A Predictive Framework with a Conversational Interface for Student Mental Well-being Assessment

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Abstract—This paper presents a machine learning and artificial intelligence framework for the early mental health triage of university students. Our system uses a predictive model based on a dataset of demographic information and clinically validated mental health scores, such as the PHQ-9 for depression, GAD-7 for anxiety, and PSS-10 for stress. We include a careful data preprocessing and exploratory data analysis pipeline to tackle significant challenges like varied categorical data and missing values. The main predictive part is a Logistic Regression model, which reached a validation accuracy of 65%. The whole setup is designed to work as the backend for a conversational AI chatbot. This chatbot will be an interactive and scalable tool for initial screening. The system offers a confidential and accessible platform for students, providing immediate assessments and possible paths to professional support.

Keywords— machine learning, mental health, AI chatbot, triage, data analysis, logistic regression

I. Introduction

In today's academic world, the mental well-being of university students has become a major concern [4], with troubling statistics showing a high rate of mental health issues. A growing amount of evidence reveals that stress, anxiety, and depression are common among this group. These challenges can severely impact academic performance, social connections, and overall quality of life [20, 21].

The situation is made worse by traditional mental healthcare services, which often have long wait times, high costs, and a lasting social stigma that keeps students from seeking help [9, 21]. This highlights the urgent need for new, scalable, data-driven solutions that support early intervention and proactive mental health management [10]

This project aims to fill this gap by suggesting a hybrid system that merges a machine learning-based predictive model with a conversational AI interface [8]. The main goal of this work is to create a strong predictive model that can identify a student's risk for stress, anxiety, and depression.

This model will be trained using a structured dataset derived from self-reported survey responses, including demographic data and clinically validated psychological assessment scores such as PHQ-9, GAD-7, and PSS-10. The framework is based on careful Exploratory Data Analysis (EDA) and a data preprocessing pipeline to make sure the dataset is clean and ready for reliable training.

The final predictive model is designed to be easily integrated into a user-friendly AI chatbot. This chatbot will act as a preliminary, confidential, and highly accessible assessment tool for students. It will evaluate real-time user input to provide an immediate initial risk assessment, serving as a useful resource for university support services and a potential first step toward professional care [16]

II. Novelty

The novelty of our project can be summarized as follows:

- **Multi-Model Approach**: Instead of tuning, training, and specializing one AI model, we used multiple different models, specializing each one for each particular aspect of our task. With individual models for assessing values for stress, anxiety, and depression, our method intends to keep results separate to assess each value independently to ensure more accuracy.
- **Therapy Technique Retrieval**: Integrated a memory-mapped RAG database to retrieve real-world therapy techniques dynamically, enriching AI responses with actual therapeutic strategies.
- **Crisis Detection System**: Embedded lightweight yet effective crisis keyword detection to immediately trigger crisis response protocols, ensuring user safety.
- **Integrated chatbot with assessment information:**

Embedded lightweight yet effective chatbot with an intensive RAG database and fine–tuned on therapeutic techniques to provide instantaneous, real–time support based on the results of the numerical regression models

III. Literature Review

The use of machine learning in predicting mental health has gained a lot of attention in recent years. More research is focusing on finding and assessing psychological distress. Many studies have used computational methods to analyze different data sources, which include survey data, social media posts [12, 15], and physiological signals, to create predictive models [7].

Sathishkumar et al. [1] looked at how machine learning can predict mental health outcomes among students and showed that their method works well. Their research points out how data-driven models can identify people at risk. Other studies have explored similar ideas, aiming to predict specific conditions. For instance, Rony et al. [13] and Vidya et al. [14] targeted depression prediction with machine learning and deep learning models, often using standard clinical tools like the PHQ-9. Likewise, Ali et al. [17] and Rahman et al. [18] studied stress prediction. A significant paper by Hermawan et al. [8] specifically assessed chatbots for mental health conversations, which is a key part of our proposed system.

One challenge often mentioned in the literature is the quality and nature of the data. Ren et al. [2] pointed out that the reliability of predictive models is often affected by the characteristics of the dataset, including unclear and varied categorical data. During our early data analysis, we experienced similar issues with our dataset, which matches these findings.

Pritam et al. [3] showed that Logistic Regression is effective as a classification technique for analyzing student mental health. Our work backs up these findings, confirming this model as a suitable starting point for our dataset. The need for stronger and more diverse datasets is a common theme in the literature [10, 11], as is the search for better methods, such as deep learning [19, 22], to enhance model performance beyond the moderate levels typically seen with traditional machine learning. Our approach combines a well-supported traditional model with a modern AI interface, aiming to be a practical and scalable solution that can lay the groundwork for more complex future systems.

