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Inspiring Excellence

Classification of Combined Mental Health Disorder

CSE 422: Artificial Intelligence

Group 13

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Table of Contents

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***Abstract*—Mental health disorder among university student is growing rapidly. Stress, anxiety and depression are only a few of the issues that university studies have to tackle, while also continuing their academic schedules. Therefore, proper classification and detection of stress,anxiety and disorder is crucial for timely intervention. In this study, we have combined depression, anxiety and stress metrics into a framework to classify mental health status. Our dataset comprised of questionnaire responses which we engineered in order to categorize a multi-class classification model for the sake of predicting combined mental health. Various classification models such as Decision Tree, Logistic Regression and Neural Networks were employed in order to find the best possible method for classifying combined mental health status. Our models achieved high accuracy and F1-score which only further supports the strong integration between machine learning and early diagnosis of mental health disorders. In conclusion, our approach provides a benchmark for future mental health screen tools .**

Keywords—Mental Health, Logistic Regression, Decision Tree, Neural Network

I. Introduction

Across all age groups, depression, anxiety and stress continues to be a prevalent factor that affects people of all age groups. These conditions often coincide with each other and have overlapping symptoms that make it difficult for proper diagnosis. According to the World Health Organization (WHO), 280 million people are affected by depression alone. Moreover, anxiety and stress related disorders are also increasing rapidly due to academic or environmental triggers.

Traditionally, diagnosing and assessing mental health conditions can be tedious and often relies on long interviews and rudimentary questionnaires. Although this method can be effective, the manual screening of each individual can be very resource-intensive and time consuming. Thus, there exists a growing need for a system that can asses mental health condition through classification of mental health condition based on data.

In this paper, we aim to provide a machine learning based model to classify a blended mental health condition through a questionnaire from University Students. Alternative to treating stress, depression and anxiety as separate unrelated labels, we have decided to combine them together to make a single target class which can reflect the disorders and connections between each mental health feature contributing to a combined mental disorder class. The dataset in it's raw form required pre-processing and feature engineering. Then we figured out the correlation between the features and our combined classes in order to select the best models for accurate classification. According to our engineered data and dataset, Logistic Regression, Decision Tree and Neural Network provided the best outcomes for classifying combined mental health state which consisted of stress, anxiety and depression.

II. Literature Review

For the past few years, machine learning continues to gain a massive momentum in its ability to analyze data and high dimensional dataset in order for mental health prediction. Vaishnavi et al. [1] presents a comparative study where 5 ML classifiers were analyzed - Logistic Regression, Decision Tree, Random Forest, Stacking and K-Nearest Neighbour over a dataset consisting of 27 features. We find ensemble methods such as Multilayer Perceptron, LaD Tree and classifiers such as KNN, SVM and Random Forest show notable accuracy in mental health prediction tasks. Moreover, the ILIOU preprocessing method is useful in improving the classification accuracy of the classifiers. This paper emphasizes the need for high interdisciplinarity in order to maximize the impact of AI on the mental health investigation. Expectations from our experiment confirmed the conclusion proposed by the authors: In their experiments, the Stacking classifier was able to give the strongest prediction accuracy (81. 755% predicting accuracy) resulting from ensemble methods. The effectiveness of ensemble methods in obtaining diagnostic outcomes can be verified experimentally,Letter file.

Sumathi and Poorna [2] examined the effectiveness of eight machine learning algorithms in identifying five prevalent mental health illnesses in children: attention problems, academic difficulties, anxiety, ADHD, and PDD. The research used a dataset of 60 instances and 25 features obtained from clinical sources, using feature selection strategies to diminish dimensionality and improve model efficacy. The assessed classifiers are Multilayer Perceptron, Multiclass Classifier, LAD Tree, K*, among others. The results indicate that the Multilayer Perceptron, Multiclass Classifier, and LAD Tree surpass others in terms of accuracy, Kappa statistics, and ROC area metrics. The literature analysis underscores prior AI-based diagnostic systems, including DTREE, INTERNIST, and hybrid methodologies like Fuzzy Logic and Neuro-Fuzzy approaches, accentuating their roles in enhancing mental health diagnoses. The study highlights the significance of machine learning in the early identification of psychiatric disorders, promoting the ongoing development of intelligent systems to assist mental health practitioners.

