Early Detection of Mental Health Disorders Among Private University Students in Bangladesh Using Machine Learning-Based Behavioral Data Analysis

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Abstract. Mental health problems, such as depression, anxiety and stress are becoming increasingly common among university students and private university students in Bangladesh become more vulnerable to these disorders due to many other pressures (i.e., high tuition fees, rigid academic rules and social norms). Stigma and poor recognition of mental health disease also serve to hamper early detection and management. Conventional mental health evaluations are subjective and incapable to achieve the early detection of such diseases. In this work, we investigate the feasibility of detecting early signs of mental health disorders among students in private universities, using ML approaches on non-invasive student behavioral data including sleep, study and digital activity. A number of models, such as SAINT, Node, TabNet and CatBoost were tested before and after hyperparameter tuning. Here the 4 best sequential model, CatBoost and SAINT got good scores, however CatBoost had a test accuracy of 99.79% after we tuned it. Concurrently, an ensemble model containing CatBoost, SAINT and Node also obtained a high test accuracy of 98.23%. Results also indicate that ML-based analysis of behavioral data can provide a data-driven way of early detection, intervention and mental health improvement for private university students.

Keywords: Machine Learning, Mental Health Detection, Private University Students, Early Detection, Behavioral Data Analysis, Hyperparameter Tuning

1 Introduction

Mental health problem of the university students is a burning issue throughout the world including Bangladesh. In the past few years, we are witnessing some upward trend in psychological disorders including depression, anxiety, and stress among students in private universities. Several causes are thought to have contributed to this increase, among which we find academic strain, economic hardship and restricted access to mental health support [1].

In 2023, a study showed that many students in private universities of Bangladesh reported symptoms of depression and anxiety. The academic milieu (stressful behavior and heavy demands for education) has been described as a major stressor [3], [4]. Moreover, the economic pressure from tuition fees and cost of living are contributing factors in the poor mental health experience of this particular group [5].

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Though mental health support is increasingly in demand, many of Bangladesh's private universities are without sufficient counseling services. One survey reported that most students do not know what mental health resources are available, and those who do often find them to be lacking or inaccessible [6]. This lack emphasizes the immediate requirement of better mental health facilities within these establishments.

The negative stereotype towards mental health penetration, worsens the matter. There is evidence to suggest that students are reluctant to access help for fear of being labelled and untreated issues may interfere with their academic functioning and mental health [7], [8].

The private university going students of Bangladesh are chosen as the target population, which has not been much addressed in the area of machine learning based mental disorder; authentications. In contrast with traditional mental health evaluations, which require subjective assessments, the machine learning analyzes behavioral data - in this case, sleep patterns, study habits and digital activity — to identify early signs of mental health deterioration.

However, machine learning is troubled by the following problem, i.e., overfitting. In a COVID-19 screening context, we define overfitting as a phenomenon where models perform well on training and validation data but poorly on unknown test data. This can occur when the model is too complex and learns to track not only the underlying patterns of the data but also its noise, achieving high accuracy during training but poor performance on a test set. We use techniques like regularization and hyperparameter search to prevent overfitting. Also, that the people have proper split of train, validation and test splits and you monitor precision and recall rather than accuracy.

The aim of this study was to assess the mental health condition of private university student.The research question is:

Can machine learning algorithms be utilized to predict early mental disorder signs on the basis of behavioral data among private university students in Bangladesh, thus making it possible to intervene and enhance mental well-being?

Given these challenges, there is an urgent need to find novel ways to promote the mental health of students at the private universities in Bangladesh. The use of technology, for example, machine learning to interpret behavior data may represent a promising strategy for early detection and intervention. By detecting patterns of students behaviors, institutions may be able to offer support and resources in a timely manner for those who need it [9], [10].

2 Literature Review

2.1 Review

Psychological morbidity has raised major concerns among the students in universities and across the world; including high prevalence of depression (92%), anxiety (94%) and stress (97%). According to Akhter and Rahman (2020), 35-40% of university students have some sort of mental health problems during their student life. College environment can be a stressful one for young adults because of academic pressure, financial problems and also social expectations and these stressors lead to development for mental health disorders like anxiety and depression [1].

