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AUTOMATING MENTAL HEALTH ASSESSMENTS: A MACHINE LEARNING APPROCH TO ANXIETY STRESS DEPRESSION PREDICTION

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Abstract—**Depression and stress are experienced by nervous individuals all over the world leading to their diminished performance and psychological health along with their life satisfaction on a daily basis. The diagnostic procedures are more effective nowadays, whereas early mental health diagnostic procedures are not available in non-medical institutions. The analysis of anxiety, stress, and the level of depressions with usage of mixed classic and innovative machine learning models is created into a predictive system. Its predictive algorithms are XGBoost and AdaBoost, including Random Forest technique and Support Vector Machine technique. The diagnostic measure examines complex stylistic relationship with biological facts and measures of observation behavior and the result of the survey of multi-source data reported to a patient. Solutions of XAI, deployed in the researches, include SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations). XAI tools provide healthcare workers along with end-users with information on a straightforward level about how a model makes decisions in regards to mental healthcare tasks, which requirement a high level of integrity in their performance and their behavior. One of the frameworks within this system applies the extent of mental health conditions as a diagnostic to the creation of interventional approaches using its recommendation module. The system is also adaptive in its suggested interventions as it keeps a record of mental health of the user even across a long period of observation. The first one is general accessibility and real-time through deployment to a cloud-based platform. The configuration of the system on a cloud platform tends to ensure that remote users can get access to live status updates as they request urgent assistance via ideal health system connectivity. The users became the fundamental part of the created entire system since the research made it possible to efficiently scale up to superior digital mental health solutions placing users at the forefront to identify and handle their mental health.**

Index Terms—**Anxiety Detection, Stress Prediction, Depression Prediction, Machine Learning, Hybrid Models, Random Forest, Support Vector Machine, Ensemble Learning, XGBoost, AdaBoost, Feature Engineering, Explainable AI (XAI), SHAP, LIME, Cloud Deployment, Healthcare Integration, Mental Health Monitoring, Multi-Modal Data, Psychometric Analysis, Real-Time Monitoring, Personalized Interventions.**

I. Introduction

Serious public health issues along with stress and depression appear throughout the worldwide health environment. The daily existence of millions of people battles these mental afflictions which damage their personal existence and raise healthcare necessity. The emerging problems create lower productivity and enhance disability rates and reduce individual life quality. An accessible intervention combined with early detection solutions becomes necessary because the disease prevalence continues to rise.

Doctoral evaluation of mental conditions combines practitioner observations together with surveys where patients evaluate their mental health status. The present diagnostic methods face multiple weaknesses through their imprecise results and delayed identification process and their unreliable capacity for extended observation. Public stigma leads people to steer clear of getting mental health care from qualified professionals. Medical institutions require developing automated detection systems that both detect problems quickly and provide prompt help to patients as their diagnosed restrictions show.

New advancements in machine learning have introduced opportunities to address these problems in recent times. The identification of hidden patterns through big and complex data clusters makes ML models deliver highly accurate prediction results. Present-day mental health analysis systems collect various kinds of information comprising behavioral patterns and physical health readings and psychological assessments and social media activity data to identify developing indications of depression and anxiety and stress. These technological implementations help medical professionals achieve better diagnoses with enhanced discovery of suppressed causes and risk elements.

This study creates a complete system with advanced ML methodologies to achieve precise stress and depression and anxiety recognition. The whole system combines both Random Forest and Support Vector Machine traditional models with XGBoost and AdaBoost ensemble methods. The models work in unison for producing more specific predictions and managing complex mental health information collected from actual environments.

XAI techniques based on SHAP (SHapley Additive exPlanations), which will be supported along with LIME (Local Interpretable Model-Agnostic Explanations), will be the basis of the system. The tools provide users with insight into model predictions because they reveal which traits generate the most significant effects on outcomes. For the mental health applications the system requires explainable AI because users together with healthcare professionals need trusted information delivery to preserve their support and engagement.

The recommendation module uses user psychological status results to suggest personalized treatments which the system generates. Customized recommendations from the system connect users with activities that combine music therapy with self-help routines and professional counseling services for individual client profiles.

