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ORIGINAL

Mental Health Monitoring for Undergraduate Students using Neural Network

Control de la salud mental de estudiantes universitarios mediante redes neuronales

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ABSTRACT

Introduction: in today's academic realm, the well-being of undergraduates is a growing concern.
Objective: our project aims to tackle this by using Artificial Intelligence (AI) and Machine Learning (ML) to track and evaluate students' mental health.
Method: we've analysed a dataset from a survey for undergraduates, using a mix of algorithms like SVM, Random Forest, Logistic Regression, and Neural Networks.
Results: our findings show Neural Networks as the standout performer, excelling in accuracy and other metrics. We've detailed our process from data preparation to model training, highlighting Neural Networks' superiority. By optimizing techniques like cross-validation, we've enhanced SVM, Logistic Regression, and Random Forest.
Conclusions: this study not only uncovers issues but also proposes a forward-thinking solution, endorsing Neural Networks as a ground-breaking tool for mental health assessment in academia.

Keywords: Mental Health Assessment; Under – Graduate Students; Neural Networks; Data Pre – Processing; MLP Classifier; Adam Optimizer; Performance Metrics.

RESUMEN

Introducción: en el ámbito académico actual, el bienestar de los estudiantes universitarios es una preocupación creciente.
Objetivo: nuestro proyecto pretende hacer frente a esto mediante el uso de Inteligencia Artificial (IA) y Aprendizaje Automático (ML) para rastrear y evaluar la salud mental de los estudiantes.
Método: Hemos analizado un conjunto de datos de una encuesta para estudiantes universitarios, utilizando una mezcla de algoritmos como SVM, Random Forest, Regresión Logística y Redes Neuronales.
Resultado: nuestros resultados muestran que las redes neuronales son las más destacadas, sobresaliendo en precisión y otras métricas. Hemos detallado nuestro proceso, desde la preparación de los datos hasta el entrenamiento del modelo, destacando la superioridad de las redes neuronales. Al optimizar técnicas como la validación cruzada, hemos mejorado SVM, la regresión logística y Random Forest.
Conclusiones: este estudio no sólo descubre problemas, sino que también propone una solución con visión de futuro, respaldando las redes neuronales como una herramienta innovadora para la evaluación de la salud mental en el mundo académico.

Palabras clave: Evaluación de la Salud Mental; Estudiantes Universitarios; Redes Neuronales; Preprocesamiento de Datos; Clasificador MLP; Optimizador Adam; Métricas de Rendimiento.

INTRODUCTION

Machine learning based algorithms are gaining popularity in the space of monitoring mental health.[1] This study analyses the popular algorithms like SVM, Random Forest, Logistic Regression and DNN and NN algorithms in order to understand the "Survey form for UG students" dataset. This dataset gives an overview of the lives of young people; undergraduate students in particular and how they overlap in specific information, specifically around questions related to mental health. The step of data pre-processing is an important step in making sure that good quality is achieved in the process of analysis. This includes data imputation for missing values to preserve data integrity and apply label encoding for categorical variables. The dataset is split into a training/testing set using an 80/20 ratio to facilitate the evaluation of the model. From the resulting confusion matrix, we will compute statistics that represent the performance of the model (i.e., accuracy, precision, recall, and F1-score). The computational time is recorded as well, to study the accuracy versus computational time trade off. Cross-Validation is used for Support Vector Machines (SVM), Logistic Regression (LR) and Random Forest (RF) for optimisation. Additionally, Adam optimization is used to improve the performance of deep learning models (DNN and NN). Analysing the results comparison, NN showed better performance than any other algorithms with good accuracy, F1-score, recall, precision and execution time. This provided strong evidence for the applicability of Neural Networks in mental health monitoring applications and an invitation to analyse how could we improve its implementations and disciplines that could lead to further experimental research.

Literature Survey

We do predictive analytics, which is a combination of machine learning and statistical data (past and present) to predict outcomes in the future. In Goyal et al.[2]; this collaborative effort involves data scientists, statisticians, and skilled analysts. This role includes the collection of relevant data by data engineers, and data visualization and reporting managed by software developers and analysts Such predictive models are critical to recognizing correlations in different datasets, including health record of patients. All of these processes involve training statistical models to predict well. The dataset used in this study is mentioned on Data Driven Investor (DDI) It consists of social media tweets (positive and depressive), and applied with Machine Learning algorithms. Binary Classification is used to derive the output. Abstract: The study is designed to analyze different types of approaches to predict depression. It proposes a new Deep Learning method for automatic detection, using relevant patterns from Twitter text data. This novel method could improve prediction accuracy in mental health analytics. Beyond Diagnosing Illness with Machine Learning A thorough overview of a group of research work on using machine learning techniques, for diagnosing illness is done in Vaishnavi et al.[3]. This comprehensive assessment globally encompassed the use of five prime machine learning algorithms routinely used in mental health studies: SVM, GBM, Random Forest, Naïve Bayes and KNN. The research showed using machine learning methods such as Naive Bayes, KNN, Random Forest, GBM and SVM. SVM, GBM, Random Forest, Naïve Bayes and KNN were found to be widely used methods in the field of mental health in this review, which we thought was interesting. However, it soon became clear that despite the benefits of each algorithm, many researchers employed them without justifying their use. Also, it was found other cases, where machine learning algorithms were used in practice without understanding the characteristics and properties of the data being analyzed. This highlights the importance of a deliberate procedure for choosing which algorithms to use, in this very important setting.

