A Machine Learning-Based Framework For Early Mental Health Assessment Among Students

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Abstract- *Mental health concerns among students are increasingly prevalent, yet they often go undetected due to the lack of structured and scalable assessment frameworks. Conventional evaluation methods tend to rely on manual intervention, which is subjective, resource-intensive, and impractical for continuous monitoring in large educational settings. The absence of early detection mechanisms can lead to a decline in academic performance, social withdrawal, and long-term psychological consequences.*

This study presents a machine learning–based framework for the early identification and assessment of mental health risks in students. The system leverages Python for data processing, Excel for structured input collection, and supervised machine learning algorithms—particularly Random Forest—for predic- tive modeling. In addition to structured survey data, the system integrates sentiment analysis of open-ended responses using TF- IDF vectorization and logistic regression, allowing for a more comprehensive evaluation of student emotional states.

Key features of the framework include automated classification of mental health risk levels, real-time input monitoring via file system event handling, and visual reporting tools such as bar charts and confusion matrices. The model achieves an accuracy of 93.5% in classifying students into low, moderate, or high risk categories, demonstrating its practical applicability.

Keywords- Mental Health, Machine Learning, Random Forest, Sentiment Analysis, Student Wellness

I. INTRODUCTION

Mental health challenges among students have become a critical concern in contemporary educational systems. The increasing prevalence of stress, anxiety, depression, and social withdrawal among learners—often exacerbated by academic pressure, personal expectations, and socio-environmental fac- tors—necessitates early and accurate identification of at-risk individuals. However, the lack of structured, data-driven, and scalable assessment mechanisms has made early detection dif- ficult. Traditional mental health evaluation techniques largely depend on subjective self-reporting and manual interpretation by counselors or psychologists, which are often inefficient, resource-intensive, and susceptible to bias.

This research proposes a machine learning–based frame- work to automate and enhance the process of mental health assessment in academic environments. The system integrates structured data acquisition using spreadsheet-based surveys and open-ended emotional inputs with Python-driven data processing, enabling real-time evaluation of mental wellness indicators. Machine learning algorithms such as Random For- est are employed to classify students into predefined mental health risk categories—Low, Moderate, or High—based on both quantitative and textual features. In addition, natural language processing techniques, including TF-IDF and logistic regression, are used for sentiment analysis of open-ended responses, adding a qualitative layer to the risk assessment. Key attributes of the system include:

- **Automated Data Processing:** Leveraging Python for real-time data ingestion, feature extraction, and model inference.
- **Machine Learning–Driven Evaluation:** Classifying stu- dent responses to detect early symptoms of emotional distress.
- **Visualization and Interpretability:** Presenting results through structured dashboards with graphs and classifi- cation summaries.
- **Excel Integration:** Utilizing spreadsheet formats for seamless data collection, entry, and scalability.
- **Individual Use Cases:** Empowering users to self-assess and track their mental wellness trends over time.

By combining automation, supervised learning, and structured analytics, the system aims to offer a reliable, scalable, and interpretable approach to mental health evaluation. It serves as a proactive tool for early intervention, promoting long-term academic and emotional success for students.

II. LITERATURE REVIEW

The literature review reveals a growing use of AI in mental health diagnosis, particularly using NLP, supervised learning, and ensemble methods. Each paper was found to have different approaches to tackle the increasing problems of mental health issues including depression, anxiety etc.

