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Student Health Risk Evaluator (SHRE): A Predictive Machine Learning Framework for Assessing Mental Health Risks in Students

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Abstract

Mental health problems in students pursuing higher education are on the rise and affect learning participation, performance, and well-being. The traditional methods such as self-reporting surveys or face-to-face interviews are restricted in their ability to provide timely information to educators and policymakers. This paper introduces the Student Health Risk Evaluator (SHRE), an artificial intelligence (AI)-based predictive analytics model that can assist the counsellors and educators to evaluate mental health risk of the students pre-emptively and take timely preventive measures.

Data was gathered using questionnaire covering major indicators to assess mental health like personal well-being, emotional and psychological health, social behavior, etc. Lasso regularization was utilized using two different alpha values (0.05 and 0.1) to identify the most influential predictors affecting mental health of the students. The selected features were then used to train and evaluate machine learning algorithms such as Logistic Regression, Support Vector Machine, K-Nearest Neighbors, and Random Forest, which were applied on the dataset to predict the mental health of the students. Logistic Regression achieved the maximum accuracy of 94.12% and F1-score of 93.98 at an alpha value of 0.05 amongst all others.

The findings demonstrate the potential of AI-driven models to support early identification of mental health risks and offer a data-driven foundation for timely interventions. While the current study focuses on questionnaire-based prediction, future work may explore the integration of additional data sources and broader institutional deployment to enhance its practical applicability.

Categories: AI applications, Predictive Analytics, Machine Learning (ML)
Keywords: ai in education, learning analytics, mental health prediction, educational decision-making, lasso regularization, student well-being, higher education

Introduction

The prevalence of mental health issues among students has become a critical concern, significantly affecting both their academic performance and personal well-being. Studies by Auerbach et al. [1] and Pedrelli et al. [2] indicate that approximately one-third of college students worldwide experience significant mental health challenges due to academic stress. There is increased dropout rates due to disorders such as anxiety, depression, and stress, which hinder academic success and can lead to long-term psychological consequences [3]. The World Health Organization (WHO) has also emphasized the urgency of addressing these issues, highlighting the growing number of young adults affected by mental health problems [4].

Even though student mental health is a growing concern, traditional methods of mental health assessment in educational settings such as self-reported surveys and periodic in-person evaluations are inherently limited. These approaches typically rely on occasional, manual interpretation of individual responses, focusing more on addressing issues after they arise rather than enabling early detection or prevention. Consequently, they often miss early warning signs or gradual behavioural changes, meaning that struggling students may not receive timely support and could experience worsening mental health issues [5].

To address this problem, we can take help of advancements in AI, particularly predictive analytics that presents a promising alternative to these conventional practices. AI has shown remarkable potential in healthcare, ranging from disease detection to treatment optimization [6,7]. Within the mental health domain, machine learning algorithms excel at analysing large datasets, identifying non-linear relationships, and uncovering hidden patterns [8]. This makes AI suitable for addressing the unique mental health challenges faced by students, thus facilitating early detection and personalized intervention. Researchers have explored various machine learning models such as Logistic Regression

(LR), Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Random Forests (RF) for predicting both general and mental health risks, which can be used to form actionable plans [9,10].

This study introduces the Student Health Risk Evaluator (SHRE) Framework, an AI-powered framework that uses predictive analytics for mental health assessment and in turn helps educational institutions to take timely action. Unlike conventional approaches, the SHRE Framework adopts a proactive, data-driven methodology. By analysing a comprehensive set of mental health indicators collected through structured questionnaires, the model identifies patterns and risk factors that might remain undetected through standard techniques.

The SHRE Framework employs different machine learning algorithms including LR, SVM, KNN, and RF to help understand students' mental health risks more accurately and in real-time. Out of all these algorithms, LR turned out to be the most reliable and easy to interpret; therefore, it was chosen for the final implementation. To make the predictions even better, the framework also uses a technique called Lasso regularization with dual values, which helps pick out the most important factors linked to mental health. This combination of machine learning and feature selection enables early detection of warning signs with greater precision, forming the analytical backbone of the SHRE Framework.