Shatte et al.[4] adopts a scoping review approach to provide a comprehensive overview of the potential implications of ML for mental health. The mental health-focused papers were naively searched across eight health and health information technology research databases. These articles have been thoroughly evaluated by two reviewers to highly informative and conservative evaluation These key details included the paper's focus (i.e. the relevant problem domain), machine learning (ML) methods employed, type(s) of data utilized, and study results. Following this rigorous approach, 300 papers were extracted, which explored Machine Learning applications within mental health. The papers highlighted four major areas: (i) identification and diagnosis of mental pathology, (ii) prediction, prevention and care, (iii) broader consequences for public health and, (iv) research and clinical practices in mental health. This is a valuable, wide-reaching perspective of different ML applications used in mental health research across the study population.

Chung et al.[5] follows a systematic structured process with steps of planning, search, analysis, discussion, and conclusion. Its main goals are to summarize recent Machine Learning (ML) research related to mental health, discuss the algorithms used, identify potential limitations, and highlight future research opportunities.[6] This inspection of Zpsych articles ensured that only recognized sources such as quality databases and respected papers like as the Journal of Psychiatric Research were used. A stringent collection of records was conducted, at once filtering out extraneous material. It is focused on anxiety, depression and PTSD. According to the PRISMA protocol, the review process carefully screened 142 records and ultimately included 30 eligible studies. This paper is a significant contribution, it emphasizes on the important role of machine learning in predicting various mental disorders including but not limited to bipolar disorder, anxiety, depression and PTSD (posttraumatic stress disorder). It provides significant insights, and analysis, and final conclusions in terms of ML approaches in those fundamental experiments.

In Garriga et al.[7], a machine learning model was developed to continuously monitor the risk of mental health crisis for patients over a 28-day period. This is important as it has the potential to improve patient outcomes, and reduce the associated burden and costs. The model performed well, with an area under the receiver operating characteristic curve (AUC) of 0,797, a sensitivity of 58 %, and a specificity of 85 %. This study proposes the application of continuous mental health crisis risk prediction at the patient level, elucidating how such an approach could transform real-life clinical practice. Information we used to conduct this study was collected on urgent mental health service events, such as the number of records, the time the data was collected, patient information, age, demographic information (including gender and ethnicity), crisis episodes, events leading up to hospitalization, and variables we would like to predict. We wanted to create a tool that can help clinicians better manage their caseloads, intervene sooner and prevent a crisis from occurring. Surprisingly, the 28-day period was a match for what the health care workers needed, and other time frames didn't alter how well the model performed.

Aldiabat et al.[8] and Zeba et al.[9] highlights the complexity of mental health problems in university students. It discusses key topics, such as prevalence rates, risk factors, and the significant impact these issues can have on individuals and their communities. In addition, it highlights the large barriers that students face when they seek help. These findings have far-reaching implications for academic institutions, administrators, educators, and health care providers and others. By recognizing and responding to these challenges, players in the university space can effectively mitigate the mental health issues and concerns present among students. Implementing this strategy would play a role in preventing mental illnesses such as depression and anxiety, promote overall mental health and wellbeing as well as foster a supportive atmosphere in academia. They've named potential outcomes ranging from self-harm to harm to others to unemployment and dropouts. Untreated mental health problems in university students can have serious repercussions including potential self-harm, harm to others, dropping out of education, increased levels of unemployment, and increased burden on family and society. Hence, proactive intervention is even more critical, as these issues compound psychosocial challenges. Administrators, educators, and healthcare providers must work together to develop comprehensive, culturally sensitive mental health programs to target these concerns successfully. Such programs seek to promote students' psychosocial well-being and engagement, prevent dropouts, preserve financial resources, and ultimately foster families and communities.

Nemesure et al.[10] performed a detailed investigation using data from 4184 university students, and used a sophisticated machine learning model to predict mental health conditions. The analysis considered many factors, from demographics to health-related behaviors. Model accuracy was extensively assessed using metrics like area under the curve (AUC). Data collected by local (in-situ) sensing sources provide a rich area of research for the identification of different Big Data types. Then, we employed a high-level model to combine the predictions. SHAP (SHapley Additive exPlanations): This method was used to understand the importance of features. The study finding hints the sophisticated approach can predicts mental health conditions such MDD and GAD. Importantly, the predictive performances of the machine learning models were superior compared to a basic LR model, with an average AUC increase of 0,08. These encouraging results illustrate the potential of our ML approach. Secondary screening is non-invasive and thus more sensitive than specific. Among MDD cases, the model detected 55 % of them and correctly identified 70 % of non-cases. For GAD, it identified 70 % of cases and ruled out 66 % of non-cases. The upshot is that advanced machine learning methods can do a good job of predicting mental health problems among college students, the results show.

Specific terminology was carefully chosen to distinguish between concepts like affect, emotion, sentiment, and mood. In Zhou et al.[11], 'affective' encompasses moods, feelings, and attitudes, while 'emotion' and 'sentiment' relate to short-term states. 'Mood' refers to long-term emotional patterns, aligning with clinical mood disorder classifications. The term 'unobtrusive sensing' describes the non-intrusive monitoring of mobile phone users' online activities. This approach utilizes computer vision, user interaction logs, and sentiment analysis of social media content to extract twelve signals reflecting mental states, contributing to stress management and suicide prevention. Webcam video analysis monitors various signals, including head movement, heart rate, eye blink rate, pupillary response, and facial expression. The Cascade Classifier locates the face, while the Tracking-Learning-Detection (TLD) algorithm tracks facial features in real time, capturing head movements as time-series data. These signals indicate that different mental states exhibit distinct head movement patterns. Positive and negative moods correlate with higher head movement rates, while neutral moods display more periodic head motions. This integration of multimodal signals holds great promise for mental health assessment. Sensitivity is prioritized for MDD and GAD. The research introduces a sophisticated multimodal signal system designed to predict mental health conditions. Using non-contact signals, user interactions, and content analysis, this system infers users' current states of mind in real-time. Thus, it is keeping our state in which there are this innovative thing that could lead our prediction of mental health and enable it with help and interventions.