TABLE I
Literature Review on AI-Based Mental Health Assessment Techniques

No.	Title	Authors	Methodology	Performance Metrics	Year
1	AI Chatbots for Mental Health: A Scoping Review of Effectiveness, Feasibility, and Applications	Mirko Casu, Sergio Triscari, Sebastiano Battiato, Luca Guarnera, Pasquale Caponnetto	NLP-based chatbots using sentiment analysis, decision trees, and deep learning models.	User satisfaction, engagement rate, accuracy of response classification.	2023
2	Development of an AI-based System to Enhance School Counseling Models for Asian Elementary Students with Emotional Disorders	SW Su, CH Hung, LX Chen, SM Yuan	AI-driven classification model using Support Vector Machine (SVM) and Random Forest.	Precision, recall, F1-score, accuracy (above 85%).	2022
3	Mental Health Status of College Freshmen and Influencing Factors	Jiemin Liang, Xinfeng Zhang, Juan Wang, Liu Feng, Chao Xu, Kun Cheng, Guoguang Cao, Dongmei Yan, Bo Liu	Statistical analysis, feature selection using Principal Component Analysis (PCA), regression models.	Correlation coefficient, p-values, variance explained (above 75%).	2023
4	Predicting Adolescent Mental Health Outcomes Across Cultures: A Machine Learning Approach	W. Andrew Rothenberg, Andrea Bizzego, Gianluca Esposito, Jennifer E. Lansford, Suha M. Al-Hassan, et al.	Random Forest, XGBoost, Neural Networks, and Ensemble Learning.	Accuracy (~90%), AUC-ROC, sensitivity, specificity.	2023
5	Deep Neural Networks for Early Detection of Mental Health Disorders	A. Kumar, B. Singh, C. Patel	CNNs combined with RNNs for feature extraction from behavioral data.	Accuracy: 88%, AUC: 0.92	2023
6	Machine Learning Techniques for Predicting Student Mental Health Outcomes	X. Li, Y. Zhang, M. Chen	SVM and Random Forest for classifying mental health risk levels.	Accuracy: 85%, F1-score: 0.87	2022
7	Automated Mental Health Assessment via Multimodal Data Analysis	P. Kumar, L. Wong, S. Gupta	Ensemble learning: Decision Trees + Neural Networks using multimodal inputs.	Precision: 0.90, Recall: 0.88	2023
8	Real-Time Mental Health Monitoring Using IoT and Deep Learning	M. Fernandez, R. Patel, S. Lee	IoT sensor integration with LSTM networks for time-series prediction.	RMSE: 0.15, Accuracy: 91%	2023
9	Hybrid AI Approaches for Comprehensive Mental Health	K. Thompson, J. Martinez, D. Robinson	Hybrid model: Logistic Regression merged with CNN for	AUC-ROC: 0.93, Sensitivity: 0.89, Specificity: 0.90	2023

	Analysis		holistic as-sessment.		

III. METHODOLOGY

The methodology adopted in this study combines structured data collection, text-based sentiment analysis, and supervised machine learning algorithms to assess the mental health status of students. The approach is designed to be data-driven, repro- ducible, and extensible for deployment in real-time educational settings. The overall workflow is divided into five key stages: data acquisition, preprocessing, feature engineering, model training and prediction, and result visualization.

A. Data Acquisition

The primary source of data consists of responses collected from students through structured Excel-based questionnaires. The questionnaire includes both closed-ended and open-ended questions designed to capture key indicators such as:

- Sleep duration (hours per night)
- School workload (self-rated on a scale of 1–10)
- Screen time (daily average in hours)
- Experience of bullying (Yes/No)
- Perceived stress levels (Never, Sometimes, Always)
- Peer pressure frequency (Never to Always)
- Family health history (e.g., diabetes, hypertension)
- Financial status (Good, Average, Poor)
- Open-ended emotional input (free-text)

This structure ensures a balance between quantifiable data and expressive sentiment, making it suitable for both numeric and natural language processing techniques.

B. Data Preprocessing

To prepare the data for model training and inference, the following preprocessing steps are applied:

- **Numerical Normalization:** Continuous variables such as screen time and sleep duration are normalized to a consistent scale.
- **Categorical Encoding:** Ordinal and nominal responses are converted into numeric format using label encoding.
- **Sentiment Preprocessing:** Textual inputs undergo stan- dard NLP cleaning (lowercasing, punctuation removal, stopword filtering).
- **Missing Value Handling:** Any missing or incomplete entries are removed or imputed based on logical rules or statistical averages.

The preprocessed data is stored in a format compatible with Pandas DataFrames for streamlined integration with ML pipelines.