The primary objective of this study is to develop and evaluate the SHRE framework, an AI-based predictive model for early detection of mental health risks among students. The SHRE Framework provides a holistic and actionable assessment of mental health risks for the dynamic and complex environment of educational institution. It helps institutions through predictive techniques to shift from reactive responses to more proactive strategies. This allows for the early identification of at-risk students, so that they get timely help. It not only mitigates the adverse impacts of mental health challenges on student's academic and personal lives but also optimizes the use of limited mental health resources within educational settings.

Related work

Traditionally, mental health risks assessment has often relied on standardized psychological and clinical assessments, and qualitative methods such as interviews and focus groups. Some of the frequently used tools are Beck Depression Inventory (used to assess depression symptom severity), Maslach Burnout Inventory (used by educational and workplace settings to examine levels of emotional exhaustion and burnout), questionnaires to assess general health or patient health, and Kessler Psychological Distress Scale (used to evaluate levels of anxiety and distress in general populations). These tools have been utilized in both clinical and non-clinical environments to diagnose or assess mental health disorders. For instance, Lipson et al. [11] employed large-scale surveys to monitor trends in the mental health of university students on different campuses. Likewise, the World Mental Health Survey Initiative [12] offers world-wide insights into mental disorder through structured interviews.

Although these tools have contributed significantly to understanding mental health patterns, they are not without limitations such as:

1. Subjective Bias: Self-reported measures are susceptible to underreporting or overreporting secondary to stigma or social desirability [13].

2. Resource-Intensive: Clinical interviews need trained personnel and are thus not practicable to deploy on a large scale in low-resource environments [14].

3. Static Nature: Conventional approaches tend to capture a moment's snapshot of mental health instead of continuous monitoring, constraining them to catch dynamic changes [15].

In colleges and universities, mental health of students is assessed through occasional surveys or through counsellor observations. These methods can miss early warning signs or act too late, especially when count of students is large. With rising mental health concerns and limited support systems, there is a need for smarter, scalable alternatives [16].

AI and machine learning offer promising solutions. They allow real-time evaluation of mental health indicators, detection of patterns not visible through traditional analysis and predictions about who may be at risk. AI tools like chatbots and language analysis apps are being tested to flag signs of depression and anxiety [17,18]. Algorithms such as LR, RF, SVM, and KNN have shown solid results in detecting mental health risks [10,19,20].

Table *1* highlights the research studies applying ML algorithms and predictive models for mental health assessment, highlighting the datasets, methods, and insights gained.

Study	Dataset Used	ML Algorithms	Feature Selection Method	Conclusions
[2]	Data on mental health problems in college students	SVM, GBM	Not Specified	Identified key predictors for early intervention in mental health issues.
[3]	College students' self-reported mental health	LR, Naive Bayes	None	Highlighted prevalence of stress, anxiety, and depression among college students.
[7]	Various mental health datasets	GBM, NLP-based models	None	Highlighted clinical applications of AI in mental health care and its barriers.
[9]	Spanish University student mental health project	RF, SVM	Principal Component Analysis (PCA)	PCA optimized model performance in predicting suicidal thoughts and behaviours.
[10]	Dataset of Chinese adolescents	LR, SVM, RF	Recursive Feature Elimination (RFE)	RF outperformed others in predicting suicidal ideation and depression with high accuracy.
[19]	Clinical, psychological, and biological datasets	Elastic Net, Ridge Regression	Elastic Net	Elastic Net effectively selected features to predict depression trajectories.
[21]	University students' survey data	Decision Trees, SVM, KNN	Not Specified	SVM achieved the highest accuracy for predicting mental health among students.
[22]	Privacy-preserving combined datasets	Lasso Regression	Lasso Regression	Lasso successfully reduced dimensionality while preserving prediction accuracy.
[23]	Stress-related features from social media	NN	Group Lasso Regularization	Group Lasso effectively enhanced feature interpretability while boosting NN performance.
[24]	Healthcare records	SVM, RF, KNN	Not Specified	Demonstrated high potential of ML tools for predictive analytics in mental health.