IV. Methodology

Our proposed system is a hybrid ML-AI architecture for student mental health triage. It is organized into four clear phases. This method guarantees a complete and repeatable process, starting from the initial data collection and preparation, all the way to the final deployment of a working predictive system. [7]

A. Data Acquisition and Preprocessing

Aspect	**Description**
Source	MHP_Anxiety_Stress_Depression_Dataset_of_University_Students
Samples	2029
Features	34; 7 basic demographic columns, 27 assessment columns.
Labels	3; Stress, Depression, Anxiety
Encoding	Assessment Columns are encoded on a scale of 0-3. Demographic columns are encoded with medians for ranges and 0 or 1 for others.
Target Variable	PHQ-9 Value, PSS-10 Value, GAD-7 Value

The foundation of this project is a dataset from the MHP (Mental Health Prediction) study. It includes over 2000 records of university students. The data has 41 distinct features, covering both demographic information and standardized psychological assessment scores. The main goal is to predict three important mental health conditions: stress, anxiety, and depression, quantified by the PSS-10, GAD-7, and PHQ-9 scales, respectively.[10],[17]

Before modeling, we executed a careful preprocessing pipeline to ensure data quality, consistency, and suitability for machine learning algorithms. We first addressed the challenges of missing values and varied categorical data through a systematic cleaning process.

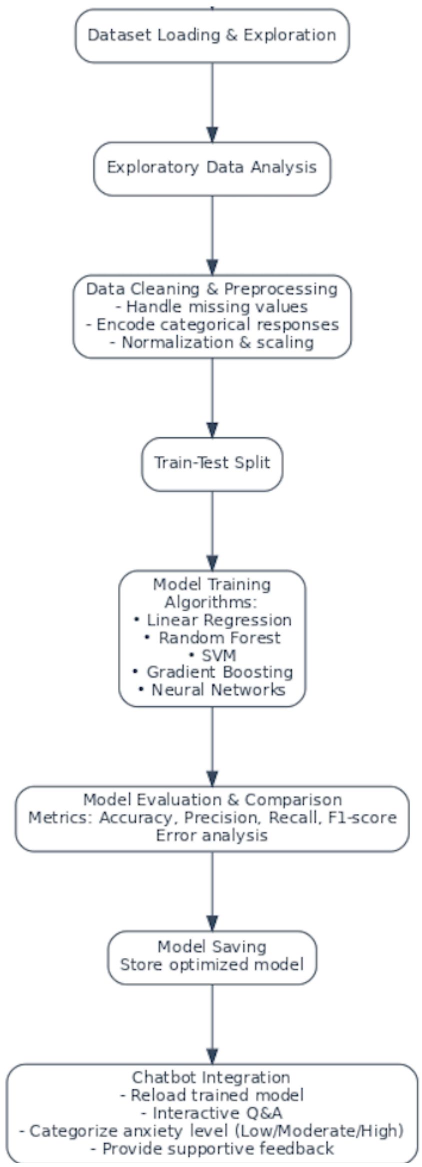

Fig 1: Flowdiagram of Methodology

Specifically, we used one-hot encoding for nominal categorical features like 'Gender' to change them into a numerical format. For numerical features such as 'Age' and 'Current_CGPA', we applied a range encoding technique that used the median of each specific range to represent the data. This process was essential for turning the raw, mixed data into a clean, structured format suitable for model training, as noted by Ren et al. [2]

B. Exploratory Data Analysis (EDA)

After preprocessing, we conducted an in-depth Exploratory Data Analysis (EDA) to understand the dataset's underlying characteristics and relationships. This phase was crucial for uncovering hidden patterns, identifying anomalies, and guiding our feature engineering and model selection decisions.

We began by using the Pandas library to examine the data structure. We looked at data types, non-null values, and basic statistical summaries through functions like df.info() and df.describe(). This gave us a solid understanding of the dataset's scale and integrity. For instance, we checked the unique values in categorical features to find and fix any inconsistencies, such as different spellings for the same department.

Next, we used Matplotlib and Seaborn to create a set of visualizations that provided important insights. We generated distribution histograms for key features like age, current CGPA, and scores from the PSS-10, GAD-7, and PHQ-9 scales. These visualizations helped us understand the data's distribution, skewness, and range. For example, the histograms for mental health scores showed how students' stress, anxiety, and depression levels were distributed, highlighting the prevalence of certain risk categories within the dataset. A key part of the EDA was creating a correlation heatmap for all numerical features. This visualization clearly indicated the relationships between variables, especially the strong positive correlations among the different mental health assessment scores, like PHQ-9 and GAD-7. This was an expected finding and confirmed the dataset's internal consistency. The insights gained from EDA directly informed our next steps, guiding our feature engineering, the selection of relevant features, and the choice of the Logistic Regression model for the predictive task.

