It achieved a precision score of 0.9814, recall of 0.9789, accuracy of 0.9789, and F1 score of 0.9788, indicating balanced performance. The Decision Tree classifier excelled, perfectly classifying all instances with no misclassification: 4 in class 1, 14 in class 2, 33 in class 3, 40 in class 4, and 4 in class 5. It achieved perfect precision, recall, accuracy, and F1 scores of 1.0000. The Random Forest model correctly classifies all instances with perfect scores of 1.000 in precision, accuracy, and F1. The SVM model effectively classified stress levels, correctly identifying 4 instances in class 1, 9 in class

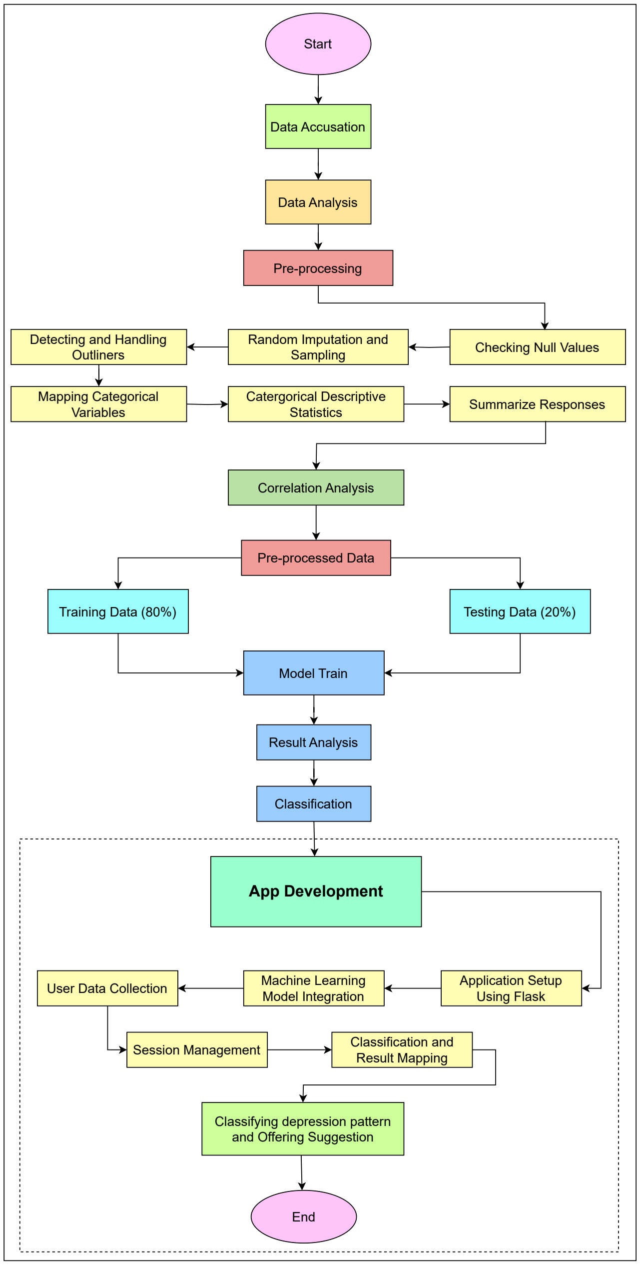

Fig. 1: Methodology Workflow

2, 33 in class 3, 40 in class 4, and 2 in class 5. However, there were misclassifications: 2 instances in class 2 and 1 instance in class 5 as class 4. It achieved a precision of 0.8729, accuracy of 0.8421, and F1 score of 0.8045. The model is reliable but needs optimization. The AdaBoost model accurately classified 33 cases in class 3 and 34 in class 4 but misclassified cases in other classes, with no correct classifications in classes 1, 2, and 5. It achieved a precision of 0.7492, an accuracy of 0.8526, and an F1 score of 0.7918, demonstrating robustness despite misclassification. The Gradient Boosting model yielded identical results to the Decision Tree model, with perfect scores (1.0000) across all metrics, indicating 100% accuracy in predicting and capturing all positive instances. The Naive Bayes model correctly classifies all instances in classes 1 and 5 but misclassifies 2 instances in class 2, 2 in class 3, and 7 in class 4 as class 3. It achieved a precision of 0.9717, an accuracy of 0.9684, and an F1 score of 0.9689, making it a reliable choice for stress management classification.