The system enables users to access it through its cloud platform deployment. Users can securely access the service from any location because this system supports real-time monitoring functions together with continuous usage. The cloud-based deployment system connects existing healthcare processing systems to mobile platforms thus enabling practical scalability and user-friendly convenience.

A solution to conventional mental health practice limitations emerges from this work which combines modern artificial intelligence along with machine learning features and explainable AI components within cloud-based delivery systems. The system aims to produce an individualized trustworthy framework that enables early mental health issue detection and promotes healthcare access for all patients.

II. Literature Survey

Researchers show growing interest in using machine learning (ML) techniques to enhance mental health diagnostics during the recent few years. The section examines recent studies which demonstrate how ML works for detecting and predicting cases of anxiety, stress and depression among patients.

Sasangohar et al. [1] conducted a detailed scoping review about different ML and deep learning techniques which researchers use for mental stress diagnosis and prediction. A number of researches tested the consistency of Support Vector Machines (SVMs), Neural Networks and Random Forest algorithm in performance rate. The skin response and the heart rate measurements were commonly used stress predictors since they would easily be acquired and also provide useful data of stress level.

The article by Salih et al. [2] is a valuable piece of information regarding SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) as techniques under explainable artificial intelligence (XAI). The authors stressed interpretability as an essential requirement due to clinical demands from patients and healthcare practitioners in mental health diagnosis.

The ”e-triage” tool developed by Limbic identified more than 210,000 patients with mental health problems at a reported diagnostic rate of 93% for depression, anxiety and PTSD as stated in axios2023. The practical operations and wide scalability capabilities of AI solutions become clear in clinical practice applications.

Researchers have discovered voice analysis as a confident method for mental health assessment. Humans can now screen depression and anxiety through voice pattern analysis tools that integrate into call centers and telehealth systems as a non-invasive detection method [4].

The FedTherapist system demonstrates that smartphone users can generate linguistic mental health data for diagnostic purposes. Federated learning systems enable proper mental health condition monitoring through their privacy-protected operation [5].

Various technological advances reveal AI and ML as strong agents of fundamental change for mental health diagnostic practices. Model interpretability requirements together with patient data protection measures and healthcare systems integration form basic conditions to maintain the ethical framework.

The field of artificial intelligence combined with machine learning techniques supports the advanced detection along with forecasting of mental health disorder symptoms like anxiety and depression and stress. Mental health experts have applied various algorithms with unique strengths across experimental studies in order to handle sophisticated psychological datasets.

Kaur et al. [6] studied depression diagnosis in university students through ensemble ML approaches including Random Forest, Gradient Boosting and Extreme Gradient Boosting methods. Social media data served as the research material and its classification accuracy was outstanding which demonstrates the increasing influence of human behavioral information in mental health analytical studies. The research done by De Choudhury et al. [7] built a prediction model based on Twitter data linguistic and behavioral features for depression assessment in users. The model used time-based analysis of online behavior patterns resulting in better prediction outcomes as well as early risk identification for individuals who may develop depression before diagnosis.

Mohammadi et al. [8] developed a stress detection model that executed stress identification from physiological sensor data through integration of CNN with LSTM resources. Through its design this model enhanced the analysis of time-dependent patterns and feature extraction process thus enabling better real-time assessment of stress levels.

The research by Nguyen et al. [9] applied natural language processing (NLP) methods to evaluate chatbot interactions for detecting initial signs of depression and anxiety. The employment of BERT in their model enabled effective emo-

TABLE I: Comparison of Recent Machine Learning Methods for Mental Health Prediction