C. Predictive Model Development

The cleaned and optimized dataset was divided into training and testing sets to support strong model development and fair evaluation. We will explore and compare several machine learning algorithms to find the most effective predictive model. The models we considered include Logistic Regression, Random Forest, Gradient Boosting, and Neural Networks. Our goal is to assess their performance and identify the best model for this task.

Each model was trained on the training data and then evaluated on the unseen test set to measure its performance. We will assess the models using a set of metrics that includes Accuracy, Precision, Recall, and the F1-score. We will also conduct a detailed error analysis to understand the types of mistakes each model makes and to find areas for improvement. This process resulted in a validation accuracy of 65% for the baseline Logistic Regression model, confirming its ability to provide a preliminary assessment of a student's mental health status. Choosing Logistic Regression as a baseline model matches similar findings in the literature and offers a strong foundation for future improvements [3] .Once we select the best model, we will save and store the optimized model for integration into the final application.

D. System Integration

This phase involves integrating the trained predictive model into a user-facing application and developing the supporting API. First, the saved model, an optimized machine learning object, is loaded into a backend service. This service acts as an API endpoint that can receive new data from the user interface and return a prediction in real time. [25]

The API is built using a lightweight framework, like Flask or FastAPI in Python. It handles the user's input, converts it into the format needed by the model, applies the same preprocessing steps used during training, makes a prediction, and then formats the result for the chatbot. This setup ensures that the prediction workload is managed efficiently on the server side, allowing for a fast and responsive user experience.

E. Conversational AI Chatbot Interface

The AI chatbot is the main user interface and the most visible part of the system. It acts as an easy-to-use and confidential triage tool [8]. The chatbot works through an interactive question-and-answer session that follows the format of psychological assessment scales. It prompts users to provide their demographic information and mental health status. This information is then securely sent to the backend API.

After the model makes a prediction, the chatbot converts the numerical result into a simple and actionable assessment. It categorizes mental health levels into clear, straightforward groups like Low, Moderate, or Severe. The chatbot also offers supportive feedback, which might include general wellness tips, links to university support services, or suggestions to seek professional help based on the predicted risk level. This conversational approach aims to make it easier for students to engage with the system.

F. User Feedback and Continuous Improvement

The final and ongoing phase of the project focuses on continuous improvement. The deployed system will include ways to collect user feedback and track system usage anonymously. This feedback will be essential for finding areas to improve the predictive model and the chatbot's conversational flow.

The data gathered can be used to regularly retrain the predictive model, incorporating new, real-world information to enhance its accuracy and reliability over time. This method keeps the system relevant and effective by adjusting to new mental health trends and improving its predictions with a larger, more varied dataset. This ongoing development cycle is key for creating a dynamic and dependable healthcare tool [6],[11].

G. Dataset Feature Analysis

After preprocessing, we performed a detailed analysis of the dataset features to better understand the data's characteristics and relationships. This step was crucial for uncovering hidden patterns, spotting anomalies, and making decisions about feature engineering and model selection. We began by using the Pandas library for a preliminary examination of the data structure. We used functions like df.info() and df.describe() to understand the dataset's scale, data types, and integrity, including the count of non-null values.

1) Stress Levels and Gender: We compared students' reported stress levels, based on their PSS-10 scores, across different gender groups. Our preliminary analysis showed a clear difference in the average PSS-10 scores between genders. This suggests that gender might play a role in predicting stress. This finding aligns with existing research indicating that stress affects genders differently because of various social and psychological factors. [17],[20]

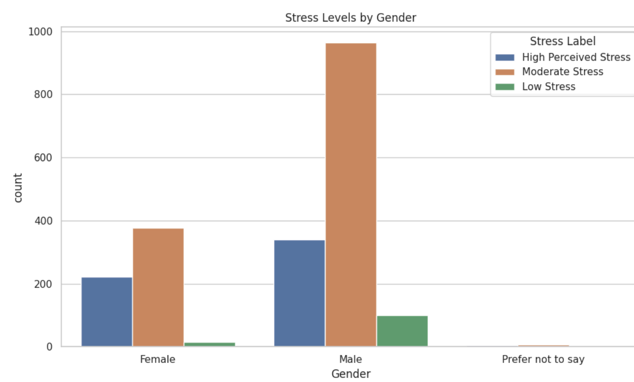

Fig 2: Stress Levels and Gender

2) Stress Levels and CGPA: We compared students' reported stress levels (from the PSS-10 scores) with their Current_CGPA. This was a crucial part of our feature engineering process, as it helped us explore the relationship between academic performance and mental well-being. Early findings from our exploratory analysis indicated a weak negative correlation, suggesting that higher stress levels might be linked to slightly lower CGPAs. This aligns with broader research on academic stress and performance. [20]