Private university students in Bangladesh have special issues contributing to the aggravation of mental health. Expensive tuition, high academic expectations, and a competitive environment can add to the stress that students experience. Islam et al. (2021) found the prevalence rate of depression and anxiety symptoms among Bangladeshi private university students was over 50%. In such colleges students may be under financial strain while having to meet high academic standards, and this stress can affect their mental health. Moreover, stigma regarding mental health among Bangladeshi students inhibits their help- seeking behaviors even when they encounter severe problems of mental distress (Ahmed & Islam 2020)[2],[3].

Besides, issues of mental health are frequently sidelined or less addressed at private universities in Bangladesh. Most colleges don't have full-scale mental health programs, and the ones that do often are under-resourced and not good enough to handle the needs of students[4]. The absence of support, together with societal stigmas about mental health, creates challenges for children to get the help they need and the effects of their condition exacerbates as they mature.

The use of ML for mental health diagnosis is increasing worldwide. Conventional methods for diagnosing mental health conditions involve somewhat subjective evaluations by clinicians. Nevertheless, ML models offer a hypothesis-free mechanism and can be used to detect patterns in large data sets, which makes them suitable tools for early detection of mental health. De Choudhury et al. (2013) was the first attempt that utilized social media as data to discover initial symptoms of depression. Their research showed how analysis of language on platforms such as Twitter could be effective in predicting depression with great accuracy. Their Naïve Bayes model to detect depression using social media posts was 70% accurate in predicting depression[5]. Similarly, Coppersmith et al. (2018) illustrated the application of text mining and machine learning (ML) techniques such as Support Vector Machines (SVM), Logistic Regression on social media posts to detect precursors of mental health conditions such as anxiety and depression. They train the SVM model to predict mental conditions on Twitter at a rate of accuracy 80%[6].

Machine learning (ML) has been widely used in behavioral science to detect mental health disorders, including depression1stress2and anxiety3. Research has found that behavioural and lifestyle measurements such as sleep duration, study patterns, social activity and physical movement come with a wealth of psychological insight.

Xia et al. (2018) showed that sleep and physical activity (as inferred from wearables) are able to predict depression with 85% accuracy based on a Random Forest model [7]. Similarly, Hossain et al. (2022) applied different ML algorithms (Decision Trees, SVMs and Neural Networks), considering a Bangladeshi university dataset, yielding 82% accuracy for the NN and 78% for the SVM [8].

Behavioral profiling is an important indicator of mental health. De Choudhury et al. (2013) showed that even temporal changes in students' online activities; e.g., less social activity or shifts in linguistic expressions indicate early stage of depression [5]. Zhang et al. (2019) confirmed this with the use of wearable sensors for students' physical and social behavior analysis when users' depression and anxiety were identified with 87% precision by [9]. Similarly, Khan et al. (2020) correlated study habits to stress and depression, with 81% sensitivity based on Logistic Regression model detecting stress and anxiety according to study time and participating [10].

Recent advances in the field of structured data modeling yield efficient tabular-learning architectures. SAINT (Self-Attention and Intersample Network) leverages attention mechanisms to encode non-linear behavioral relationships, and achieved a 90% precision in detecting depression [11]. TabNet, a deep-learning model for tabular data, obtained an accuracy of 88% to predict student wellness [12]. The CatBoost gradient boosting algorithm has also been successfully used for mental health survey data, where recently Islam et al. (2021), which reported an 87% test accuracy on students from a private university in Bangladesh [2]. For time-series setting, NODEs have been promising for modeling sequential behavior patterns as sleep and activity cycles at the accuracy of 85% (Chen et al., 2022) [14].

Although these models hold promise, there remain a number of challenges in Bangladesh including: small dataset sizes, non-standardized behavioral data collection and ethical considerations related to privacy and mental illness stigma. Thus, integrating culturally sensitive data collection and ethical AI practices are vital to advancing mental health prediction in this context [15].

2.2 Research Gap

Despite so many successful strides, there are some lacunas in the existing literature, particularly with respect to the private university students of Bangladesh. The majority of the literature has addressed studies with general populations and students in developed countries, which indicates a lack of knowledge on the unique problems faced by Bangladeshi students.