Paper	Methods Used	Performance	Limitations	Features Analyzed
Sasangohar et al. (2024) [12]	Review of ML/DL methods	Qualitative insights (no numerical metrics)	No unified dataset; lacks experimental validation	Physiological and behavioral indicators
Salih et al. (2024) [13]	SHAP, LIME (Explainable AI)	Emphasis on interpretability, not prediction	Model sensitivity to input feature changes	Clinical and tabular health features
Heath (2023) [14]	AI Triage Tool (Limbic), Voice AI (Kintsugi)	93% accuracy (Limbic)	Validation needed for new contexts; privacy issues	Questionnaire data; voice acoustic features
Shin et al. (2023) [16]	Federated learning on user speech/text	AUROC improvement; MAE reduction	Small sample size; data privacy concern	Speech and linguistic expression
Kaur et al. (2023) [17]	Ensemble ML (RF, XGBoost, GBM)	High classification accuracy (not quantified)	Generalization to unseen user behavior unclear	Behavioral and linguistic features
de Choudhury et al. (2013) [18]	Probabilistic classifier on tweets	70% predictive accuracy	Relies on self-reported mental health status	Temporal and linguistic tweet features
Mohammadi et al. (2024) [19]	CNN-LSTM hybrid model	90.2% accuracy (3-class stress)	Small dataset size; lab-controlled setting	ECG, EMG, respiration, etc.
Nguyen et al. (2023) [20]	BERT for chatbot conversations	Effective emotion detection (no exact values)	Domain-specific; interpretability tradeoff	Semantic and sentiment-based NLP features

tional distress detection in conversational text making strong contributions to digital therapy and remote counseling systems.

Lo´pez et al. [10] developed personalized ML models which learn individual behavior patterns through active learning strategies. Through their adaptive character these models gained superior ability to spot anomalous mental health-related conditions during continuous patient tracking.

Sinha et al. [11] studied different methods for stress prediction through analysis of physiological and behavioral markers in their research. The combination of feature selection methods enhanced standard ML algorithms like SVM and Decision Trees which produced improved classification results according to research findings.

The research shows that AI and ML can transform mental health diagnosis and ongoing disease management, highlighting both technological advances and the need for ethical, flexible healthcare solutions.

III. Methodology

This research employs a structured and iterative machine learning framework to forecast mental health conditions—specifically, anxiety, depression, and stress—among college students. The solution combines data-driven analysis and solid classification models, explainable AI, and real-time deployment architecture. The approach will be in six important steps; Data Collection, Data Preprocessing, Feature Selection, Model Training, Model Evaluation, and Prediction. Every single workflow is outlined in Fig. 1.

A. Data Collection

The source of main data used in the study is the DASS-21 (Depression, Anxiety, and Stress Scale- 21 items) questionnaire which is a widely known psychological analysis instrument which is used to evaluate the emotional conditions of depression, anxiety and stress. Students in colleges of different academic disciplines were voluntarily used in the survey, and they had an array range of different people, since everybody took part, in terms of age category, gender category and performance of students.

Each participant responded to 21 questions rated on a Likert scale from 0 to 3. The scoring system translates the raw data into categorized severity levels, as shown in Table II.

TABLE II: Levels of Severity

Severity Level	Depression	Anxiety	Stress
Normal	0–7	0–9	0–14
Mild	8–9	10–13	15–18
Moderate	10–14	14–20	19–25
Severe	15–19	21–27	26–33
Extremely Severe	20+	28+	34+

This structured scoring facilitates consistent labeling of the dataset, which is essential for supervised learning tasks.

B. Data Preprocessing

Before training machine learning models, the collected dataset underwent several preprocessing operations:

- **Missing Value Treatment:** The missing or inadequate responses in rows were imputed (mean and mode) or discarded depending on the rate of missing data.
- **Encoding Categorical Features:** The categorical data that were presented in their original formats (e.g., gender, course stream) were converted into one-hot encoding or label encoding to provide them into a machine-readable format.

- **Normalization:** The numerical characteristics like CGPA and age would be scaled into similar range either by Min-max scaling or Standard Scaling to have similar assumptions on the model.
- **Outlier Detection:** Box plots were used to identify and handle outliers, especially in academic metrics like CGPA.