It provides a quick overview of machine learning, which is the process of teaching a computer to learn about a subject by using machine data that has been provided to them.[12] There are four categories of machine learning — supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Supervised learning: algorithms learn from the sample data with target response (e.g regression, classification). Supervised learning learns from examples with corresponding responses, which includes classification and regression. The combination of both classified and unclassified data for enrichment of insights is called semi-supervised learning and reinforcement learning uses an agent receiving observations in order to get a reward (maximize outcome) or punishment (minimize risk). Tools: Data mining is accomplished with the help of tools such as Python, RapidMiner, and R Language, which provide functions for formatting and cleansing the data, equipment is used in delivering the desired fabrication as well as output assessment. In this phase, you will use a dataset called the 'Edu – Mental Health Dataset' and will be focusing on parameters like social support, financial problems, and learning environment. This paper looks into mental health issues of higher education students highlighting research gaps by comparative analysis of the research papers. It reviews mental health challenges in this student demographic and highlights potential causes, including poor social support, financial struggles, and learning environments. One of the most prominent supervised learning techniques is Support Vector Machine (SVM), which gave the best results among the studies in review with a high accuracy ranging from 70 % to 96 %.

Sumathi et al.[13] began by addressing the challenge of diagnosing common mental health issues, particularly in children. It involved interviews with clinical psychologists to understand the diagnostic methods used in practice. Subsequently, a machine learning model was developed to aid professionals in effectively diagnosing these issues. The model utilizes patient evidence as input and outlines the research approach. For dataset creation, 60 text instances related to mental health prediction were acquired from a clinical psychologist. The dataset comprised 25 attributes, including the class label, which were identified and verified. Irrelevant attributes were removed through the Best First Search technique to focus on relevant factors. In today's medical field, expert systems play a vital role in early disease and mental health issue prediction for effective treatment. This study compared 8 ML techniques for classifying the mental health dataset, highlighting Multilayer Perceptron, Multiclass Classifier, and LAD Tree as high-accuracy classifiers. Although the study used a limited dataset, applying these techniques to larger data sets could further enhance accuracy. It's worth noting that these classifiers require training before real-world implementation.

Dedgaonkar et al.[14] delves into using a mix of health data from wearable devices, emotional expressions captured in facial histograms, and input from a simplified questionnaire to screen for autism using deep learning. The aim is to help behavioral therapists tackle the challenges of existing screening tools. The document also looks into the application of machine learning and deep learning algorithms for detecting autism and sensory processing disorder (SPD). The results show 100 % accuracy in identifying autism, 86 % in recognizing emotions, and 100 % in detecting SPD.

METHOD

Figure 1 shows the block diagram. It indicates all the key steps followed in our research.

Methodology

Data Collection

For this study, we utilize the "Survey form for UG students" dataset, which comprises responses from young individuals, including undergraduate students. This dataset provides insights into various aspects of students' lives, including mental health-related questions.

Data Pre-processing

Data pre-processing involves the following steps:

- Handling missing values, ensuring data completeness.
- Convert categorical variables into numeric format using label encoding.

Model Selection

We select a range of models for this analysis, including:

1. SVM: SVM is a versatile classification algorithm that performs nicely in scenarios with clear

separation between classes. This property makes SVM beneficial in mental health monitoring, enabling individuals to be effectively classified based on survey responses.

2. Random Forest: random Forest improves prediction accuracy by combining predictions from multiple decision trees (ensemble learning method). In the context of mental health monitoring, it can point out significant features leading to mental health states.

3. Logistic Regression: although its name suggests otherwise, Logistic Regression is a very stable classifier. It can predict probability of specific mental health conditions based on survey responses which can be useful as a baseline model.

4. DNN (Deep Neural Network): DNNs, which have many layers, are adept at capturing complex patterns and relationships. In mental well-being monitoring, they may reveal subtle relationships in questionnaire responses, possibly discover subtle detection of mental health conditions.

5. Neural Network: neural network provides a versatile and scalable modelling method, suitable for different types of data. In your case, a generic neural network could be used in your project to understand the mappings from survey features to mental health states.