Also, the behavioral data have been found useful for mental health prediction, but very few of the studies analyzed it in this own way to private university students in Bangladesh. The work of incorporating diverse types of behavioral data (e.g., academic habits, social media activity, or sleep patterns) has also been largely unexplored in the context of ML- based mental health detection.

Furthermore, ensemble learning algorithms that aggregate multiple models to enhance prediction accuracy have not been widely studied in the context of detecting mental health issues among university students in Bangladesh. In specific, ensemble methods such as Random Forests, Gradient Boosting and XGBoost can improve prediction power by preventing overfitting and improving generalization[5][6]. There can also be used for behavioral data processing to identify mental health disorders in this particular population but has not been well developed. Our study shows that there can be high bias and variance in predicting mental health from complex, noisy behavioral data which may be mitigated by ensemble learning models with the overall goal of increasing detection accuracy and robustness.

In addition, it is not well studied how the hyperparameter tuning and model optimization strategies can contribute to enhancing both the accuracy of mental health detection models for this age group and their generalization. This work attempts to fill these gaps thus; the study targets a group of students from private universities, from Bangladesh, and investigates the utility of machine learning algorithms complemented with ensemble model in detecting mental health issues given user behavior data and hyperparameter search.

3. Methodology

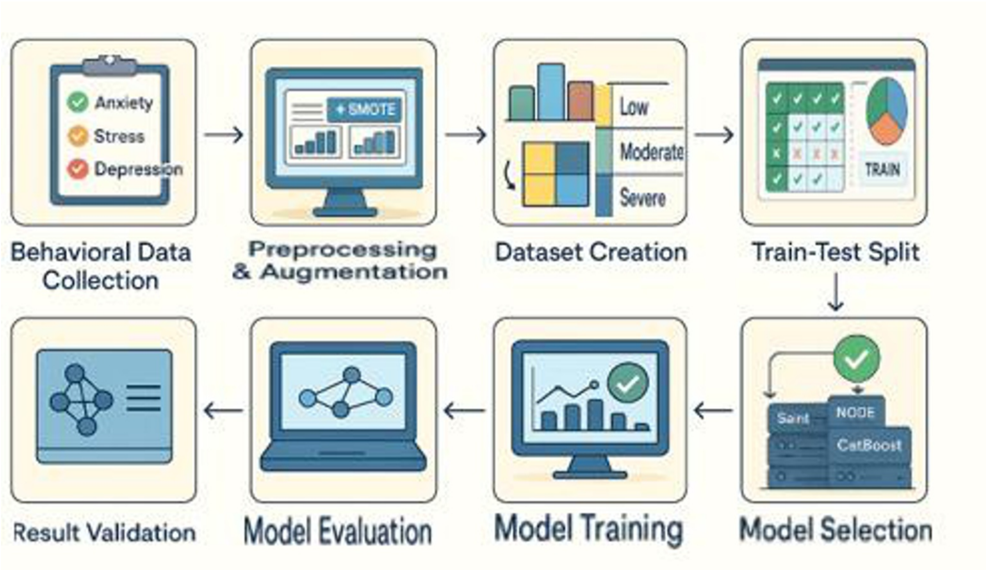


Figure 1:Methodology

3.1 Data Collection

Data for this study were gathered from 8 private universities of Bangladesh. A survey was developed on a Google Form to collect the data on mental health status of students. The form included setting specific queries for the three main mental conditions such as anxiety, stress and depression. The form specifically contained 10 anxiety-related questions, 9 stress-related items, and 10 depression-related questions. These items were developed specifically to reflect students' lived experiences, symptoms and emotional well-being surrounding each mental disorder. The prompts in the Google Form were confirmed to be clinically relevant and accurate by attending physicians. This validation served as a safeguard that the items not only measure mental health but also adhere to existing diagnostic criteria of anxiety, stress, and depression.