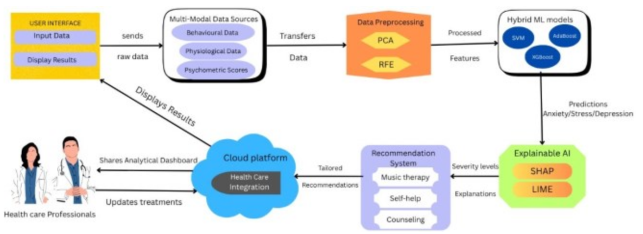

Fig. 1: System Architecture for Mental Health Prediction and Recommendation

Preprocessing ensures the dataset is clean, consistent, and suitable for training robust and generalizable machine learning models.

C. Feature Selection

To avoid interpolating, feature selection was used in order to reduce dimensionality:

- **Recursive Feature Elimination (RFE):** Used with cross-validation to rank features by their predictive power and iteratively remove the least important ones.
- **Correlation Heatmaps:** Helped identify redundant features that exhibit multicollinearity, which could distort model interpretation.
- **Principal Component Analysis (PCA):** Investigated as an additional optional form of dimensionality reduction in which the data can be projected to a lower-dimensional space without losing variance.

All these methods make the prediction models more interpretable and more computationally economical.

D. Model Training

Different classification algorithms were trained and tested to identify the accurate and interpretable one.model:

- **Naive Bayes (NB):** Fast and effective for probabilistic classification, assuming feature independence.
- **Support Vector Machine (SVM):** Applicable in high dimension spaces and favorable in dealing with non-linear boundaries with the help of kernels.
- **K-Nearest Neighbors (KNN):** A non-parametric method which classifies based on proximity in feature representation space.
- **Decision Tree (DT):** Simple and interpretable model that partitions data using a tree structure.
- **Logistic Regression (LR):** A binary and multi-class classification modelling method that is easy to interpret.

The data was divided into the training and the test portions (80 and 20 per cent, respectively). Training consisted of hyperparameters tuning by means of GridSearchCV when possible, as well as cross-validation, which was required to establish the stability of performance.

E. Model Evaluation and Prediction

Post-training, the models were evaluated using the following metrics:

- **Accuracy:** Overall correctness of the model.
- **Precision, Recall, and F1-score:** Especially critical in identifying cases of severe or extreme mental health risks.
- **Specificity and Sensitivity:** Used to understand false positives/negatives in mental health categorization.

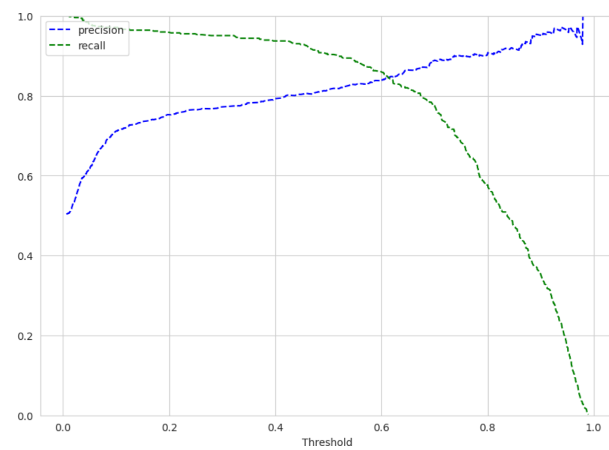

Fig. 2: Graphical representation of precision and recall.

The best-performing model (KNN in this study) was then used for final prediction and analysis on unseen test data. Visualization techniques such as confusion matrices and ROC curves were also employed.

F. Explainability and Interpretation

To ensure the model is interpretable and trustworthy:

- **SHAP (SHapley Additive exPlanations):** Used to understand the contribution of each feature to individual predictions.
- **LIME (Local Interpretable Model-agnostic Explanations):** Provided insight into local decision boundaries.

These tools support the explainable AI component and ensure the model's decisions can be understood by mental health professionals.