Among the models assessed, Random Forest, Decision Tree, and Gradient Boosting are the standout performers, achieving perfect accuracy and precision scores. Logistic Regression also shows high reliability with an accuracy of 97.89% and precision of 98.14%. SVM exhibits respectable performance with an accuracy of 84.21% and precision of 87.29%. Naive Bayes demonstrates commendable performance with an accuracy of 96.84% and precision of 97.17%. AdaBoost, while achieving a relatively high accuracy of 85.26%, has a lower precision of 74.92%, indicating a higher rate of false positive predictions. From all of the models we chose the Decision Tree model for its simplicity, interpretability, and perfect classification performance, as evidenced by its True Positive and True Negative counts. Additionally, decision trees take less time for modeling as they require minimal data analysis, work well with both categorical and numerical data, and despite tendencies to overfit, remain effective classifiers due to their flexibility and ease of interpretation. This combination of characteristics makes the Decision Tree model a robust and practical choice for accurately identifying depression levels in the dataset.

A. *Comparative Analysis*

The summary of various studies on technological approaches to managing stress and anxiety among university students includes insights from different research endeavours. Sen et al. (2023) [30] utilized survey data from 750 students, achieving the best accuracy of 87% with Random Forest. Gabrielli et al. (2021) [18] evaluated the Atena chatbot with 1,496 students during COVID-19, reporting qualitative improvements. Fitzpatrick et al. (2021) [20] studied the Woebot chatbot with 101 college students, noting significant anxiety reduction. Patel et al. (2019) [19] utilized chat data from 150 students, finding the CNN model to be most accurate at 85%. Klos et al. (2021) [16] assessed the Tess chatbot with 150 students, observing reduced anxiety symptoms. Meng & Dai (2021) [14] compared emotional support from chatbots and humans with 300 users, determining that human support was more effective overall. Our Proposed Approach analyzed data from 473 students, achieving the highest accuracy of 100% and an average accuracy of 95%. These findings underscore the diverse techniques and their effectiveness in stress management among students.

VI. App Development

A. ***Chatbot Application Development***

The web application uses a Flask framework in Python to predict depression severity and provide personalized treatment recommendations, utilizing a pre-trained decision tree model for user input analysis.

TABLE II: Results of Different Models Architecture

Models	Accuracy	F1-score	Precision	Statistics		
				Classes	T-P	T-N
Logistic Regression	97.89%	97.88%	98.14%	Class 1	4	0
				Class 2	8	5
				Class 3	33	0
				Class 4	40	0
				Class 5	4	0
Decision Tree	100%	100%	100%	Class 1	4	0
				Class 2	14	0
				Class 3	33	0
				Class 4	40	0
				Class 5	4	0
SVM	84.21%	80.45%	87.2%	Class 1	4	0
				Class 2	9	5
				Class 3	33	0
				Class 4	40	0
				Class 5	2	2
Random Forest	100%	100%	100%	Class 1	4	0
				Class 2	12	2
				Class 3	33	0
				Class 4	40	0
				Class 5	4	0
AdaBoost	85.26%	79.18%	74.92%	Class 1	0	4
				Class 2	0	14
				Class 3	33	0
				Class 4	34	6
				Class 5	0	4
Gradient Boosting	100%	100%	100%	Class 1	4	0
				Class 2	14	0
				Class 3	33	0
				Class 4	40	0
				Class 5	4	0
Naive Bayes	96.84%	96.89%	97.17%	Class 1	4	0
				Class 2	3	11
				Class 3	24	9
				Class 4	33	7
				Class 5	4	0

