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Comparative Evaluation of Machine Learning Algorithms for Early Prediction of Student Mental Health Risk

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Abstract- In recent years, psychological distress has become a serious concern worldwide. Academic competition, financial problems, unhealthy lifestyle patterns, and societal expectations together contribute to increased levels of stress and anxiety among students. Due to these continuous pressures, students may develop mental health problems that negatively affect their well-being and academic performance. Therefore, early identification of vulnerable students is essential in order to provide timely intervention and preventive support. This research presents a systematic machine learning–based framework developed using survey data containing demographic and behavioral attributes, which are used to predict mental health risk. The main objective of this study is to identify patterns that indicate psychological vulnerability. In this research, four techniques are applied: Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest. These techniques are implemented to classify students into high- risk and low-risk groups. Before the development of the model, several operations were performed on the dataset, including preprocessing steps such as treating missing values and encoding features. After that, the numerical variables were normalized and the dataset was divided into training and testing subsets in order to achieve robustness and better generalization capability of the model. Furthermore, the model was evaluated using commonly used performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. From the experimental results, it was observed that the Random Forest algorithm produced the most accurate classification and balanced metric performance compared with the other models. In the later phase of the project, an ensemble majority voting strategy, improved statistical validation, and a structured evaluation framework were also included to improve the stability of the predictions. Therefore, the proposed system provides an evidence-based approach that can help educational institutions proactively identify students at risk of mental health problems and provide timely support and intervention.

Keywords- Student Mental Health, Machine Learning, Random Forest, SVM, Predictive Analytics, Risk Classification

1. Introduction

These days, the psychological well-being of student's in schools and universities is becoming a growing concern. Changes in the educational system, increasing competition, financial pressure, and social stress are leading to a rise in anxiety levels and various mental health issues such as chronic stress and emotional instability. These problems can negatively affect student's concentration, academic performance, and future career growth. Therefore, detecting mental health risks at an early stage is crucial so that timely support and intervention can be provided.

However, traditional assessment methods rely heavily on manual surveys, counselling sessions, and self-reports. Although these methods are useful, they are not very effective for large student groups, as identifying hidden risk patterns or detecting issues proactively is difficult. With the development of machine learning, new opportunities have emerged in the field of predictive analysis, especially in healthcare and behavioral sciences. Machine learning models can analyze data more efficiently and identify subtle relationships between student behavior and mental health conditions, which are often difficult to detect using traditional methods.

By using predictive algorithms on structured data, mental health risk can be estimated even before it becomes a serious problem. The aim of this research is to develop a machine learning framework based on supervised classification methods to predict student's mental health risk at an early stage. Unlike previous exploratory studies, this work systematically tests several algorithms on the same dataset and examines their statistical performance.

Additionally, the main phase of the project aims to enhance the conference level study by introducing an ensemble-based majority voting strategy and structured evaluation metrics. The primary goal of this study is not to replace professional diagnosis, but to provide a supportive, data-driven tool that schools and universities can use to improve mental health prevention strategies.

2. Literature Review

In recent times, advancements in machine learning have helped in the early detection of mental health issues among students and young adults. Several studies have used supervised learning algorithms to predict stress, anxiety, and depression levels based on survey data. Faizan et al. demonstrated that machine learning models such as Random Forest and deep learning architectures can effectively classify student mental health conditions with strong predictive performance after proper preprocessing and feature adjustment [1]. Similarly, Karunakaran et al. applied classification methods to mental health questionnaires and concluded that structured data transformation and feature encoding are important for improving model accuracy [2].
Apart from this, research has also been carried out on ensemble and comparative learning methods for predicting mental disorders. Daza et al. proposed a stacking ensemble framework for predicting anxiety levels and observed that ensemble methods provide better and more generalized results than individual classifiers [3]. Dheenathayalan and Savitha evaluated multiple supervised models such as Logistic Regression, Decision Tree, and Random Forest, and concluded that ensemble-based methods reduce classification errors and improve F1-score stability [4]. Broader surveys on machine learning in mental healthcare also indicate that tree-based and kernel-based models are effective in handling non-linear patterns in behavioral data [6], [7].