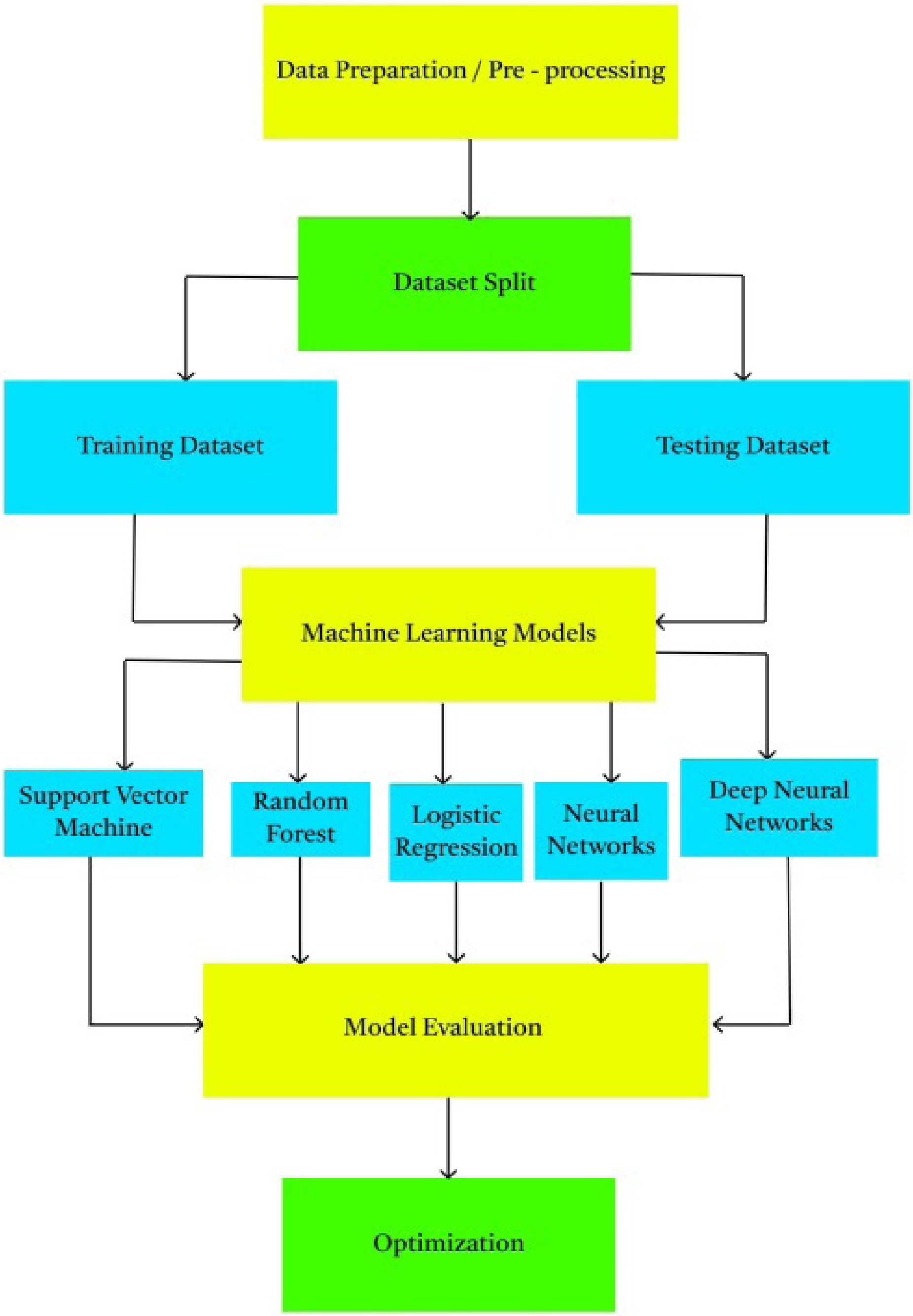

Figure. 1 Block Diagram

Training and Testing Split

To assess the models, we divide the dataset into training and testing sets, using an 80/20 split.

Model Training

Each selected model is trained on the training set, with model-specific hyperparameters and configurations.

Evaluation Metrics

We evaluate model performance using the following metrics:

i. Accuracy: accuracy stands as a foundational metric, gauging the overall correctness of predictions. This metric is computed by determining the ratio of instances correctly predicted to the total number of instances. In this project, accuracy provides a holistic view of how well the models perform across all mental health states.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}$$

ii. Precision: precision assesses the accuracy of positive predictions. It calculates the ratio of true positive predictions to the total predicted positives. In this project, precision would be useful in understanding how reliable the models are when they predict a specific mental health state.

$$Precision = \frac{True\ positives}{True\ positives + False\ positives}$$

iii. Recall: recall, or sensitivity, gauges the model's ability to capture all instances of a particular class. It is calculated as the ratio of true positive predictions to the total actual positives. In this, recall is crucial for ensuring that all cases of a specific mental health state are identified.

$$Recall = \frac{True\ positives}{True\ positives + False\ negatives}$$

iv. F1-score: the F1-score serves as the harmonic mean of precision and recall, striking a balance between these two metrics. This becomes particularly valuable in scenarios where there is an uneven distribution among classes. Within the context of this project, the F1-score stands as a valuable tool for offering a thorough assessment of the model's performance.

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

v. Hinge loss function for SVM: the hinge loss is the objective function used in SVM. It quantifies the model's ability to correctly classify instances while penalizing misclassifications. In your project, the hinge loss for SVM is essential for optimizing the model's parameters and improving classification accuracy.

$$Hinge\ Loss = \sum_{i=1}^{n} \max(0,1 - y_i\,.\,f(x_i))$$

$,where\ f(x_i)\ is\ the\ decision\ function\ and\ y_i\ is\ the\ true\ class\ label$

Execution Time Measurement

Execution time measures the time taken by the models to process and make predictions. In your project, monitoring execution time is essential for understanding the computational efficiency of each algorithm, aiding in model selection for real-time applications.

Cross -Validation

Implement 5-fold cross-validation to evaluate the models.

Confusion Matrix and Metrics

Generate confusion matrices and calculate relevant performance metrics.

Visualization

Visualize the results using heatmaps.

Datatset

For this study, we collected responses from young individuals, including undergraduate students via a Google form named "Survey form for UG students". This dataset provides insights into various aspects of students' lives, including mental health-related questions. We have used 1500 records.

i. Demographic Information:
- Choose Your Gender (Categorical).
- Region of Residence (Categorical).
- Age of Student (In Years).

ii. Academic Metrics:
- CGPA.

iii. Daily Activities:
- Time spent on social media (In Daily Hours).
- Time spent on E-Learning (In Daily Hours).
- Time spent on self-study (In Daily Hours).
- Time spent on fitness (In Daily Hours).
- Time spent on sleep (In Daily Hours).
- Time spent on TV (In Daily Hours).

iv. Health and Lifestyle:
- Facing any health issue (Binary: YES/NO).
- Number of meals per day (Categorical).
- Diet quality (Categorical).
- Change in weight (Categorical).
- Connection with family, friends, and relatives (Binary: YES/NO).
- Giving time for personality development, self-care, hobbies, etc. (Binary: YES/NO).
- Depression or anxiety regarding family, placement, career, relationship, and panic attacks (Binary: YES/NO).
- Seeking specialist treatment for mental health (Binary: YES/NO).
- Stress Busters Activity Which You Follow (Categorical).
- Hobby For Stress Busters (Categorical).
- Time spent on personality development, self-care, hobbies, etc. (In Daily Hours).