TABLE 1: Comparative overview of machine learning techniques in mental health research

SVM, Support Vector Machine; GBM, Gradient Boosting Machine; LR, Logistic Regression; NLP, Natural Language Processing; RF, Random Forest; KNN, K-Nearest Neighbors; ML, Machine Learning; NN, Neural Networks

Table *1* demonstrates that ML models significantly enhance the accuracy and efficiency of mental health risk assessments. Feature selection methods like Lasso, Elastic Net, and RFE are critical for reducing dimensionality and identifying the most relevant predictors, improving model interpretability and performance [22,23]. However, there is limited research focusing on student-specific mental health datasets, particularly in Indian contexts. Furthermore, integrating advanced feature selection techniques with predictive models for real-time risk evaluation in university students remains underexplored.

Thus, this study aims to address the gaps by developing a predictive analytics framework tailored to assess mental health risks in students. By leveraging robust feature selection methods and ML algorithms, the research strives to create an efficient, scalable, and accurate framework for early intervention.

Materials And Methods

Proposed framework methodology: SHRE

The SHRE framework is a predictive analytics system (Figure *1*) designed to evaluate mental health risks among students based on their responses to a structured questionnaire. This framework employs a Lasso (L1) regularization technique for feature selection and integrates multiple machine learning algorithms to classify students into distinct risk categories: low, medium, and high.

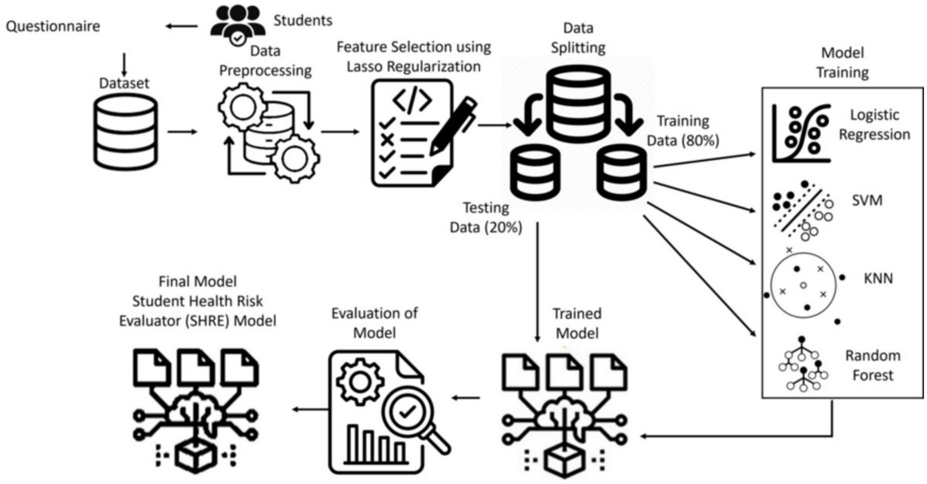

FIGURE 1: Architecture of the Student Health Risk Evaluator (SHRE) framework

SVM, Support Vector Machine; KNN, K-Nearest Neighbors

The methodology outlines the key stages of developing this predictive framework, focusing on the systematic integration of data preprocessing, feature selection, and algorithmic modelling to ensure both accuracy and interpretability. This section discusses in detail the critical steps and components involved in the methodology of the SHRE framework.