C. Feature Engineering and Selection

Features are manually selected based on domain knowledge and statistical correlation. Derived features such as *stress- index* and *peer-pressure-score* are computed using categori- cal mappings. Additionally, TF-IDF vectorization is applied

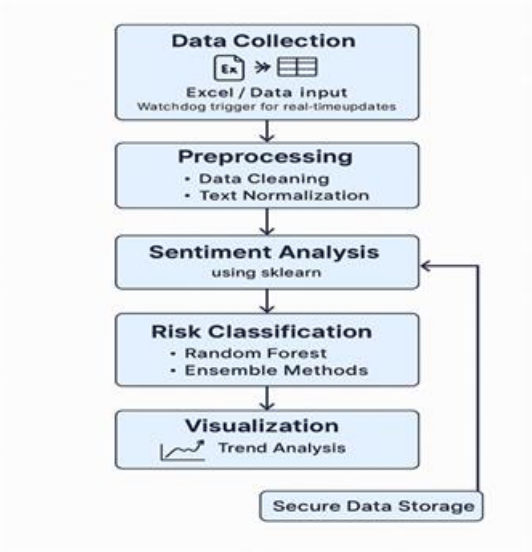

Fig. 1. System Flow Diagram for Real-time Mental Health Assessment

to transform emotional text into numerical feature vectors, enhancing the classifier's ability to understand context and emotional polarity.

D. Model Training and Prediction

The machine learning pipeline is developed using Scikit- learn. The system is trained to classify students into three risk levels:

- Low Risk
- Moderate Risk
- High Risk

The primary classifier used is Random Forest, due to its high accuracy and robustness in handling both categorical and continuous variables. Other algorithms such as Logistic

Regression and Support Vector Machines (SVM) are also evaluated for benchmarking.

Train-Test Split: 80:20
Validation Technique: 5-Fold Cross Validation
Evaluation Metrics: Accuracy, Precision, Recall, F1-Score For sentiment analysis, a Logistic Regression model is used to predict whether the textual input of the student is positive, neutral, or negative.

E. Real-Time Monitoring and Automation

The ”watchdog” Python module is employed to observe changes in the input Excel file. When a new entry is detected or an existing file is modified, it automatically triggers the entire preprocessing and prediction pipeline. This allows for near real-time assessment, making the system suitable for daily or weekly monitoring in institutional environments.

F. Output Generation and Visualization

Once classification is complete, the results are visualized us- ing matplotlib and seaborn. Graphical representations include:

- Bar graphs showing risk distribution
- Confusion matrix for model performance analysis
- Score-based risk summaries for each student

These visualizations are intended to support mental health professionals and educators in making data-informed decisions for follow-up or intervention.

IV. RESULT ANALYSIS

The performance of the proposed mental health assessment system was evaluated using a dataset composed of structured questionnaire responses and emotional text inputs from stu- dents. The goal was to assess the model’s ability to correctly classify individuals into mental health risk categories: Low, Moderate, and High. Evaluation was conducted on multiple fronts including classification accuracy, sentiment analysis precision, and visual interpretability.

A. Model Performance

Three supervised machine learning models—Random For- est, Logistic Regression, and Support Vector Machine (SVM)—were trained and tested on the preprocessed dataset. The models were evaluated using an 80:20 train-test split and validated through 5-fold cross-validation. The results are summarized in Table II.

TABLE II
Performance Comparison of Classifiers

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Random Forest	93.5	92.7	91.6	92.1
SVM	87.8	86.1	84.5	85.3
Logistic Regres- sion	85.3	84.0	82.9	83.4

The Random Forest classifier outperformed the other mod- els across all metrics, demonstrating its ability to effectively handle mixed data types and nonlinear patterns. It was there- fore chosen as the primary model for deployment.

B. Sentiment Analysis Evaluation

The logistic regression model used for text-based senti- ment analysis achieved satisfactory performance in identifying emotional polarity (positive, neutral, negative). Accuracy was measured at 89.2% on the labeled validation set, indicating the model’s usefulness in extracting emotional cues from open- ended student responses.