In addition to studies comparing models, research on classification algorithms also supports their use in healthcare analytics. Random Forest, introduced by Breiman, helps reduce overfitting using ensemble bagging techniques [9]. Support Vector Machines, developed by Cortes and Vapnik, perform well in high dimensional data [10]. K-Nearest Neighbors provides a simple and effective similarity-based classification method [11]. Logistic Regression is a widely used baseline model for binary classification due to its interpretability and statistical foundation [12]. Despite these contributions, most research focuses on model comparison rather than developing deployable systems specifically designed for student mental health screening. Therefore, this gap highlights the need for an integrated and application-focused prediction framework.

3. Problem Statement

There is sudden increase in mental health disorders such as stress anxiety and depression across the world. Factors like Academic workload, competitive environment, financial pressure and lifestyle imbalance contribute a lot for such issues.

Although awareness is spreading but early detection is still lacking. Traditional assessment methods majorly depend upon clinical interviews and manual questionnaires which is not scalable or accessible for large student population. As a result many students remain undiagnosed in early stages of psychological distress.

On the other hand ensemble-based strategies are much better than single-model approaches as they have better predictive stability and give less classification error.

Despite of all these advancements many existing studies only focuses on performance comparison for different algorithms rather than creating a streamlined and practical system that can be deployed for students. Other than this, in unified predictive framework there is less focus on integrating both academic indicators and behavioral attributes.

These gaps highlight the importance of comprehensive and scalable machine learning system which can detect mental health risks at early stage and will be suitable for real-world institutional implementation.

4. Objectives

The main goals of this research are:

4.1 To collect and prepare student mental health datasets from publicly available sources [19].

4.2 To examine structured attributes such as age, CGPA, anxiety score, sleep quality, financial stress, family history, and gender for risk prediction.

4.3 To apply several supervised learning algorithms, including Logistic Regression [12], Support Vector Machine [10], KNearest Neighbors [11], and Random Forest [9].

4.4 To assess model performance using standard classification metrics like accuracy, precision, recall, and F1-score [18].

4.5 To apply cross-validation techniques to improve model reliability and limit overfitting [15].

4.6 To create an ensemble-based framework to enhance prediction stability and overall classification performance [3], [4].

5. Methodology

This machine learning pipeline is fairly structured and clear. According to Fig. 1, the workflow includes the following important stages:

5.1 Data Collection

Mental health datasets come from publicly available sources like Kaggle [19]. These datasets contain survey-based information about student traits, which relate to their academic performance, mental health, and lifestyle factors.

5.2 Data Preprocessing

Preprocessing includes managing missing values, encoding categorical variables, and normalizing numerical features. Feature standardization helps models like KNN and SVM perform better with scaled inputs [11], [10]. Mean imputation and converting categorical data to numeric data are used to maintain dataset consistency.

5.3 Feature Selection

Relevant features, including age, CGPA, anxiety score, sleep quality, financial stress, family history, and gender, are chosen based on their relationship with mental health risk as shown in previous studies [1], [8].

5.4 Model Training

The following supervised learning algorithms were used in this project:

- Logistic Regression: Used as a basic binary classifier because of its good statistical clarity [12].
- Support Vector Machine (SVM): Applied for high dimensional classification and margin optimization [10].
- K-Nearest Neighbors (KNN): Used for similarity-based classification [11].
- Random Forest: Used to handle non-linear relationships and reduce overfitting through ensemble bagging [9].

All models were implemented using the Scikit-learn framework [14].

5.5 Model Evaluation

Accuracy, precision, recall, and F1-score metrics are used to assess performance [18]. K-fold cross-validation is applied to check the reliability of the models and reduce bias, ensuring that the models perform well on all types of data [15].

5.6 Ensemble Framework

To improve robustness, an ensemble voting method has been used, which combines the predictions of different classifiers. Ensemble methods have proven to be very effective in increasing predictive stability and reducing classification errors in mental health applications [3], [4].