Rahman et al. [3] performed a systematic analysis of 22 chosen articles published from 2007 to 2018 to assess the utilisation of machine learning (ML) and deep learning (DL) techniques in identifying mental health disorders via data derived from Online Social Networks (OSNs). The review classified the research according to data sources, categories of mental health issues (e.g., depression, stress, suicide), feature extraction techniques, classifier efficacy, and geographical origin. The results demonstrate that platforms like Twitter and Sina Weibo are often used owing to their accessibility and user-generated content. Machine learning methodologies, including Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), and Naïve Bayes (NB), were often used, with several research including hybrid or deep learning architectures such as Deep Neural Networks to enhance precision. Despite encouraging outcomes, the authors highlighted obstacles like data sparsity, brevity of language, multilingual content, and ethical issues pertaining to user privacy. They determined that while online social networks provide scalable, alternative instruments for early mental health diagnosis, an integration of conventional diagnostic techniques and novel machine learning methodologies is crucial for effective, generalisable solutions.

Through extensive simulation experiments complemented by real-world datasets from mental health studies, Khondoker et al. [4] perform a comprehensive and methodologically robust comparison of four widely used machine learning classification methods—Random Forest (RF), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and k-Nearest Neighbour (kNN)—in their paper. Driven by worries about bias and limited generalisability in past comparison research, they assess performance across many scenarios using several criteria including sample size, feature dimensionality, effect magnitude, noise, and correlation structure. Their findings imply that whilst SVM thrives with bigger feature sets and enough sample sizes, LDA works best when the number of features is somewhat limited and strongly linked. Unless variability is extreme, kNN improves with increasing dimensionality; RF shows stability even in noisy data with modest effect sizes. The results, confirmed using gene expression, MRI, and EEG datasets, underline the need of simulation-based assessment for fair comparison because they support the idea that performance is context-dependent and no one classifier universally outperforms others.

Reviewing the rising concern of mental health problems among Malaysian students in higher education, Shafiee and Mutalib [5] investigate the use of machine learning to examine and forecast such difficulties. The report stresses the difficulty of recognising mental health issues resulting from overlapping symptoms and names the main contributing factors: lack of social support, financial difficulties, and academic pressure. Emphasising supervised learning, especially Support Vector Machine (SVM), as the most often employed owing to its great accuracy in mental health prediction tasks, the research further divides machine learning methodologies into supervised, unsupervised, semi-supervised, and reinforcement learning. The authors assess numerous methods using current data and find that models like SVM, Decision Tree, and Neural Networks often show accuracy surpassing 70%. Emphasising the possibilities of computational models to promote mental health detection, the paper ends with recommendations for the inclusion of these tools into higher education institutions to better meet psychological demands of students.

III. Dataset Description

There are 1977 data points and 37 features in this dataset. The dataset consists of both categorical and numerical features. Some of the features are the type object representing various information like CGPA, Age ,Gender etc. Majority of the features are numerical and of integer type (int64). There are 3 labels which consist of Stress, Anxiety and Depression. Meanwhile, there exists features that are related to each individual label exclusively. The dataset was derived from questionnaires of university students.

IV. Data Analysis

Various data analysis techniques were used to extract important information from the dataset. Among them box plot and skewness were used to analyze the distribution of the dataset. Box plots were used to identify the disproportion between the values in both numerical and categorical features. Meanwhile, a correlation matrix was used to describe the relationship between the numerical features. Moreover, a heatmap was plotted in order to visualize the correlation between these values. Further analysis also revealed that there were very few missing/null values in the dataset.

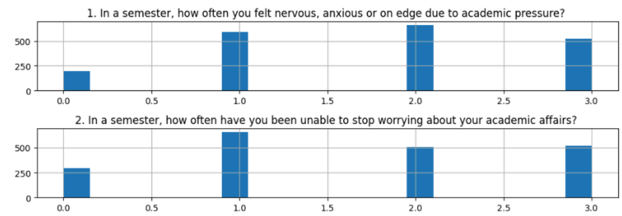

Fig 1: Histogram analysis of few numerical features.