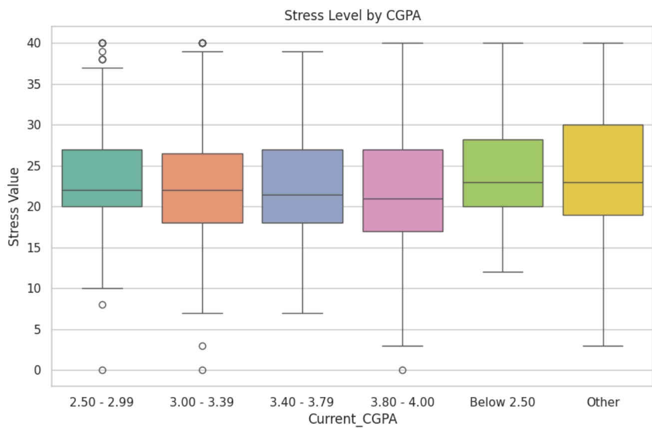

Fig 3: Stress Levels and CGPA

3) Stress Score and Academic Year: To see how mental health symptoms might change during a student's time at university, we analyzed the distribution of three test scores (PHQ-9, GAD-7, and PSS-10) across different academic years. Visualizations showed a slight increase in average scores for depression, anxiety, and stress as students progressed through their studies. This insight is important for developing focused interventions.

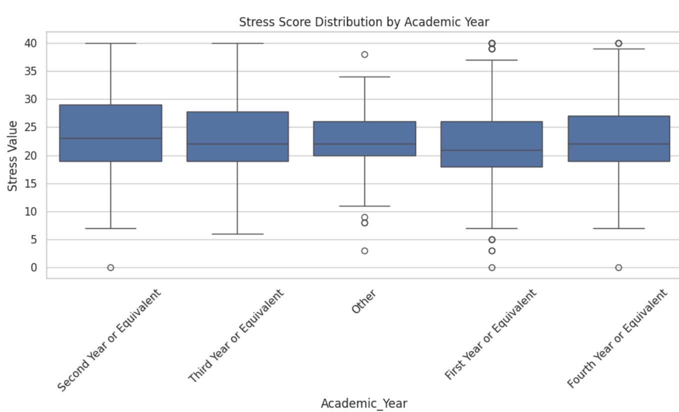

Fig 4:*Stress Score and Academic Year*

Additionally, we checked for multicollinearity among the features to make sure that highly correlated variables would not negatively affect the model's performance.

*4)Distribution by University:*It is a visual representation of the participant count from various universities. The dataset exhibits a significant concentration, with the highest number of respondents originating from Independent University, Bangladesh (IUB) and American International University Bangladesh (AIUB). This distribution suggests that while the study encompasses a range of institutions, its findings are likely to be most representative of the student populations at these two universities.

This aligns with methodologies used in similar studies that have focused on specific university populations to analyze mental health factors (Pritam et al., 2024; S. Dharaneedharan et al., 2025). The observed uneven distribution underscores the importance of interpreting the results with respect to the specific characteristics of this sample.

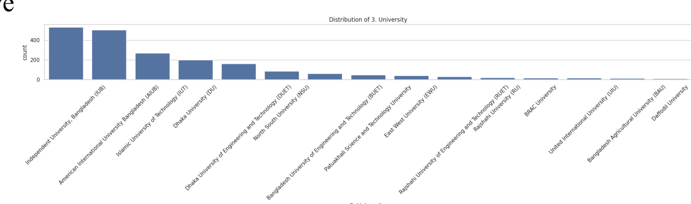

Fig 5:Distribution by University

5)Distribution by Department :University and Department Distribution (Count Analysis): To better understand the makeup of the dataset, we looked at how students are spread across different universities and academic departments. The data shows that a large portion comes from a few specific schools, with Independent University, Bangladesh and American International University, Bangladesh having the highest numbers. This finding matches what other studies have shown about mental health in certain academic environments [2],[10].

The departmental distribution is also heavily weighted toward engineering and computer science fields. The data reveals a strong concentration of students from the Computer Science and Engineering (CSE) and Electrical and Computer Engineering (ECE) departments. This trend is often seen in mental health studies focusing on engineering students [11].