RESULTS

SVM

Table 1. Confusion Matrix for SVM

Actual classes	Predicted classes			
	Depression	Stress	Control	Anxiety
	9	65	36	2
	45	246	66	13
	20	66	255	12
	4	13	3	1

Table 2. Evaluation Metrics for SVM

Accuracy	0,54
Precision	0,52
Recall	0,54
F1-Score	0,53
Execution Time	4,39 seconds
Hinge loss	0,59

SVM is effective for binary classification tasks and can handle non-linear relationships. In mental health monitoring, SVM can be useful for identifying distinct patterns or traits indicative of mental well-being. Table 1 shows the confusion matrix for SVM. Confusion matrix represents how well the model predicted the classes (Depression, stress, control and anxiety) compared to the actual labels. Table 2 gives the obtained performance measures which indicates poor classification of depression and anxiety. Table 3 gives the improved accuracy of SVM after implementation of 5-fold cross validation.

Table 3. After applying cross validation on SVM

CV Score for Depression level experienced	0,45
CV Score for Anxiety level experienced	0,50
CV Score for Stress level experienced	0,72

Logistic Regression

Logistic Regression is suitable for binary classification, providing probabilities for each class. In mental health analysis, it helps predict the likelihood of a particular mental health outcome based on given features. Stress might have clearer symptoms compared to Depression or Anxiety, leading to better prediction. Table 4 shows confusion matrix for logistic regression and table 5 for shows the evaluation measures. The model fails in classifying depression and anxiety due to imbalanced and a smaller number of samples. Table 6 shows the improvement in accuracy after 5-fold cross validation.

Table 4. Confusion Matrix for LR

Actual classes	Predicted classes			
	Depression	Stress	Control	Anxiety
	20	50	33	9
	58	190	90	32
	41	117	197	20
	7	24	6	6

Table 5. Evaluation Metrics for LR

Accuracy	0,35
Precision	0,37
Recall	0,35
F1-Score	0,36
Execution Time	0,02 seconds

Table 6. After applying cross validation on LR

CV Score for Depression level experienced	0,48
CV Score for Anxiety level experienced	0,52
CV Score for Stress level experienced	0,72

Random Forest

Table 7. Confusion Matrix for RF

Actual Classes	Predicted Classes			
	Depression	Stress	Control	Anxiety
	1	81	30	0
	2	328	40	0
	0	145	230	0
	0	41	2	0

Random Forest (RF) outperformed SVM and Logistic Regression (LR) in terms of Accuracy, Precision, and Recall. Stress Detection was the most accurate, with a CV score of 0,76, indicating clear differentiation in symptoms. Anxiety Detection remains a challenge across all models. Execution Time for RF was reasonable compared to SVM (4,39 sec), making it a practical choice. Table 7 shows the confusion matrix, table 8 shows the performance measures for random forest and table 9 shows the improvement in measures due to 5-fold cross validation.

Table 8. Evaluation Metrics for RF

ACCURACY	0,62
PRECISION	0,63
RECALL	0,62
F1 – SCORE	0,56
EXECUTION TIME	0,49 seconds

Table 9. After applying cross validation on RF

CV Score for Depression level experienced	0,56
CV Score for Anxiety level experienced	0,59
Mean CV Score for Stress level experienced	0,76

NN

This preprocesses the data by encoding categorical features, scaling the data, and handling missing values. It then splits the data, initializes and trains an MLP classifier, evaluates its performance on a test set, and prints the results along with the execution time. The NN model correctly classified 67 % of the instances, which is better than both Logistic Regression (35 %) and Random Forest (62 %). Table 10 shows the obtained confusion matrix and table 11 shows the evaluation metrics for neural network.

Table 10. Confusion Matrix for NN

Actual Classes	Predicted Classes			
	Stress	**Control**	**Anxiety**	**Depression**
	2	1	26	0
	5	6	28	0
	14	20	195	1
	1	0	1	0

Table 11. Evaluation Metrics for NN

ACCURACY	0,67
PRECISION	0,64
RECALL	0,67
F1 – SCORE	0,53
EXECUTION TIME	2,69 seconds

DNN

Table 12. Confusion Matrix for DNN

Actual Classes	Predicted Classes			
	Stress	**Control**	**Anxiety**	**Depression**
	1	81	30	0
	2	328	40	0
	0	145	230	0
	0	41	2	0

The training of a simple DNN model on synthetic data, visualizes the training progress, makes predictions on a test set, and evaluates the model's performance using common classification metrics. The use of TensorFlow and Keras simplifies the process of building and training neural networks. DNNs often require large amounts of data to perform well. SVMs might struggle with large datasets. Poor classification for Depression and Stress was obtained with DNN. Control classification was better. Table 12 shows the obtained confusion matrix and table 13 indicates evaluation metrics for DNN.

Table 13. Evaluation Metrics for DNN

ACCURACY	0,54
PRECISION	0,31
RECALL	0,54
F1 – SCORE	0,39
EXECUTION TIME	3,8 seconds

The comparison of performance of SVM, Random Forest & Logistic Regression models is shown by bar graph. Figure 2 shows comparison of accuracy, figure 3 shows comparison of precision, figure 4 shows comparison of recall, figure 5 shows comparison of F1-score. From all these graphs, it is observed that Random forest model works better than linear regression and SVM.