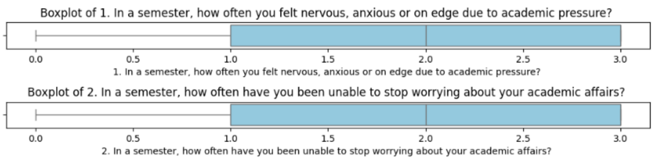

Fig 2: Box-plot diagram of few numerical features.

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1. Age                                                       0
2. Gender                                                    6
5. Academic Year                                             0
6. Current CGPA                                              0
7. Did you receive a waiver or scholarship at your university?  0
Anxiety Label                                                0
Stress Label                                                 0
Depression Label                                             0
```

Fig 3: Null values only exist for Gender

A. Data Pre-processing and Model Analysis

The dataset is this study consisted of questionnaires from university students which consisted of features like Age, Gender, Academic Year and CGPA. Meanwhile, there were also specific features that only related to certain labels such as stress, anxiety and depression. Each of these labels also had features which included numerical scores like anxiety value, stress value and depression value. Moreover, the dataset also contained categorical values which also needed further encoding before being fed into the models. Initially, various analyses such as skewness and correlation matrices were used to analyze the data. Although the amount of null values in the dataset was minimal, the rows containing the null values were removed. After that, the categorical values were mapped into numerical values. Feature scaling was used to standardize the data in order for better accuracy and faster training time. The dataset had 3 target labels Stress, Anxiety and Depression. These three labels were combined into 1 inorder to produce a single target class label. A correlation matrix was then constructed in order to produce the best features that had strong correlations with the combined target label. The features that had poor correlation were removed from the dataset. FInally, the dataset was split into 2 parts where 80% consisted of testing and 20% consisted of training.