G. Support Vector Machine Algorithm

Support Vector Machine establishes the best possible hyperplane for data classification while maximizing the separation gap between classes. The optimization function for Support Vector Machine establishes the following format:

$$\min_{\mathbf{w},b,\xi} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n} \xi_i \tag{1}$$

Objective: Minimize the classification error and maximize the margin. *Explanation:* The object $\frac{1}{2}\|\mathbf{w}\|^2$ attempts to maximize the distance between the classes (the smaller the weight vector, the greater the margin). The expression $C\sum_{i=1}^{n}\xi_i$ is a penalty to the misclassified data point or soft violation, C is regulating the trade-off among margin size and classification error.

$$\text{subject to: } y_i(\mathbf{w}\cdot\mathbf{x}_i+b)\geq 1-\xi_i, \quad \xi_i\geq 0 \quad \forall i=1,2,\ldots,n \tag{2}$$

Constraints: Ensure correct classification with allowable slack. *Explanation:* - $y_i(\mathbf{w}\cdot\mathbf{x}_i+b)\geq 1-\xi_i$: ensures that each point is either correctly classified or allows some error (if $\xi_i > 0$). - $\xi_i \geq 0$: ensures that slack values (margin violations) are non-negative.

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Where:

- $\mathbf{w}$: weight vector, which determines orientation of the hyperplane,
- b: bias term (offset from origin),
- C: regularization constant that balances margin size and misclassification penalty,
- ξ_i: slack variable for the i^{th} sample allowing misclassification,
- $\mathbf{x}_i$: feature vector of the i^{th} sample,
- y_i: class label of the i^{th} sample, either $+1$ or -1.

Result Interpretation: The solution to this optimization problem obtains us a hyperplane, which simply classifies the data into two categories with a maximum margin and minimum misclassification. The points closest to the decision boundary (though in a very small infringement with slack) are known as the support vectors.

H. Model Evaluation

The performance metrics Standard Error Rate, Precision, Recall, Specificity, F1-Score, and Accuracy evaluated the different classifiers. Table 4 contains results about depression and stress and anxiety measurements from various classification methods.

Use of an optimized dataset combination together with chosen features and diverse machine learning methods enables an effective approach for stress and anxiety and depression identification. The predictive system achieved reliable and efficient performance measurements for mental health assessment of college students.

IV. Results and Discussion

The following section demonstrates how the machine learning models predicted the psychological condition levels in Anxiety, Depression and Stress using the information gathered from DASS-21 questionnaires. The system performed tests by applying five popular classification methods that included Na¨ıve Bayes and Support Vector Machine (SVM) with K-Nearest Neighbour (KNN) and Decision Tree and Logistic Regression.

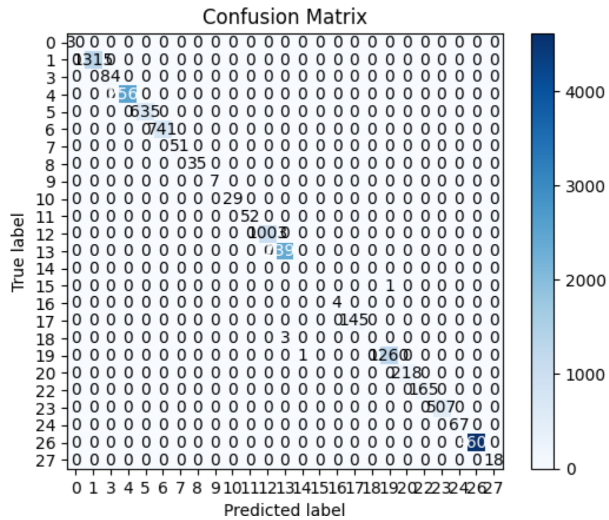

Fig. 3: Confusion matrix for mental health detection.

The predictive capabilities of each classifier regarding mental health conditions were assessed through Accuracy, Precision, Recall, Specificity, F1-Score, as well as Error Rate measurement data points. The K-Nearest Neighbour technique generated the most effective results among all algorithms since its accuracy hit 98.5% for Depression and 98.6% for Stress and 93.5% for Anxiety. Percentual error showed the smallest values across all predictions thus providing minimum incorrect outcomes.