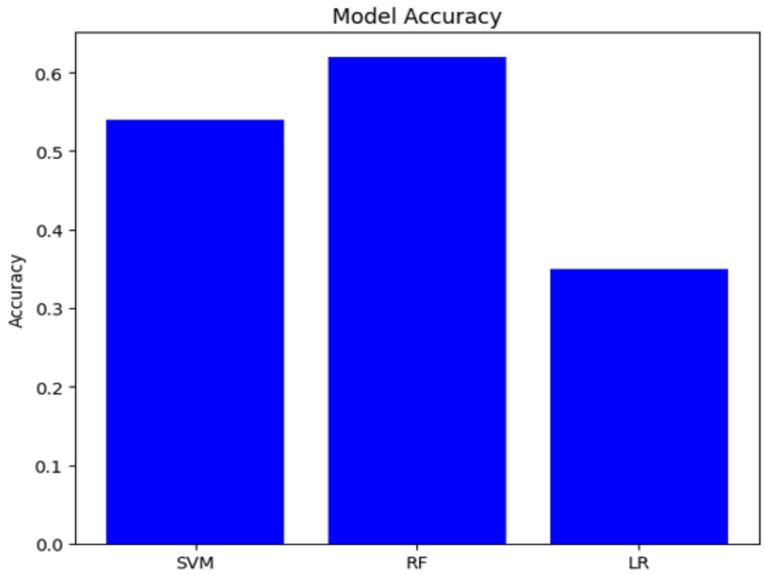

Figure 2. Model Accuracy for SVM, RF and LR

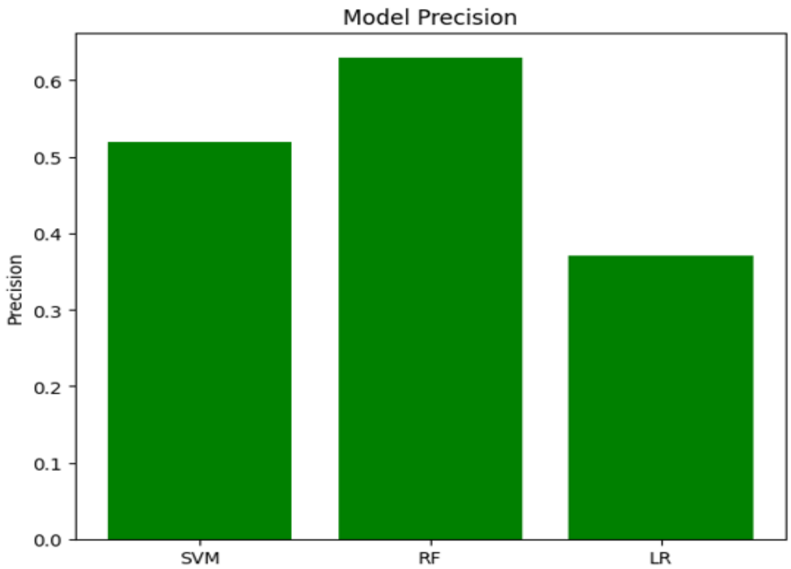

Figure 3. Model Precision for SVM, RF and LR

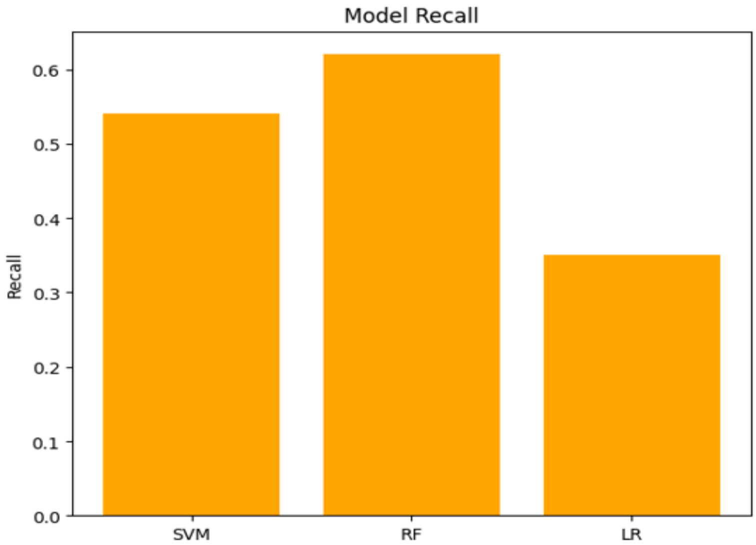

Figure 4. Model Recall for SVM, RF and LR

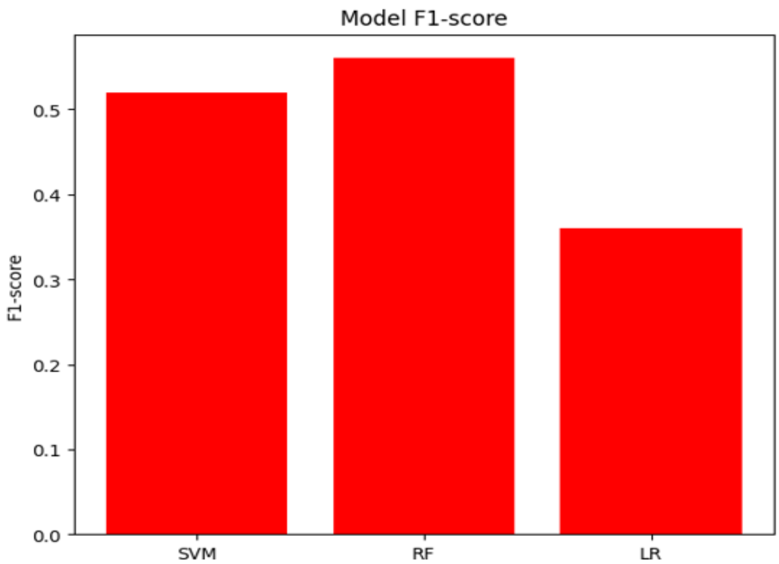

Figure 5. Model F1 – Score for SVM, RF and LR

The graph given in figure 6 shows the Training and Validation Accuracy over epochs. Initially, both accuracies increase rapidly, but after around 4 epochs, the training accuracy plateaus near 0,60, while the validation accuracy stagnates just below it, indicating possible slight overfitting. The graph in figure 7 displays the Training and Validation Loss over epochs. Both losses decrease consistently, with the training loss declining faster than the validation loss. However, the widening gap between the two losses in later epochs further supports evidence of overfitting.