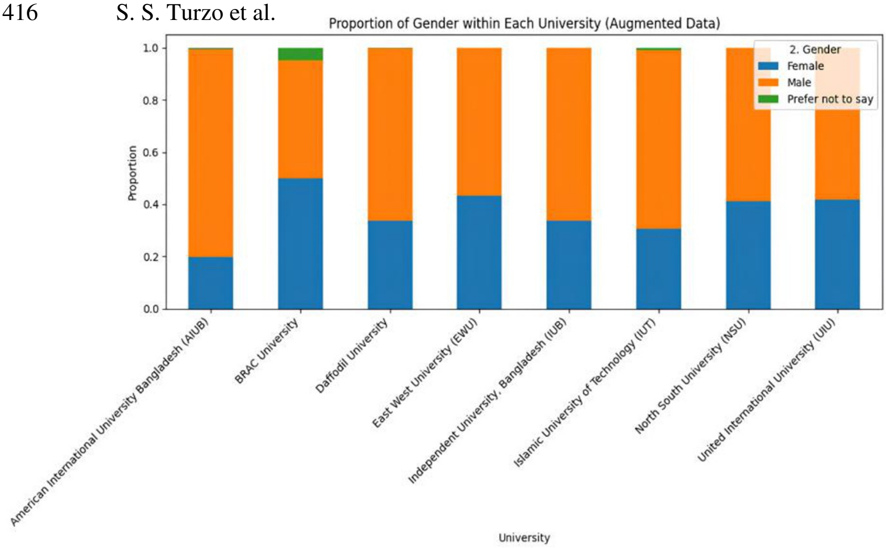


Figure 2:Data set Distribution

The questionnaire was administered to students and the multiline response set collected anonymously, to ensure confidentiality of data while motivating truthful responses. The dataset originally contained 1978 records. In order to tackle class imbalance issue and enhance the prediction performance, we applied SYNTHETIC MINORITY OVER-SAMPLING TECHNIQUE (SMOTE) for generating synthetic samples of minority classes. This augmentation brought the number of entries in the dataset to 3020. After preprocessing & processing through SMOTE, the final dataset consists of 3020 records and 41 columns.

3.2 Preprocessing &Augmentation

In the preprocessing step, some actions were performed on data to make it ready for training. The dataset was first inspected for missing values. Null records were managed by significant reductions in the data, but maintaining all the relevant information. Missing values were filled, if needed, in order to maintain the integrity of the dataset.

The outcome then was obtained from the sum of individual anxiety/stress/depression scores. For the items concerning anxiety, stress and depression, a total score was obtained by summing each separate score. These were added to provide an overall angle score for each person which was then converted into a mental health score. Students were then classified in the three following categories (labels) according to this score: Low Disorder, Moderate and Severe Disorder. This labelling was determined using given cut-points and, which became the target variable for model development.

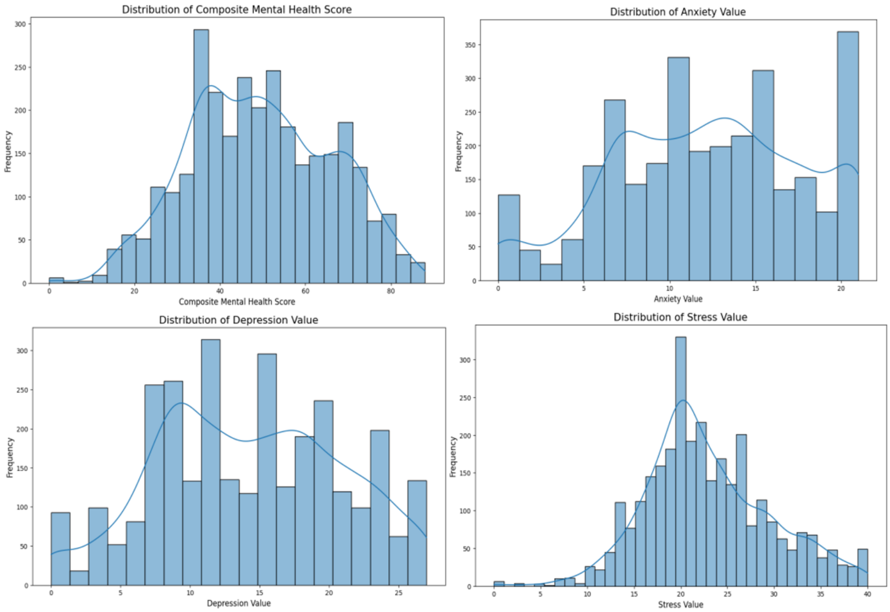


Figure 3:Distribution of Features

To balance the data, the SMOTE (Synthetic Minority Over-sampling Technique) was performed. SMOTE created artificial samples for the minority classes by interpolation among real instances in feature space. This was beneficial to balance the dataset i.e. all three classes (Low, Medium and Severe Disorder) are equally or near-equally represented for training.