The Support Vector Machine with Decision Tree algorithms delivered strong performance in detecting Anxiety and Depression because their accuracy rates exceeded 90%. Na¨ıve Bayes demonstrated acceptable results for diagnosing Anxiety yet displayed inadequate ability for identifying Depression which led to elevated error rates when compared to different models. Stress detection was among the strongest cases for Logistic Regression yet the model performed somewhat less efficiently when predicting cases of Anxiety and Depression.

TABLE III: Performance Metrics of Classification Algorithms

Classifier	Illness	Err. Rate	Precision	Recall	Specificity	F1	Accuracy
Naive Bayes	Anxiety	0.079	0.951	0.912	0.915	0.974	0.921
	Depression	0.258	0.793	0.769	0.921	0.765	0.742
	Stress	0.050	0.926	0.951	0.983	0.927	0.950
SVM	Anxiety	0.065	0.937	0.952	0.979	0.936	0.935
	Depression	0.143	0.892	0.858	0.954	0.856	0.857
	Stress	0.208	0.775	0.830	0.935	0.793	0.792
KNN	Anxiety	0.020	0.972	0.967	0.991	0.982	0.935
	Depression	0.015	0.985	0.988	0.995	0.986	0.985
	Stress	0.008	0.984	0.993	0.997	0.988	0.992
Decisic Tree	Anxiety	0.089	0.951	0.912	0.974	0.915	0.927
	Depression	0.093	0.936	0.899	0.969	0.904	0.921
	Stress	0.050	0.926	0.951	0.983	0.907	0.950
Logistic Regres: io n	Anxiety	0.143	0.889	0.864	0.954	0.852	0.974
	D epression	0.208	0.847	0.810	0.935	0.811	0.857
	Stress	0.015	0.975	0.976	0.995	0.985	0.985

Additionally, Table severity-levels clearly outlines the scoring criteria for each mental health condition severity level, and Tablealgorithm-metrics summarizes the performance metrics for each algorithm and condition. These results underline the critical role that data-driven models can play in the proactive

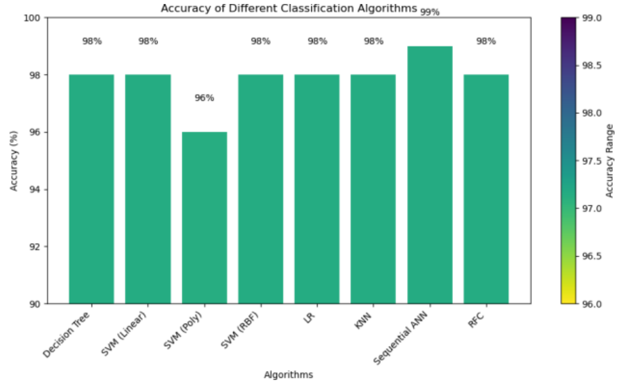

Fig. 4: Graphical Visualization of the Algorithms

identification of mental health issues, enabling timely interventions and support systems in academic institutions.

V. Conclusion and Future Work

A machine learning-based tool was created to evaluate and categorize mental health conditions of college students as they relate to anxiety depression and stress levels. Standard assessment scales helped us measure mental health levels through classification systems which included Na¨ıve Bayes, Support Vector Machine and K-Nearest Neighbor and Decision Tree and Logistic Regression.

The K-Nearest Neighbor algorithm achieved superior success in detection of stress-related symptoms alongside superior accuracy and precision and recall and F1-score evaluation. The model demonstrates adequate performance for preliminary detections of student mental health demands which enables early intervention responses.

The model became more reliable due to structured datasets and its clear definition of severity levels. Institutions receive support for well-being assessments through this monitoring system to offer timely counseling services.

Future Work, The existing framework shows encouraging results yet more modifications can help its development. Real-time data obtained through mobile applications combined with wearable devices would boost prediction precision as well as response speed. The assessment accuracy could improve by adding demographic factors including student ages and genders as well as their academic results.

Deep learning models utilizing Recurrent Neural Networks (RNNs) or Transformers should be studied further since they excel at detecting intricate patterns among user behaviors together with emotional shifts across time intervals. A secure platform for mental health data tracking which ensures privacy protection should be implemented to build trust between users and Encircle systems for expanding its adoption base.

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