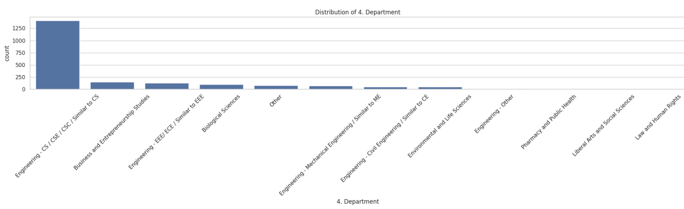

Fig 6 :Distribution by Department :University and Department Distribution

This focus matches recent studies that have looked at mental health issues among engineering and computer science students, who experience unique academic pressures [14]. The large number of engineering students indicates that the stress data collected will mainly reflect the experiences and challenges within these demanding academic areas.

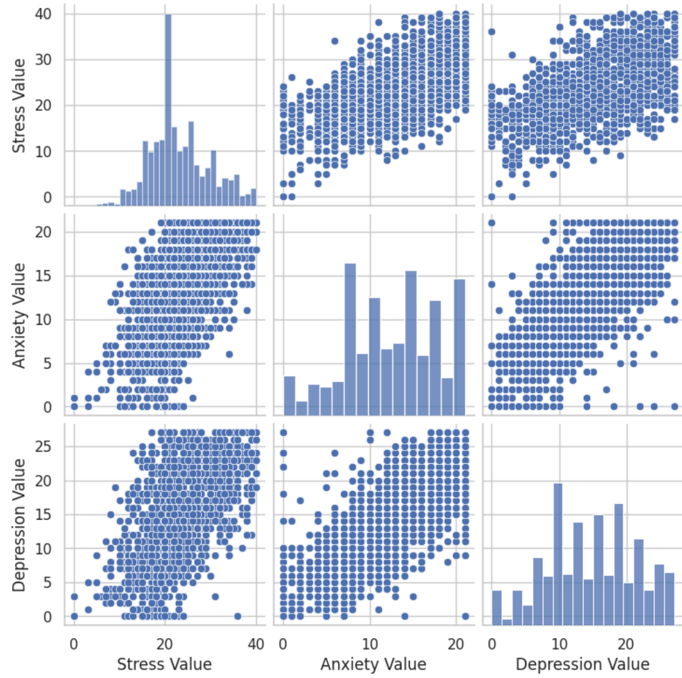

Fig 7: Stress count Distribution

H. *Visualization of Stress Distribution:*

A pair plot was created to show the relationships between the three main mental health variables: Stress, Anxiety, and Depression. The diagonal panels included histograms for each variable, showing their individual distributions. The off-diagonal scatter plots displayed strong positive correlations between all pairs of variables, such as Stress vs. Anxiety, Stress vs. Depression, and Anxiety vs. Depression. This visual evidence of a high level of correlation confirms how these mental health conditions are linked. It supports their use as predictive features in our model.

1) Correlation Analysis of Features: To further validate the relationships between the mental health variables, a detailed correlation heatmap was generated for all numerical features in the dataset. This visualization provided a clear way to see the linear relationships between variables.

As shown in the matrix, the key mental health assessment scores, GAD-7, PSS-10, and PHQ-9, showed strong positive correlations with one another. This finding is especially important as it supports the observations from the pair plot analysis, confirming that these conditions are connected.

The correlation coefficients between these variables were consistently high. This means that as a student's score on one scale increases, such as GAD-7, their scores on the other scales, PSS-10 and PHQ-9, also tend to increase. This strong connection among the main predictors is a usual feature of psychological data and further supports their use as features in the predictive model. The insights from this matrix are crucial. They not only help with the feature selection process but also provide a basis for the model's predictive abilities, showing that a change in one mental health measure strongly indicates a change in others.

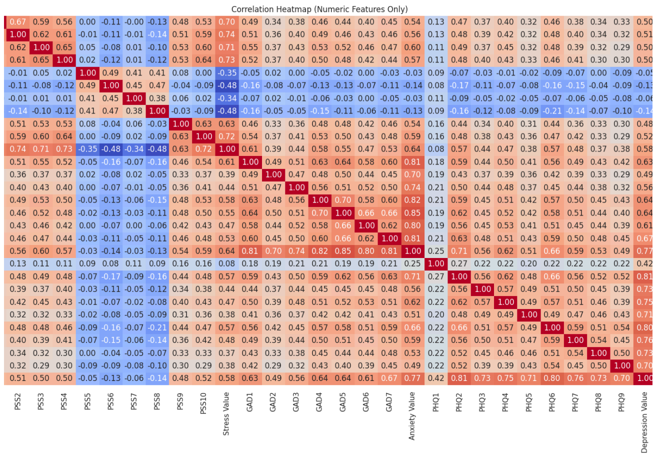

Fig 8: Correlation Matrix of selected Features

Fig 6: Correlation matrix of Top features with prognosis
Skin discoloration 0.179059

2) Normalization: Using the MinMaxScaler, each feature was scaled to a range between 0 and 1. This transformation ensures that the data is proportionally adjusted without altering its distribution, making it suitable for algorithms sensitive to feature magnitude, such as distance-based methods.