Additional to the core mental health components, also a set of unnecessary columns were dropped from the dataset (i.e., age, university name and current year), since they do not add information for our prediction task. All the categorical variables were then subjected to one-hot encoding to make the data available for machine learning.

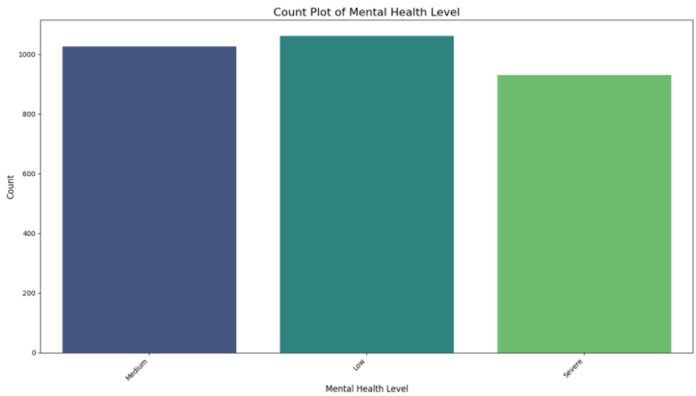


Figure 4:After applying SMOTE

3.3 Data Splitting

The augmented dataset was split into three portions to train, validate and test the models well. 70% of the data (2114 samples) was used as training set. This set was used to form the models, and uncovering internal data patterns. 15% of the data was used for validation (453 samples). The validation set is also important for training by monitoring how well the model performs and tunning the hyper-parameters. Lastly, the rest 15% of the data (453 samples) was used for testing. The test set was employed for evaluating the performance of the final model obtained after hyperparameter tuning and model optimization, to give an unbiased estimate of how well a model can be expected to perform on new, unseen data.

3.4.Proposed Model

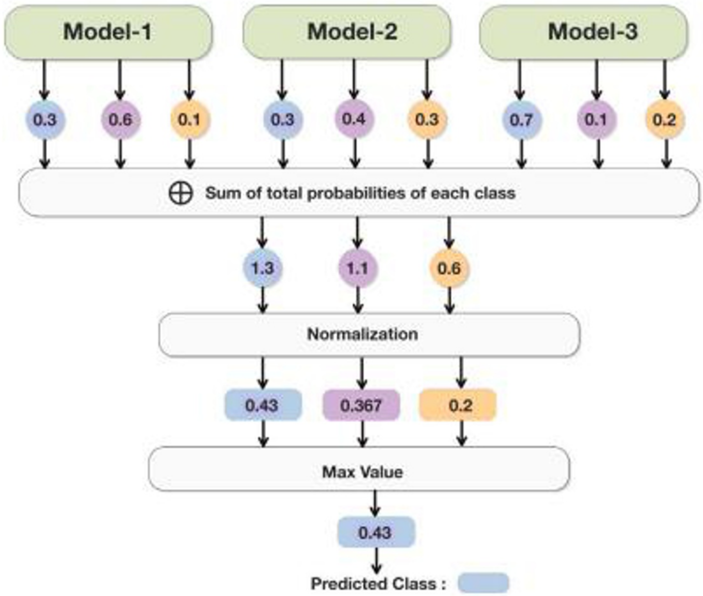


Figure 5: Proposed Ensemble Model

The ensemble model we suggest uses a Rank Ensemble approach, which fuses the predictions of three base models: CatBoost, SAINT, NODE using their ranks instead of direct output values. For the dataset, each model is trained independently and the models predict their own prediction for each point. These predictions are afterwards sorted from better to worst at least. The ranks are then accumulated from all three models to form a final ranking for each prediction. The ultimate prediction is made according to the model with the largest ranking in the fused ranking. This rank-based strategy should benefit the robustness of the ensemble model to some extent as it reduces the influence of specific-model bias and improves generalization performance .