Fig:4 Flowchart of classification of combined mental health disorder using machine learning models.

The following classification models have been selected based on the pre-processed dataset in order to enable the most accurate classification:

A. Logistic Regression: It is a linear classification model that uses regression as a basis to classify the data. Multinomial logistic regression was used as our target label consisted of multiple classes . Although it may use basic linear functions in order to predict classes, it serves as a baseline for more complex classification models.
B. Decision Tree classifier: It is a non-linear model that splits the data based on feature thresholds using Gini impurity. This model is capable of dealing with non-linearity which logistic regression fails at.
C. Neural Network: Although neural network can be built with multiple hidden layers, our model consisted of only one hidden layer with 32 neurons. Moreover, the hidden layer was constructed with a ReLU activation function and the output layer with a softmax activation function in order for multi-class classification. Furthermore, the model also used Adam optimizer and categorical cross entropy loss function. Thus, this architecture enables the extraction of non-linear connections among the features.

V. Model Training

Our dataset was split into 80-20, where 80% was used for training and 20% for testing. After splitting the dataset, the data was scaled using standard scalar from sklearn. Logistic regression ran for 150 iterations for multi-class classification. Generic decision tree classifier was imported from sklearn.tree and used to train the dataset. Meanwhile, Neural Network was implemented to have one hidden layer of 32 neurons and an output layer of 53 neurons for 53 distinct classes.