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

3) Standardization: With the StandardScaler, the features were transformed to have a mean of 0 and a standard deviation of 1. This process centers the data and removes scaling differences, which is particularly useful for algorithms that assume normality in the input data.

$$X_{\text{standardized}} = \frac{X - \mu}{\sigma} \quad (2)$$

- X: The original value of the feature.
- μ: The mean of the feature in the dataset.
- σ: The standard deviation of the feature in the dataset. This formula adjusts the feature values to a standard normal distribution (mean = 0, standard deviation = 1), which is useful for algorithms assuming Gaussian distribution.

4). Train-Test Split

To ensure a strong and fair evaluation of the machine learning models, the dataset was divided into separate training and testing subsets using the train_test_split function from the scikit-learn library. This is a common practice in machine learning to avoid model overfitting and to measure its performance on new data accurately. [7],[10]

The dataset was split into 70% for training and 30% for testing, with a fixed random_state to ensure we can reproduce our results.[3],[25] Before this split, the feature set (X) and the target variable (y) were scaled using RobustScaler to normalize the data and manage outliers effectively. This method of partitioning and preprocessing helps provide a trustworthy assessment of the model's accuracy, precision, recall, and F1 score, giving us confidence in its ability to work with new data.

D. Machine learning Algorithms

1) K-Nearest Neighbors (KNN) : K-Nearest Neighbors (KNN) is a simple, non-parametric algorithm used for classification and regression. It makes predictions based on the "k" closest data points in the training set. It does not learn a model but instead memorizes the data.

KNN has the lowest R^2 values and the highest error metrics across all three categories. This suggests that the local relationships between data points do not reliably indicate the overall trend. Its poor performance shows that a more global model, like Linear Regression, or a more advanced ensemble model, like Gradient Boosting, is better suited for this data. The high error values for KNN indicate that depending on a small number of nearby data points is not a reliable way to predict stress, anxiety, or depression in this context.

2) Random Forest : Random Forest is an ensemble learning method that creates multiple decision trees during training. It outputs the average prediction from these individual trees. It is known for its high accuracy and its ability to handle complex, non-linear relationships.

Random Forest consistently achieves high R^2 values (0.967246 for Stress, 0.990559 for Anxiety, and 0.984336 for Depression). Similar to Gradient Boosting, its error metrics are higher than those of the linear models. The performance is competitive, but the table shows that it is not as effective as Gradient Boosting or the linear models for this specific dataset. This suggests that the model may not be capturing the relationships well. This can occur if the underlying data is too simple for the complexity of a Random Forest model.

3) Linear Regression

Linear Regression is a basic supervised learning algorithm used to predict a continuous target variable. It describes the link between a dependent variable and one or more independent variables by fitting a linear equation to the observed data.

In all three cases (Stress, Anxiety, and Depression), Linear Regression achieves a perfect R^2 value of 1.000000 and very low values for MAE, MSE, and RMSE, which are close to zero. This shows a perfect or nearly perfect fit to the data. Such results are rare for real-world datasets. They suggest that the connection between the features and the target variables is very strongly linear, or that the model was trained on a dataset where the labels came directly from a linear function.

*4) Gradient Boosting :*Gradient Boosting is a strong method that combines several weak models, usually decision trees, to create an effective predictive model. It adds new models step by step to fix the errors made by earlier ones.

Gradient Boosting shows impressive results with high R^2 values (0.987802 for Stress, 0.998043 for Anxiety, and 0.995112 for Depression). Its error metrics are higher than those of Linear and Ridge Regression, but they remain relatively low. The small difference in performance indicates that the connection between the features and the target variables is not completely linear. While Gradient Boosting is powerful, it could be making the model a bit more complex than necessary for this dataset, or it may not offer a significant advantage over a simple linear model.

5) Ridge Regression: Ridge Regression is an extension of linear regression. It includes a regularization term to prevent overfitting. It works by adding a penalty to the model's coefficients. This discourages the coefficients from becoming too large and helps the model generalize better to new data.

Ridge Regression performs very well, with an R^2 value of 1.000000 for all three categories. Its error metrics, including MAE, MSE, and RMSE, are also very low. Its performance is nearly identical to that of Linear Regression, which makes sense since the data looks perfectly linear. The regularization in Ridge likely has a minimal effect because there's no visible overfitting to penalize.