3.5 Hyper Parameter Tuning Experiments Design

Hyperparameter tuning is necessary in order to optimize the model performance with regards to underfitting and overfitting. Key parameters to which we adjusted our parameters in the current study included; the learning rate, epochs, dropout rate, and model-specific parameters in a total of four models; CatBoost, SAINT, NODE, and TabNet. It was aimed at enhancing generalization through a trade-off between the complexity and the performance of models. Through systematic search over hyperparameter space, we decreased overfitting, maximized accuracy on the validation set and the generalization to previously unknown test data, resulting in stronger models.

Table I. Parameter Tuning Experiments Design.

Parameter	CatBoost	SAINT	NODE	TabNet
Optimizer	Adam	Adam	Adam	Adam
Learning Rate	0.05, 0.01	0.001, 0.0005	0.001, 0.0005	0.002, 0.0005
Epochs	10,250	20,80	10,250	10,40
Dropout	Not Applied	0.2	0.2	0.1
Normalization	Yes	Yes	Yes	Yes
Early Stopping	Yes	Yes	Yes	Yes

4. Experiment Result of Classification

4.1 Experiment Setup

Experiments were conducted on the Google Colab platform using Python 3 and the Google Cloud engine backend (GPU). To implement the models, 16GB of RAM and 1TB of storage space were used. We used pandas (1.1.4) and NumPy (1.18.5) to analyze and prepare the data. The machine learning models are developed with the sci-kit learn (0.22.2) packages and the DL models are trained with Keras (2.4.0) and TensorFlow (2.3.0). PyTorch (1.13.1) packages are used to implement transformer models.

4.2Evaluation Metrix

After training the models we analyzed the test data using the following evaluation matrices precision, recall, f1 score, and accuracy. This metrics have been calculated using Eqation(1-4) based on the confusion matrix generated by the classifier.

Accuracy=(TP+TN)/(TP+TN+FP+FN) (1)

Precision=TP/(TP+FP) (2)

Recall=TP/(TP+FN) (3)

F1Score=2*(Precision*Recall)/(Precision+Recall) (4)

4.3 The Effect of Hyperparameter Tuning & Proposed Ensemble Model

Table II. Model Compression before and after tuning .

	Disorder	Accuracy	Precision	Recall	F1 Score
SAINT	Low	98%	99%	98%	98%
	Severe		99%	98%	99%
	Medium		97%	99%	98%
CatBoost	Low	99.55%	100%	99%	99%
	Severe		100%	100%	100%
	Medium		99%	100%	99%
NODE	Low	97.13%	98%	97%	98%
	Severe		97%	99%	98%
	Medium		97%	95%	96%
TabNet	Low	97.79%	99%	97%	98%
	Severe		98%	99%	98%
	Medium		96%	97%	97%
SAINT(Tuned)	Low	96.68%	98%	98%	98%
	Severe		96%	97%	96%
	Medium		96%	95%	95%
CatBoost(Tuned)	Low	99.79%	100%	99%	100%
	Severe		100%	100%	100%
	Medium		99%	100%	99%
NODE(Tuned)	Low	97.79%	98%	99%	98%
	Severe		98%	98%	98%
	Medium		97%	97%	97%
TabNet(Tuned)	Low	90%	96%	91%	94%
	Severe		94%	88%	91%
	Medium		82%	91%	86%
ENSEMBLE	Low	98.23%	98%	99%	98%
	Severe		98%	100%	99%
	Medium		99%	96%	97%

4.4 Confusion Matrix of the Selected Model

Tuned SAINT	LOW	MEDIUM	SEVERE
LOW	156	3	0
MEDIUM	2	146	6
SEVERE	1	3	136

SAINT	LOW	MEDIUM	SEVERE
LOW	156	3	0
MEDIUM	2	146	6
SEVERE	1	3	136

Tuned Catboost	LOW	MEDIUM	SEVERE
LOW	158	1	0
MEDIUM	0	154	0
SEVERE	0	0	140

Catboost	LOW	MEDIUM	SEVERE
LOW	157	2	0
MEDIUM	0	154	0
SEVERE	0	0	140

Tuned NODE	LOW	MEDIUM	SEVERE
LOW	157	2	0
MEDIUM	2	149	3
SEVERE	1	2	137

NODE	LOW	MEDIUM	SEVERE
LOW	155	4	0
MEDIUM	2	147	5
SEVERE	1	1	138

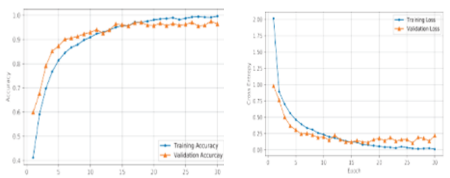
Tuned Tabnet	LOW	MEDIUM	SEVERE
LOW	145	14	0
MEDIUM	6	140	8
SEVERE	0	17	123