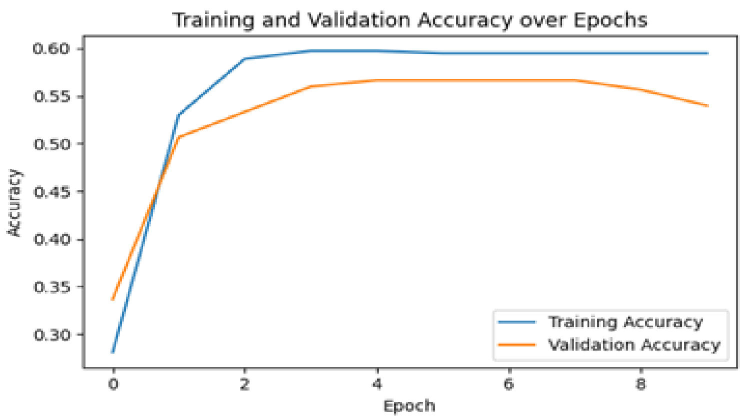

Figure 6. Training and Validation Accuracy over Epochs

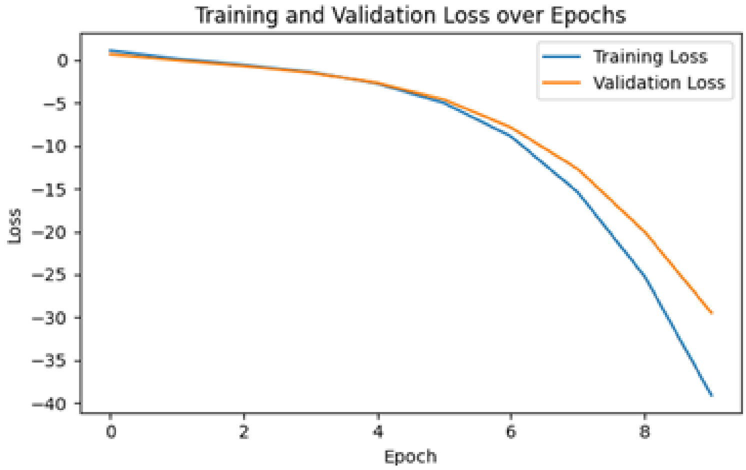

Figure 7. Training and Validation Loss over Epochs

The comparison of performance of SVM, Neural Network and Deep Neural Network is shown by bar graph. Figure 8 shows comparison of accuracy figure 9 shows comparison of precision, figure 10 shows comparison of recall, figure 11 shows comparison of F1-score. From all these graphs, it is observed Neural Network performs better than SVM and Deep Neural Network. This indicates that the NN performed better in capturing patterns in the data compared to the other models. While SVM and DNN may still be useful in specific cases, further fine-tuning or using techniques like regularization or additional data might improve their performance.