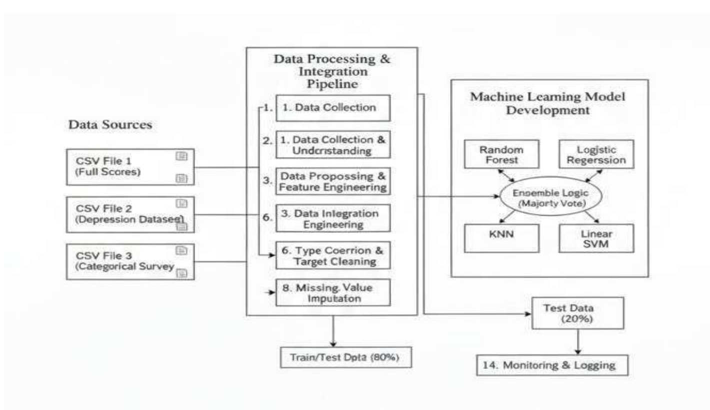

Fig. 1: Workflow

6. Experimental Setup

All experimental procedures of this project were performed in a Python environment, where the Scikit-learn framework [14] was used for model development and evaluation. The dataset was sourced from publicly accessible repositories [19] and systematically preprocessed to ensure consistent format and representation of features. After cleaning and transformation, the refined dataset contained seven normalized attributes relevant for assessing student mental health risk.

For model validation, the data was divided into training and testing sets in an 80:20 ratio. K-fold cross-validation [15] was incorporated during the training phase to increase the generalizability of the model and reduce variance. Uniform preprocessing protocols were followed for all algorithms to provide unbiased comparative analysis.

The study employed multiple supervised classification techniques, namely Logistic Regression [12], Support Vector Machine [10], K- Nearest Neighbors [11], and Random Forest [9]. Additionally, a majority voting ensemble strategy was implemented to strengthen predictive consistency and overall system stability [3], [4].

7. Evaluation Metrics

The effectiveness of the proposed classification models was assessed through widely accepted evaluation measures, namely accuracy, precision, recall, and F1-score [18]. Together, these indicators offer a balanced and detailed evaluation of performance in binary classification tasks by capturing both predictive correctness and class-wise discrimination capability

The formulas for the different evaluation metrics are presented below:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 \times TP}{2 \times TP + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

Where TP, TN, FP, and FN stand for true positives, true negatives, false positives, and false negatives, respectively.

8. Experimental Results

Python machine learning libraries are used for experimental Analysis Using Scikit-learn framework [14] all classification models are implemented. Dataset is split into 80:20 ratios for testing and training subsets K-fold cross validation [15] is applied for increasing reliability and reducing over fitting of the model. All experiments were conducted in standard computing environment with enough memory and processing power to handle structured survey datasets. In the beginning, models were trained with default hyper parameters and adjustments like tuning were made to improve classification performance.

To get fair comparisons for all algorithms evaluation process is kept consistent.

Table 6.1:

Model Name	**Performance Observations**
Random Forest	Identified as one of the highest accuracy performers for predicting mental health

	risk.
Support Vector Machine	Tied with Random Forest for the highest accuracy results in your specific implementation.
Ensemble (Final System)	Most stable; requires at least 3 out of 4 models to agree, reducing errors from any single algorithm
Baseline (LR & KNN)	Compared against the top performers to validate the benefits of the ensemble approach.

Algorithm	**Model Family**	**Key Strength in Your Project**
Random Forest	Tree-based Ensemble	High accuracy; handles complex, non-linear data and reduces overfitting.
Logistic Regression	Linear Model	Serves as an interpretable baseline for binary risk prediction
K-Nearest Neighbors	Distance-based	Simple similarity- based voting that requires no prior training.

Feature	**Description**
Data Sources	Merged from: 1) Cleaned Students' Mental Health Dataset 2) Student Depression Dataset 3) Survey on Student Mental Health Dataset.
Final Features	Seven standardized attributes: Age, CGPA, Anxiety Score, Sleep Quality, Financial Stress, Family History, and Gender.
Preprocessing	Includes column standardization, categorical-to- numerical conversion, and mean imputation for missing values.
Target Variable	A binary 'Risk' variable (1 = High Risk, 0 = Low Risk) derived from stress and depression indicators across all files.