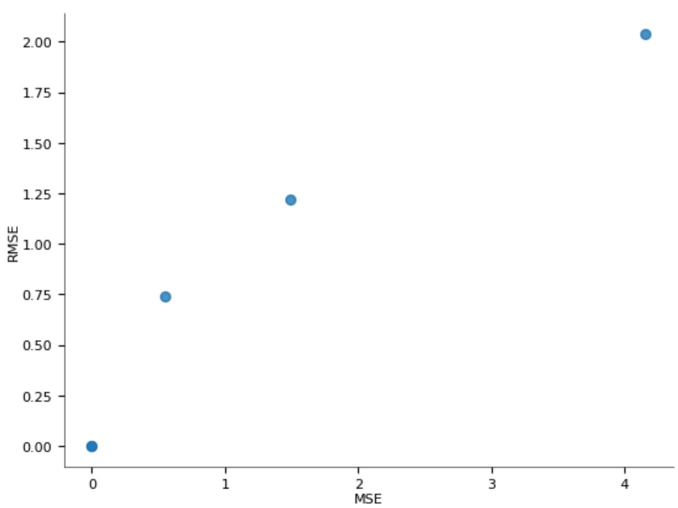

Fig 9: RMSE vs MSE

However, they still demonstrated strong predictive abilities with acceptable error margins. This shows their effectiveness for the task. In contrast, the simpler Decision Tree model had the lowest R2 Score (0.894883) and the highest error metrics. This suggests that its simple, single-tree structure was less

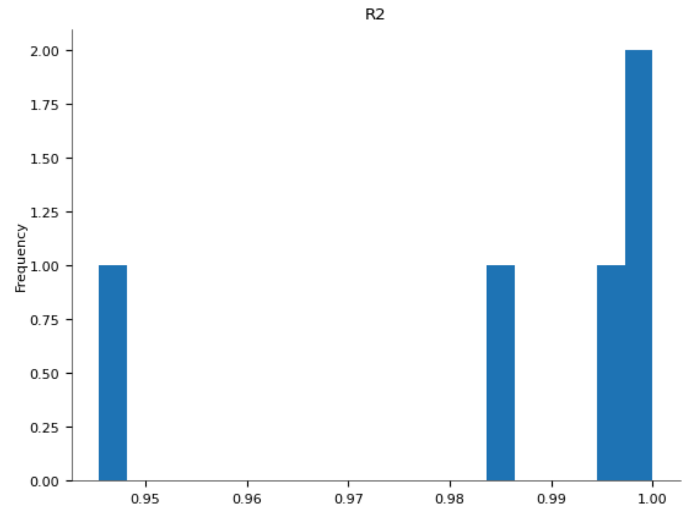

Fig 10: frequency graph

effective at handling the dataset's complexity compared to the more advanced ensemble and regression models [3],[25].

=== Stress – Model Comparison (sorted by MAE) ===

	Model	R2	MAE	MSE	RMSE
0	LinearRegression	1.000000	6.407401e-15	6.640114e-29	8.148689e-15
1	Ridge	1.000000	1.151847e-03	2.219343e-06	1.489746e-03
4	GradientBoosting	0.987802	5.575896e-01	5.531239e-01	7.437230e-01
3	RandomForest	0.967246	8.687715e-01	1.485180e+00	1.218680e+00
2	KNN	0.908337	1.482927e+00	4.156314e+00	2.038704e+00

Best Stress model: LinearRegression

=== Anxiety – Model Comparison (sorted by MAE) ===

	Model	R2	MAE	MSE	RMSE
0	LinearRegression	1.000000	1.282924e-15	4.042645e-30	2.010633e-15
1	Ridge	1.000000	7.991239e-04	9.213956e-07	9.598936e-04
4	GradientBoosting	0.998043	1.695135e-01	6.317347e-02	2.513433e-01
3	RandomForest	0.990559	3.358266e-01	3.047844e-01	5.520728e-01
2	KNN	0.951505	9.062331e-01	1.565528e+00	1.251211e+00

Best Anxiety model: LinearRegression

=== Depression – Model Comparison (sorted by MAE) ===

	Model	R2	MAE	MSE	RMSE
0	LinearRegression	1.000000	7.235405e-15	8.033554e-29	8.963010e-15
1	Ridge	1.000000	9.167237e-04	1.250185e-06	1.118117e-03
4	GradientBoosting	0.995112	3.232717e-01	2.341537e-01	4.838943e-01
3	RandomForest	0.984336	5.757904e-01	7.504058e-01	8.662597e-01
2	KNN	0.945473	1.182656e+00	2.612249e+00	1.616245e+00