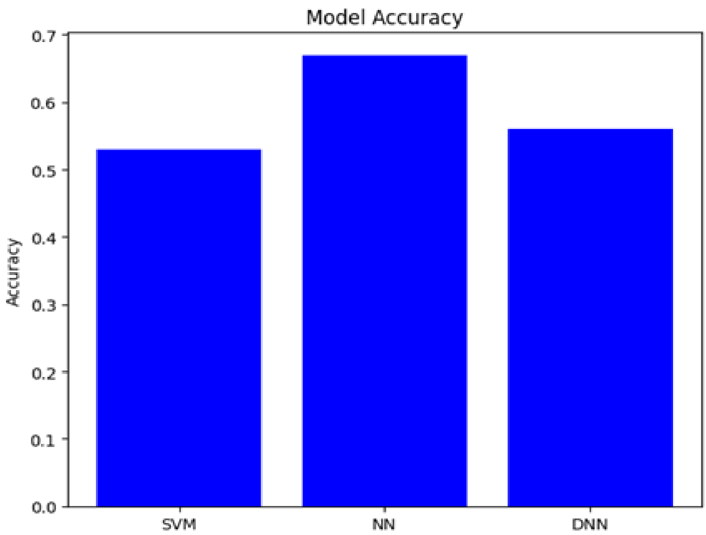

Figure 8. Model Accuracy for SVM, NN and DNN

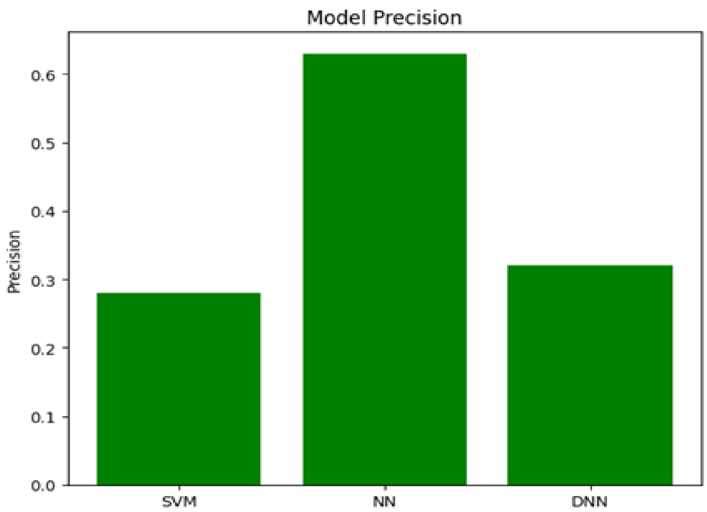

Figure 9. Model Precision for SVM, NN and DNN

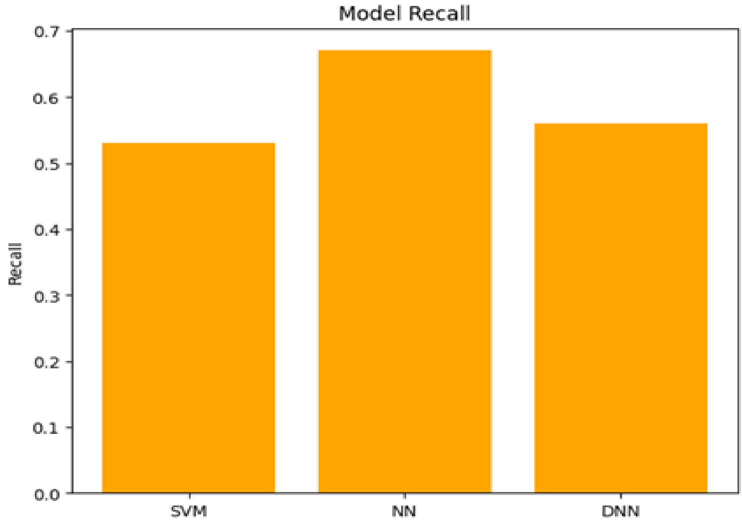

Figure 10. Model Recall for SVM, NN and DNN

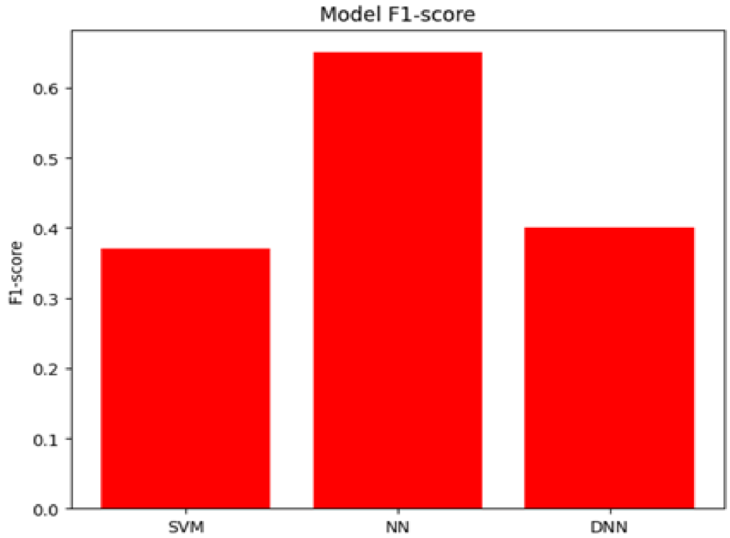

Figure 11. Model F1 – Score for SVM, NN and DNN

Table 14. Comparison of algorithms to identify the one with the highest accuracy

Algorithm	Accuracy	Precision	Recall	F1-Score
NN	0,67	0,63	0,67	0,65
RF	0,62	0,63	0,62	0,56

As shown in table 14, NN outperforms RF in terms of accuracy, recall, and F1-score, making it the better choice for the mental health disorder classification task.

Future Scope

The future, however, lies in harnessing novel physiological sensors for improving mental health prediction models. HRV and EDA sensors: HRV sensors provide detailed measurements related to stress and emotional regulation, while EDA sensors measure the conductance of skin for insights into stress levels. And sleep-monitoring devices, eye-tracking sensors, and voice analysis also provide a spectrum of data points to help assess mental health.

The futuristic frills come in the form of body temperature sensors to identify emotions and Brain-Computer Interface (BCI) tech for direct cognitive insights. Such strides are far from traditional self-reporting, offering real-time, tailor-made mental health evaluations. By utilizing the full spectrum of physiological signals, this method seeks to transform predictions and, as a result, enable accurate and bespoke interventions. Through the integration of these sensors, the project aims at reshaping the avenues of mental health assessment, paving the way for a transformative approach to well-being measurement that is unique to each individual.

CONCLUSIONS

This is a case study on mental health monitoring using the "Survey form for UG students" dataset. The data up to October 2023, mostly focused on undergrad students, reflected the emotional aspects of mental health very well. After performing data preprocessing (handling missing values, converting categorical data to numeric form using label encoding), we prepared the dataset for model training. Our analysis included the assessment of a variety of ML models, SVM, Random Forest and Logistic Regression. All three models were trained on an 80/20 stratified split of the data, using hyperparameters and parameters tailored to each model. Apart from computing accuracy, we computed precision, recall, and F1 score along with execution time and hinge loss for SVM.

This information provided insights into the accuracy with which each model was able to classify mental health-related responses. Additionally, to ensure the robustness of our findings, a 5-flod cross-validation strategy was used. Confusion matrices and related metrics: accuracy, precision, recall and F1 score, gave nuanced insights into the strengths and weaknesses of each of the models. They used visualization techniques, like heatmaps to present the results to people in an understandable way. In summary, our findings offer important insights into the feasibility of machine learning model-based monitoring of mental health in undergraduate students. This may pave the way for establishing measures that also address mental health within a learning environment.

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