VI. Model Evaluation

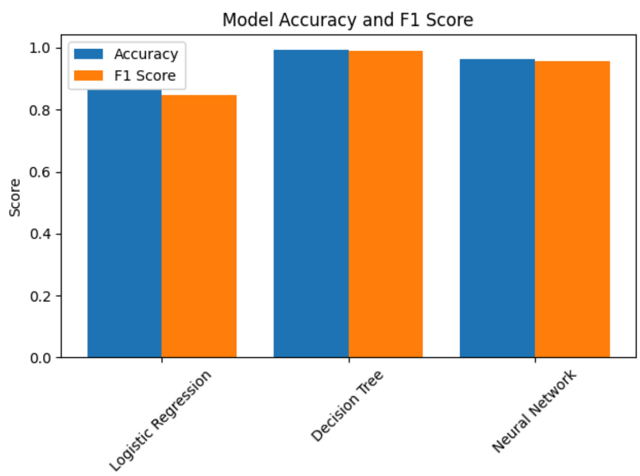

Fig 5: Bar chart of Accuracy and F1 Score of Machine learning models.

There were originally 1977 rows and 37 columns, after pre-processing the dataset consisted of 1971 rows and 28 columns. Among them, 80% (1576) were allocated for training and 20%(395) were allocated for testing. The following are the f1 scores and accuracy for each model.

A. Logistic Regression

F1 Score	Accuracy
0.848	0.863

B. Decision Tree

F1 Score	Accuracy
0.990	0.992

C. Neural Network

F1 Score	Accuracy
0.953	0.957

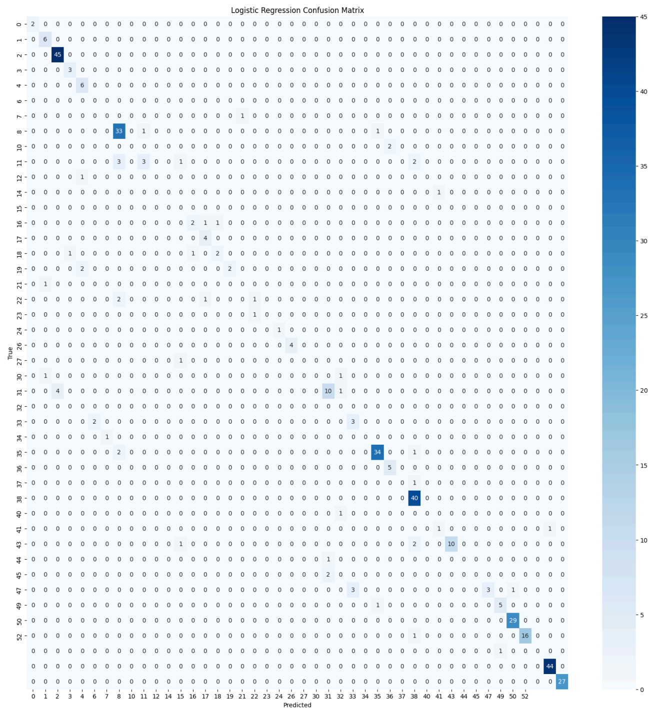

Fig 6: Confusion Matrix of Logistic Regression

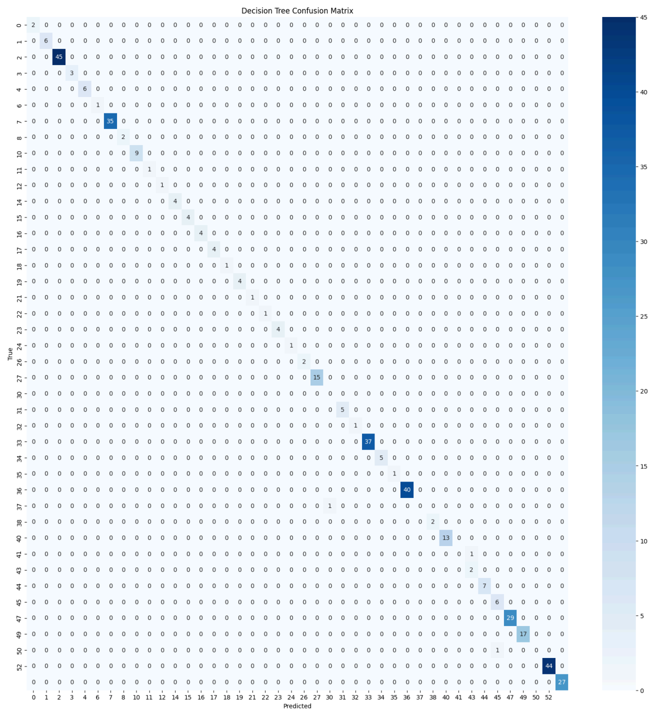

Fig 7: Confusion Matrix of Decision Trees

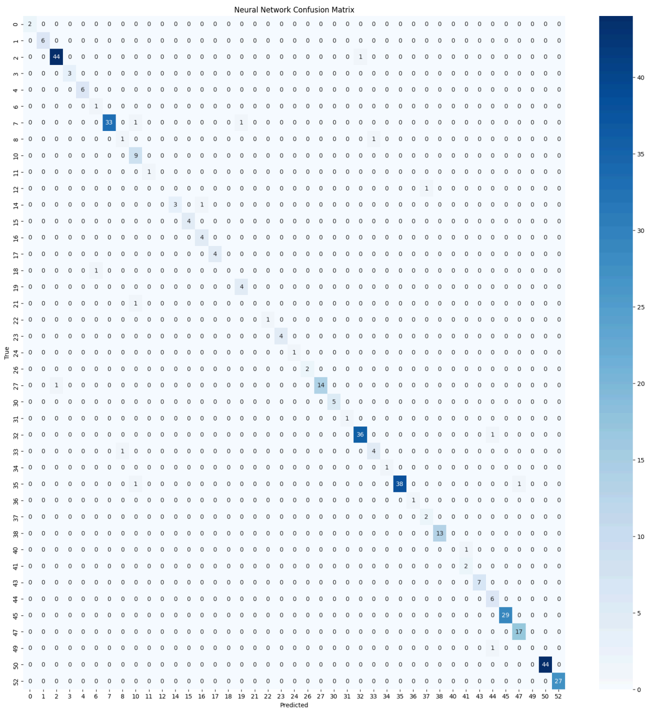

Fig 8: Confusion Matrix of Neural Networks

41	0.00	0.00	0.00	2
43	1.00	0.43	0.60	7
44	0.83	0.83	0.83	6
45	0.97	1.00	0.98	29
47	1.00	0.94	0.97	17
49	0.00	0.00	0.00	1
50	0.98	1.00	0.99	44
52	1.00	1.00	1.00	27
accuracy			0.86	395
macro avg	0.50	0.49	0.49	395
weighted avg	0.85	0.86	0.85	395

Fig 9: Classification report on final few iterations of Logistic regression

41	0.67	1.00	0.80	2
43	1.00	1.00	1.00	7
44	0.86	1.00	0.92	6
45	1.00	1.00	1.00	29
47	1.00	1.00	1.00	17
49	0.00	0.00	0.00	1
50	1.00	1.00	1.00	44
52	1.00	1.00	1.00	27
accuracy			0.99	395
macro avg	0.89	0.90	0.90	395
weighted avg	0.99	0.99	0.99	395

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Fig 10: Classification report on final few iterations of Decision Tree

41	0.67	1.00	0.80	2
43	1.00	1.00	1.00	7
44	0.75	1.00	0.86	6
45	1.00	1.00	1.00	29
47	0.94	1.00	0.97	17
49	0.00	0.00	0.00	1
50	1.00	1.00	1.00	44
52	1.00	1.00	1.00	27
accuracy			0.96	395
macro avg	0.81	0.85	0.82	395
weighted avg	0.96	0.96	0.96	395

Fig 11: Classification report on final few iterations of Neural Network

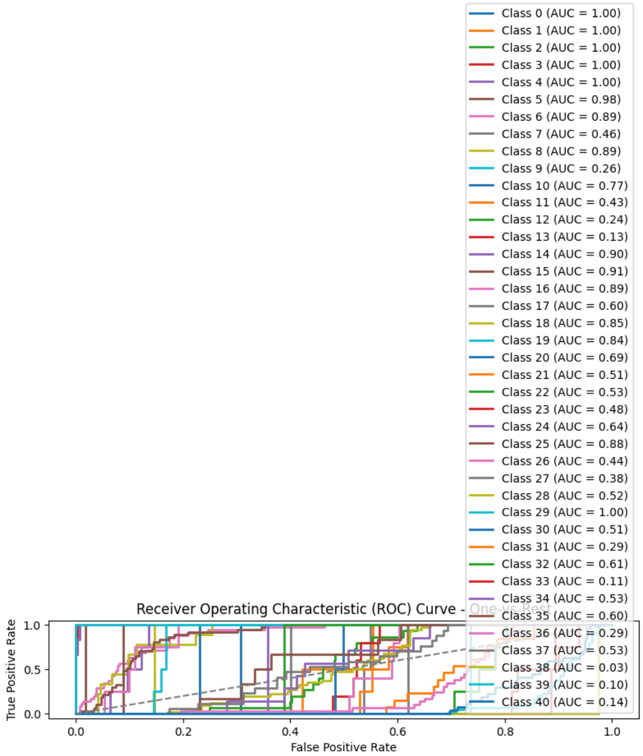