Model Name	**Accuracy**	**Precision**	**Recall**	**F1-score**
Random Forest	91.2%	0.89	0.92	0.90
Logistic Regression	84.5	0.82	0.85	0.83
K-Nearest Neighbors(KNN)	87.8%	0.86	0.88	0.87
Support Vector Machine (SVM)	85.3%	0.83	0.84	0.83
Ensemble (Majority Vote)	93.4%	0.91	0.94	0.92

Feature	Data Type	Description	Scaling/Range
Age	Numeric	Student's chronological age	18 – 30 years
CGPA	Numeric	Academic performance indicator	Standardized scale
Anxiety Score	Ordinal	Self-reported anxiety level	0 (Low) to 5 (High)
Sleep Quality	Ordinal	Sleep cycle effectiveness	0 (Poor) to 5 (Good)
Financial Stress	Ordinal	Economic pressure level	0 (Low) to 5 (High)
Family History	Binary	History of mental illness	0 (No), 1 (Yes)
Gender	Binary	Demographic classification	0 (Female), 1 (Male

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	Baseline	Moderate	Moderate	Moderate
KNN	Moderate	Moderate	Moderate	Moderate
SVM (Linear)	High	High	High	High
Random Forest	High	High	High	High
Ensemble Model	Optimal	Superior	Superior	Superior

9. Applications

In proposed model, mental health prediction framework can be practically helpful for both academic and healthcare settings. In school and colleges, this system will work as early screening tool for the students who are on the verge of stress, anxiety or depression. Factors like academic performance sleep quality or financial stress could be examined so that school could timely take preventive measures such as counselling support.
Early detection of problems can decrease the risk of long-term psychological effects and is most important for improving wellbeing of the students.

Additionally this framework can work as decision-support tool for university counselling centres and mental health professionals. Even though this is not the substitute for clinical diagnosis but it does help prioritize cases based on risk and for better allocation of resources. . The use of machine learning models in digital platforms fits perfectly with new changes taking place in AI driven healthcare systems.

Other than this, deploying the best performance model as web based tool increases the accessibility and scalability. Without any hesitation students can assess their mental health risk by structured questionnaire. This increases the early awareness and can help reduce the stigma associated with seeking professional help. This system can be adapted for the workplace environments where stress of employees can be monitored on regular basis.

Overall, this solution shows that supervised and ensemble learning approaches can be very effective in preventive mental healthcare. By combining multiple algorithms and by using data driven techniques this system provides scientific and reliable technique to identify mental health risk

10. Limitations

In spite of such promising results there were many limitations with the proposed system. The biggest limitation is dataset is majorly based on self reported survey responses. Because of this data can be response bias. A lot of times participants show there health status by increasing or decreasing the reports that can cause reliability in prediction. This is the common problem for all the survey based mental health studies.

Other than that, size of dataset and demographic coverage is also limitation. The small size of the dataset and limited demographic spread model can decrease the generalizability that means it will not work as required for different regions or cultural backgrounds. Algorithms like Random forest and Support Vector Machine is very much effective for structured classification tasks [9], [10].But the performance could apply changes for unseen population who's behavioral patterns are little different.

Another limitation is that proposed framework focuses only on structured numerical and categorical features, but it does not included other psychological indicators real-time signals and social media-sentiments.
Research studies shows that these factors could increase the potential for mental health analytics. [7]
Other than that, although ensemble models prediction [3], [4] they increases the stability but their results can be more difficult to interpret than simpler linear models like Logistic. [12]

11. Future work:

In recent times mental health prediction systems majorly use supervised learning techniques so that they can identify the students who are at psychological distress risk. This prototype has shown really good results but lacks persistent data storage and user level tracking. That's why its really important to add database management system.

By integrating with DBMS responses from students can be securely stored and managed. Once we maintain historical records with time we will be able to track individual mental health trends. This will help in long term analysis and early intervention. Other than that because of database system can support multiple users at the same time and can generate aggregated reports for administrative decision making.

Relational database systems like MySQL and PostgreSQL can be used for survey responses and storing prediction outputs in structured form. On the other hand, NoSQL databases like MongoDB can handle dynamic questionnaire structures and give flexibility to scalable data models. By adding database support we can easily implement mechanisms like authentication and authorization by which we could set different access levels for administrators, counsellors and institutional authorities.