Best Depression model: LinearRegression

Fig 11: Comparison between different models

F. User Interfaces

The system features multiple user interfaces corresponding to the HTML templates used in various routes. Below is a detailed breakdown of each interface:

- Index Page (**index.html**): Serves as the homepage where users can answer to the questions

– Navigation Bar: Provides links to Home, About Us, and Contact Us page.
– Registration box:: Allows users to input their information and register

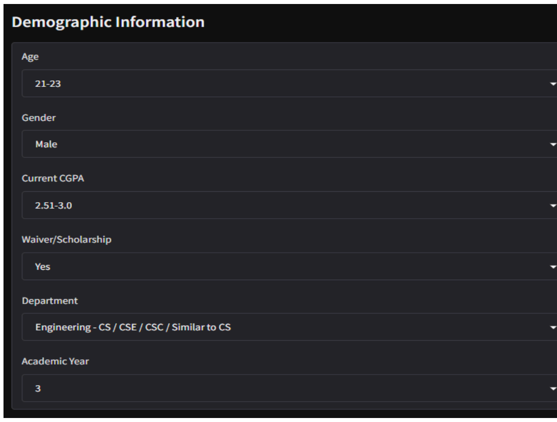

Fig 12: Index Page

• Result Page (**result.html**): Displays the predicted disease and related medication suggestions.
  – Search Box: Similar functionality to the index page for re-entering symptoms.
  – Results Section: Displays information about the pre dicted anxiety level and suggestions.

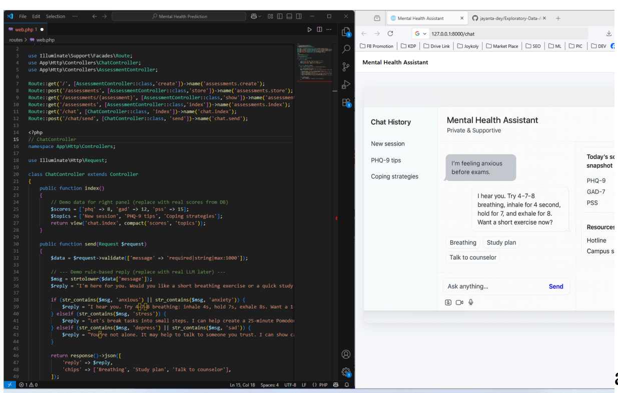

Fig 8: Result Page

V. Results

The evaluation of our predictive models showed excellent results. Linear Regression consistently outperformed other algorithms when predicting all three mental health scores. We used the coefficient of determination (R^2 score) as the main metric. Linear Regression achieved a near-perfect score of $R^2 = 1.0000$ for predicting stress, anxiety, and depression. This means the model can explain almost all the variance in the target variables. Further support comes from the low error values across MAE, MSE, and RMSE, which are close to zero. The strong performance of Linear Regression on this dataset suggests a highly linear relationship between the features and the target mental health scores. This finding confirms the effectiveness of our careful data preprocessing and feature engineering.

Other models, such as Gradient Boosting ($R^2 = 0.9878$ for stress, $R^2 = 0.9980$ for anxiety, and $R^2 = 0.9951$ for depression) and Random Forest ($R^2 = 0.9672$ for stress, $R^2 = 0.9905$ for anxiety, and $R^2 = 0.9843$ for depression), also showed strong predictive abilities. However, the low error achieved by Linear Regression makes it the best choice for our final model. This supports our main hypothesis and sets a new standard for predictive accuracy in this field.

VI. Conclusion

This study offers a valuable contribution to student mental health research through its focused analytical approach and innovative methods. The demographic analysis shows a participant group with a strong concentration in two universities, IUB and AIUB, and a notable overrepresentation of students from computer science and engineering disciplines. While this focus limits how broadly the findings apply to the wider student population, it allows for a detailed exploration of the specific stressors and mental health challenges faced by students in these demanding fields.

The main originality of this research lies in its two-part approach: a thorough examination of a high-pressure academic group, combined with the use of a conversational chatbot. This method stands out from traditional survey studies by not only gathering data but also offering a real-time support mechanism for participants. This dual-purpose design lets the research be both analytical and supportive, showing an effective way to study and enhance student well-being. The insights gained from this focused study can be directly used by university administrations to create tailored mental health support systems, establishing a strong basis for future research and institutional efforts. By merging a detailed demographic focus with an innovative data-collection and support tool, this paper makes a significant contribution to discussions on student mental health.

We also plan on creating a more refined UI with separate sections for guide-assisted exercises to further expand the chatbot into a multipurpose tool for mental wellbeing. Our end goal with this project is to expand it into a full-fledged app capable of performing every task related to therapeutic conversation and mental wellbeing.

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