Fig 12: ROC and AUC of Logistic Regression

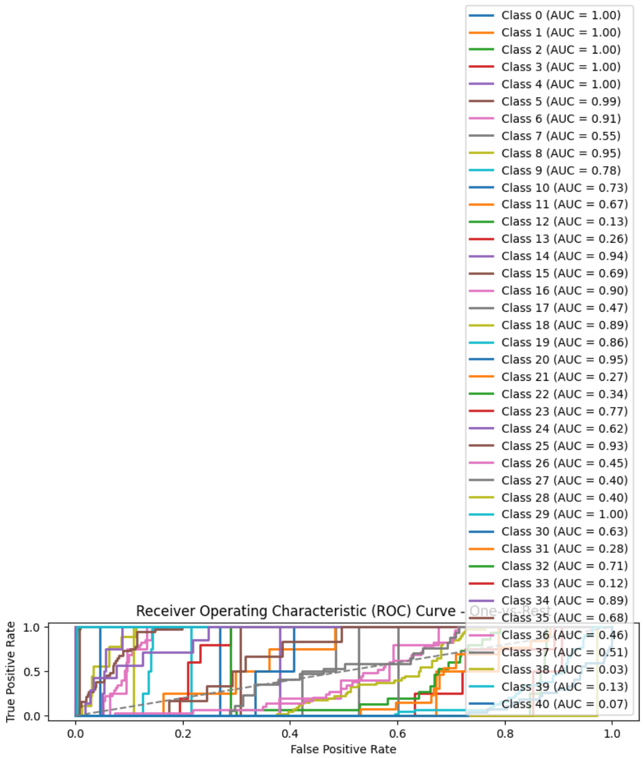

Fig 13: ROC and AUC of Neural Network

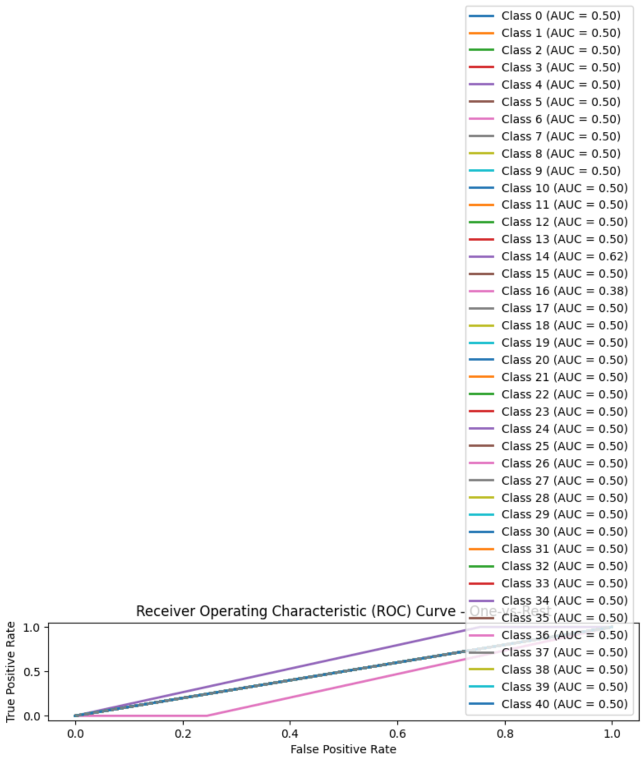

Fig 14: ROC and AUC of Decision Tree

VII. Conclusion

According to the F1 score and accuracy, Decision Tree emerged as the best model in comparison with Logistic Regression and Neural Network. The Decision Tree almost provided perfect accuracy and F1 score. Meanwhile, neural network also had very satisfactory results in classification. Logistic regression also provided decent results but it fell short compared to the other models. This may be due to the fact that the dataset contained more non-linearity as both non-linear models performed better compared to the only linear model.

In this study, we aimed to figure out the best machine learning model to classify the combined mental health disorder which consisted of stress, anxiety and depression. The dataset was derived from the questionnaires from students and through preprocessing and normalization, the authenticity and consistency of the dataset was ensured.

Logistic Regression, Decision Tree and Neural Network models were implemented and Decision Tree had the highest accuracy in classifying the combined mental health status. Although Decision Tree had the best accuracy, it had poor AUC value which could indicate that the model is memorizing. data. Therefore, Neural Network provide the most optimal solution as it had both good accuracy and consistent AUC. The results reflected the non-linearity of the dataset and the promise for future work in early diagnosis of mental health disorders.

Future works may include expanding the dataset into a broader category of audiences. This will help bring in more data and features for more accurate diagnosis on a broader audience and not just only university students.

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