TABLE III: Depression level mapping and recommendation

Decision Level	Description	Recommendations
Decision 1	No symptoms of depression. Feeling normal and mentally well.	1. Regular exercise and a balanced diet. 2. Joining support groups. 3. Emotional support from friends or loved ones. 4. Engaging in enjoyable activities like music. 5. Travel and entertainment.
Decision 2	Mild symptoms such as occasional sadness or low energy. Noticeable but not significantly impacting daily functioning.	1. Psychotherapy: CBT or IPT. 2. Combination Therapy: Psychotherapy and medication. 3. Lifestyle Changes: Regular exercise, nutritious diet, structured activities. 4. Continue engaging in enjoyable activities.
Decision 3	Moderate symptoms with frequent sadness, difficulty concentrating, and decreased motivation. Starting to interfere with daily activities.	1. Intensive Psychotherapy: Frequent CBT or other intensive therapy. 2. Higher doses or combinations of antidepressants. 3. Hospitalization for safety and intensive treatment. 4. Electroconvulsive therapy (ECT). 5. Strong support system and case management.
Decision 4	Moderate to severe symptoms including persistent sadness, hopelessness, and significant difficulty functioning daily.	1. Hospitalization for stabilization and safety. 2. Combination of antidepressants and antipsychotics. 3. ECT. 4. Intensive Psychotherapy: Post-psychosis treatment.
Decision 5	Extreme symptoms with high impairment risk of self-harm or suicidal thoughts. Urgent intervention needed.	1. Advanced Medication Strategies: Combinations, mood stabilizers, ketamine infusions. 2. ECT. 3. Transcranial magnetic stimulation (TMS). 4. Vagus nerve stimulation (VNS). 5. Intensive Psychotherapy: CBT or DBT. 6. Regular exercise, healthy diet, sleep hygiene, integrative therapies. 7. Strong support network, frequent healthcare visits, support groups.

*1) **Application Setup and Security**:* The application development starts with the Flask framework, chosen for its simplicity and flexibility, ideal for rapid prototyping. A secret key ensures user data security and session integrity, making user sessions secure and tamper-proof.

*2) **Machine Learning Model Integration**:* A pre-trained decision tree model is the core predictive component of the application. Previously trained on a relevant dataset and saved in a joblib-compatible file, the model is loaded upon initialization to predict depression severity based on user inputs.

*3) **User Data Collection**:* User interaction with the application is facilitated through web forms containing a few questions spread across multiple pages, helping to collect data on various factors.

*4) **Classification and Result Mapping**:* User data is fed into a decision tree model to predict depression levels, ranging from mild to severe, including conditions like psychotic and treatment-resistant depression. The table III outlines five decision levels for depression, each with corresponding descriptions and tailored recommendations. The severity of symptoms ranges from no symptoms to extreme depression, with recommendations spanning lifestyle changes, psychotherapy, medication, and intensive treatments based on the severity. The web application harnesses the power of Flask, a lightweight and versatile Python framework, to create a user-friendly interface for predicting depression severity and providing personalized treatment recommendations.

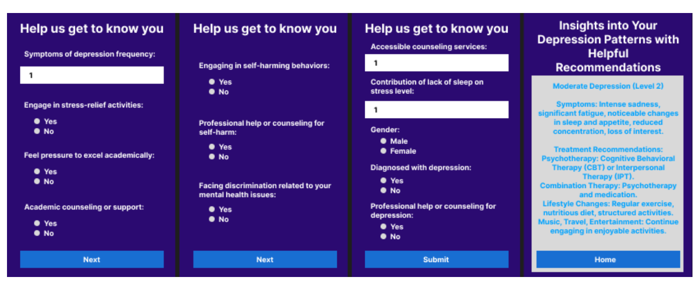

Fig. 2: Interface prototype sample of the app

VII. Conclusion

In conclusion, Our study explores stress among undergraduate students using advanced machine-learning algorithms and human-computer interaction techniques. It identifies stress levels and patterns using survey data. A chatbot was integrated to assist students in stress management. The findings provide insights into potential interventions to support student mental health in academic settings, contributing to a deeper understanding of stress.

A. Future Work

We aim to enhance the practicality by integrating natural language processing (NLP), strengthening our chatbot system, and enabling more interactive user input and voice assistance. Hence, consulting a broader group of medical specialists will ensure scientifically proven interventions that meet the diverse needs of students.

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