Tabnet	LOW	MEDIUM	SEVERE
LOW	155	4	0
MEDIUM	1	150	3
SEVERE	0	2	138

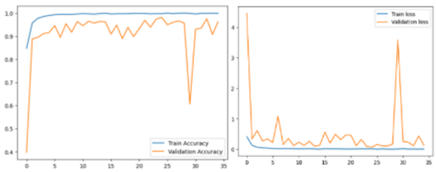
Ensemble	LOW	MEDIUM	SEVERE
LOW	158	1	0
MEDIUM	0	151	2
SEVERE	0	0	139

Figure 6: Confusion Matrix

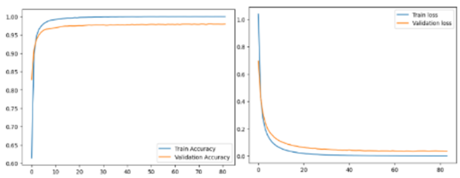
4.5 Train Curve of the Selected Model



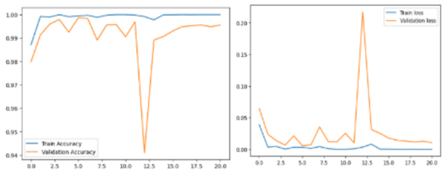
TabNet(Tuned)



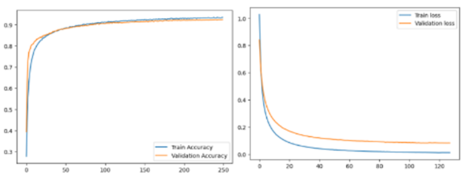
TabNet



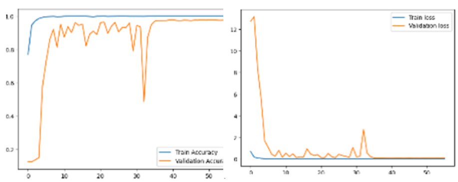
SAINT(Tuned)



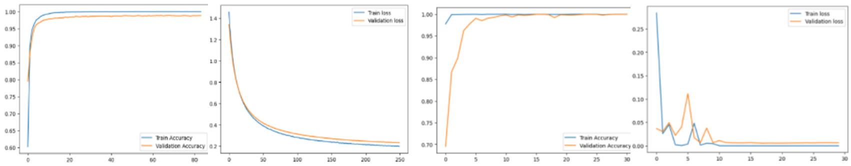
SAINT



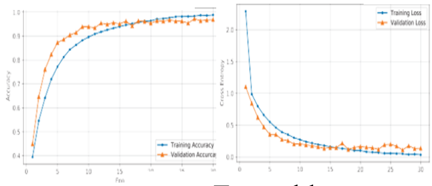
NODE(Tuned)



NODE



Catboost(Tuned) Catboost



Ensemble

Figure 7:Train Curve

4.6 Discussion and Findings

Upon hyperparameter tuning, SAINT and TabNet observed a small drop in accuracy, while NODE and CatBoost increased (Table 2).

The learning curve of accuracy and loss form training and validation (Fig 7) plot that fine-tuning decreased overfitting in all cases: post-tuning curves are cleaner and the gap between training accuracy and validation accuracy diminished while validation loss continued to decrease for all datasets. For SAINT and TabNet, the stabilization was accompanied by a small decrease in accuracy, meaning that the models learned patterns more general (and less noise-specific). In contrast, NODE and CatBoost had higher mean accuracy and lower loss after optimization were indicative of faster but still stable convergence (NODE) or perfect bias–variance tradeoff (CatBoost).