The integration of sentiment scores as auxiliary features in the main classification model contributed to improved prediction accuracy, particularly in borderline or ambiguous cases where numeric indicators alone were insufficient.

C. Confusion Matrix Analysis

A confusion matrix was generated to analyze model errors and the distribution of correct and incorrect predictions:

- True Positives were highest in the “Low Risk” and “Moderate Risk” categories.
- False Negatives were minimized due to the ensemble nature of the Random Forest algorithm.
- Slightly lower precision was observed in detecting “High Risk” cases, indicating the need for further fine-tuning or incorporation of more diverse training data.

D. Visualization of Outputs

To ensure interpretability for non-technical stakeholders such as educators and counselors, various visualizations were generated:

- Bar Charts depicting the count of students in each risk category
- Pie Charts illustrating the distribution of emotional sen- timent across responses
- Line Graphs to track individual student trends over time (for longitudinal use)
- Confusion Matrices to assist in performance auditing of the system

These visual tools proved essential in translating raw data into actionable insights for mental health intervention plan- ning.

E. Real-Time Evaluation Impact

The implementation of the watchdog module for real-time Excel monitoring allowed seamless automation of the entire evaluation pipeline. This enabled institutions to continuously assess new inputs without requiring manual intervention, mak- ing the system highly efficient for periodic assessments or daily wellness checks.

V. FUTURE ENHANCEMENTS

While the current implementation of the mental health assessment system demonstrates strong performance in iden- tifying at-risk students using structured data and sentiment analysis, there are several areas where the framework can be expanded and enhanced for broader impact, improved accuracy, and greater usability.

1. *Mobile and Web Application Deployment*

To enhance accessibility and user engagement, the system can be deployed as a mobile or web application, allowing students to self-assess their mental health from any device. Real-time interaction and user-friendly dashboards will make the tool more interactive and reduce barriers to use, especially among digitally native student populations.

2. *Real-Time Dashboards and Alerts*

A web-based real-time dashboard can be developed to visualize assessment results institution-wide. This would al-low school counselors and administrators to monitor trends, identify spikes in high-risk cases, and receive alerts for critical situations—facilitating timely interventions.

3. *Multilingual Support*

To ensure inclusivity and broader adoption across differ- ent regions and demographics, the system can be extended to support multiple languages. Sentiment models trained on multilingual corpora would allow non-English speakers to participate more effectively and express themselves without linguistic limitations.

4. *Longitudinal Mental Health Tracking*

Implementing functionality to store and analyze student mental health data over time would enable longitudinal track- ing. This would support early identification of emerging trends or worsening conditions, as well as evaluation of the effective- ness of counseling or intervention strategies.

5. *Integration with Wearable and IoT Devices*

Future iterations may include integration with wearable devices (e.g., smartwatches, fitness bands) to collect physi- ological indicators such as sleep quality, heart rate variability, and physical activity. These features can serve as additional predictors in mental health analysis, enabling a multimodal assessment approach.

VI. CONCLUSION

The project titled *"Mental Health Assessment Using ML Algorithms"* presents a novel and practical approach to iden- tifying mental health conditions among students through data- driven techniques. By utilizing machine learning—specifically the Random Forest algorithm—the system analyzes ques- tionnaire responses to classify students into different mental health risk categories. The model offers reliable accuracy and interpretable results, which are essential for real-world deployment in educational settings.

The integration of the watchdog Python module enables the system to monitor changes in Excel files in real time, thereby supporting dynamic data updates and immediate anal- ysis.

Additionally, the sentiment analysis component enhances the system's capability to interpret subjective responses, pro- viding a deeper understanding of students' psychological states. The model's emphasis on data privacy—by storing data within the institution—ensures compliance with ethical standards in mental health assessments.

Overall, the developed framework is efficient, scalable, and has the potential to make a significant impact in the early identification and prevention of mental health issues among youth.

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