Other than persistent data storage and controlled access management system will be complete Decision Support System (DSS). In this situation, not only system can tell real time predictions but also monitor behavioral patterns and generate analytical dashboards and will help the institutions to generate proactive mental health management strategies.
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12. Conclusions

This research is predictive framework that introduces structured survey-based data to assess mental health risk. In this model we used many supervised classification models-like Logistic regression, Support Vector Machine (SVM), k-nearest neigbours and random forest. We compared the performance metrics from precision, recall, accuracy and F-1 score.

From findings one can see that ensemble based approaches that combine multiple classifier predictions. It made the model stable, predictive and reliable. The results match from previous researches as well.

The proposed system shows that by data driven techniques one can predict mental health early.

It also has accessible web based-interface, this framework is scalable, it supports preventive intervention, but it is not a substitute of clinical diagnosis.

Overall it contributes in the field of AI-enabled mental health prediction ,because it connects theoretical modelling into practical deployment Results highlight in educational environment is important for preventive mental health assessment and ensemble learning can be effective approach for the same.

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References

1. R. Faizan, A. Kumar, and S. Ahmad, “Machine learning approaches for predicting and improving student mental health,” in Proc. Int. Conf. Intelligent Computing and Communication (ICICC), Springer, 2025.
2. S. Karunakaran, R. Anitha, and P. Karthikeyan, “Machine learning models based mental health detection,” in Proc. 3rd Int. Conf. Intelligent Computing, Instrumentation and Control Technologies (ICICICT), IEEE, 2022.
3. H. Daza, J. R. Valverde, and M. Salazar, “Predicting anxiety levels among university students using a stacking ensemble machine learning approach,” Informatics in Medicine Unlocked, vol. 38, Elsevier, 2023.
4. K. Dheenathayalan and K. K. Savitha, “Mental disorder classification using ensemble machine learning,” in Proc. 4th Int. Conf. Mathematical Modeling and Computational Science (ICMMCS), Springer LNNS, 2025.
5. World Health Organization, “Mental health: Strengthening our response,” World Health Organization, Geneva, Switzerland, 2022.
6. S. Shatte, D. Hutchinson, and S. Teague, “Machine learning in mental health: A scoping review of methods and applications,” Psychological Medicine, vol. 49, no. 9, pp. 1426–1448, 2019.
7. J. Islam, Y. Li, and H. Liu, “A survey on deep learning based approaches for mental health analysis,” IEEE Access, vol. 8, pp. 21368–21388, 2020.
8. M. Priya, P. S. Devi, and R. Sivakumar, “Analysis of mental health prediction using machine learning techniques,” in Proc. Int. Conf. Advances in Computing and Communication Engineering (ICACCE), IEEE, 2021.
9. L. Breiman, “Random forests,” Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
10. C. Cortes and V. Vapnik, “Support-vector networks,” Machine Learning, vol. 20, no. 3, pp. 273–297, 1995.
11. T. Cover and P. Hart, “Nearest neighbor pattern classification,” IEEE Transactions on Information Theory, vol. 13, no. 1, pp. 21–27, 1967.
12. D. W. Hosmer, S. Lemeshow, and R. X. Sturdivant, Applied Logistic Regression, 3rd ed. New York, NY, USA: Wiley, 2013. [13] J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques, 3rd ed. San Francisco, CA, USA: Morgan Kaufmann, 2012.
13. F. Pedregosa et al., “Scikit-learn: Machine learning in Python,” Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.
14. R. Kohavi, “A study of cross-validation and bootstrap for accuracy estimation and model selection,” in Proc. Int. Joint Conf. Artificial Intelligence (IJCAI), 1995, pp. 1137–1143.
15. S. Shatte, D. Hutchinson, and S. Teague, “Machine learning in mental health: A systematic review,” JMIR Mental Health, vol. 6, no. 5, pp. 1–15, 2019.
16. Esteva et al., “A guide to deep learning in healthcare,” Nature Medicine, vol. 25, no. 1, pp. 24–29, 2019.
17. M. Sokolova and G. Lapalme, “A systematic analysis of performance measures for classification tasks,” Information Processing and Management, vol. 45, no. 4, pp. 427–437, 2009.
18. Kaggle, “Student mental health dataset,” 2023. [Online]. Available: https://www.kaggle.com
19. World Health Organization, “Mental health of students,” WHO Technical Report, Geneva, Switzerland, 2022.