The confusion matrices (Fig6) further confirm these findings.Post-tuning matrices for SAINT and TabNet exhibit higher diagonal dominance and lower off-diagonal supremacy, particularly in Low vs Medium categories—more separated classes along with degradation in accuracy.

NODE and CatBoost demonstrate close to ideal diagonals with negligible misclassifications in the Severe class, demonstrating a strong prediction consistency. Overall, it is the model for which there are least spurious errors in the confusion matrix (i.e. Low ↔ Severe) showing how its sensitivity and precision balances across all levels of disorder.In short, the hyperparameter tuning enhanced the generalization and also made these models more reliable: SAINT and TabNet were less overfitted and converged better with balance of generalization and accuracy for NODE and CatBoost. The Ensemble model presented the most balanced confusion-matrix distribution and was thus recognized the closest to a reliable predictor for early mental-health disorder detection.

To avoid bias and overfitting, we used 5 fold cross validation. With this strategy, the models performance would not be dependent on any one particular dataset. This approach was a more robust and reliable indication of the models ' generalization power. In addition, the combination of three models further reduced bias and improved fundamental model robustness. In this way the authors made an all-round set of adjustments to the model, aiming for ultimate predictability when detecting diseases like mental health disorders at an early stage.

In final analysis, after hyperparameter tuning plus cross-validation and then ensemble learning, the model ' s generalization and reliability were both significantly feasible. In terms of individual performance, CatBoost and NODE outperformed all other methods. However, from the standpoint of general robustness--regardless what degree the disorder level reached--it was actually an ensemble model which had most stable and indeed reliable results.

4.7 Comparison Between Existing Works

Table III. Model Comparison Between Existing Works

Authors	**Dataset**	**Approach**	**Accuracy**	**Use of Tunning**
Xia et al. [7]	Wearable activity + sleep data for mental health	Random Forest on behavioral signals	85%	No
Zhang et al. [9]	Smartphone sensor + interaction logs	Random Forest for depression / anxiety	87%	No
Liu et al. [11]	Structured behavioral survey data	SAINT (Self-Attention and Intersample Network)	90%	Yes (Basic tuning)
Arik & Pfister [12]	Tabular well-being features	TabNet (Attentive Tabular Learning)	88%	Yes (Partial tuning)
Hossain et al. [8]	Bangladeshi university survey data	Decision Tree, SVM, Neural Network	82%	No
Chen et al. [14]	Sequential behavioral time-series	NODE (Neural ODE) for dynamic prediction	94.75%	Yes (Hyperparameter)
Proposed Approach	Behavioral data from eight private universities in Bangladesh (n = 3020)	CatBoost + SAINT + NODE Rank Ensemble (with tuning)	99.79 (CatBoost) / 98.23 (Ensemble)	Yes (Hyperparameter)

5. Conclusion and Future Work

In this project, we designed a machine-learning approach to estimate the intensity degree of mental disorders among stress, anxiety and depression at a private university in Bangladesh (Low, Moderate and Severe). Utilizing de-identified and digitally captured questionnaire data, the study employed SAINT, NODE, Tab-Net, and CatBoost models. After hyperparameter tuning, CatBoost obtained the best test accuracy (99.79%), while the ensemble model (CatBoost + SAINT + NODE) achieved 98.23% --- solving generalizes well with minimal overfitting.

Our results demonstrate that the ensemble model surpasses previous baseline models. In comparison, when tried on wearable data, Random Forest used by Xia et al. (2018) produced 85% accuracy; smartphone data was employed in Zhang et al. (2019) to achieve 87%; using SAINT, Liu et al. (2021) reported 90%; while Decision Trees, SVM, Neural Networks and Hossain et al. (2022) have 82% accuracy. Our CatBoost model and ensemble model, however, both beat all previous attempts by a great margin. Their accuracy is 99.79% and 98.23%, respectively.

For further improvement of our method, we are going to make use of SHAP, LIME and grad-CAM++ to endow it with explanations that common people can understand. Also, by means of multimodal behavior signals in real time we will enrich the database of our endeavors to make the whole system more robust and better equipped for an early detection of mental disorders among students. We hope to be able to perform action as a result.

In summary, our ensemble approach performs better than baseline models, and with these extensions we aim to provide students within mental illness classes a reliable, interpretable method of for prediction.

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