Data Collection: Questionnaire Design and Administration

The Mental Health Risk Assessment Questionnaire for Students was meticulously designed to evaluate a wide range of factors influencing student mental health. Grounded in established research, the questionnaire captures key psychological, social, and lifestyle indicators identified as critical predictors of mental health outcomes. The questionnaire comprises multiple sections, each targeting specific dimensions of mental health:

• Personal Well-Being: Questions addressing academic workload, stress, and exhaustion (e.g., "How often do you feel overwhelmed by academic workload?") were included to evaluate primary sources of anxiety and burnout. Studies by Beiter et al. [3] and Duffy et al. [5] highlight the significant impact of academic pressures on student mental health, emphasizing the importance of understanding stress levels and students' ability to balance personal life with academic demands.

• Emotional and Psychological Health: These questions explore feelings of sadness, concentration difficulties, and changes in eating or sleeping habits. Questions such as “Over the past month, how often have you felt sad or hopeless for no apparent reason?” were chosen based on findings from Auerbach et al. [4] and Lipson et al. [11], which identify these indicators as predictors of mental health issues like depression and anxiety, particularly in student populations experiencing fluctuating psychological states.

• Social Behaviour and Support: Queries about social connections, participation in extracurricular activities, and comfort discussing mental health with others provide insights into students' sense of belonging and social resilience. Research by Stewart and Suldo [25] and Zhang [26] highlights the role of strong social networks as a buffer against stress, making this section pivotal in assessing students' social well-being.

• Coping Mechanisms and Support Systems: Questions about relaxation techniques, access to counselling, and willingness to seek professional help underscore the importance of adaptive coping strategies. This section is supported by Boucher et al. [17] and Nithya and Ilango [24], who emphasize how effective coping mechanisms foster resilience and mitigate stress.

• Family Support and Lifestyle: This section explores the effects of family dynamics and lifestyle choices, including physical activity and substance use. Questions such as “How often do you engage in physical exercise?” reflect findings from Pedrelli et al. [2] and Feinberg et al. [27], which link these factors to mental health outcomes and stress-buffering capacity.

Responses were recorded using a combination of Likert scales (e.g., "Never," "Sometimes," "Often," "Always") and binary options (e.g., Yes/No) to capture nuanced perspectives. The survey was administered to students across various institutions, yielding a total of 253 valid responses. By addressing diverse facets of mental health through carefully selected questions, the questionnaire provides a holistic assessment of the personal, social, and lifestyle factors shaping student mental health.

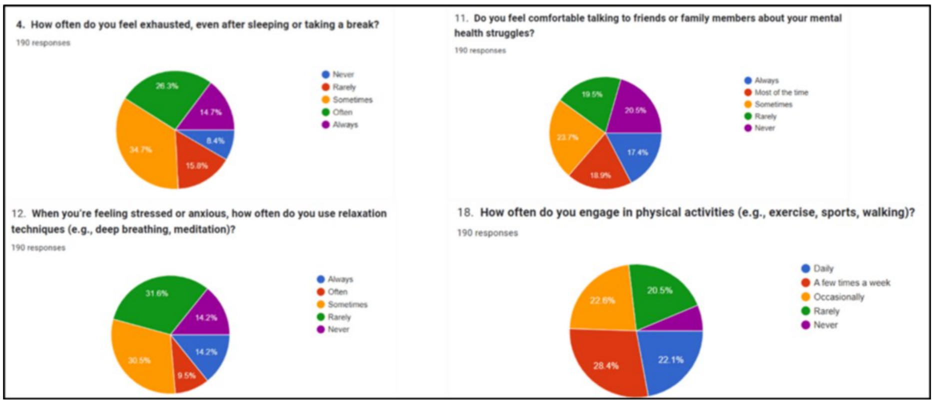

FIGURE 2: Sample questions and their response summary from the questionnaire

Figure *2* depicts summary of responses collected against few questions from questionnaire used for data collection. Ethical considerations such as informed consent, data privacy, and voluntary participation were strictly followed.

Data Preprocessing

Once the data were collected, it underwent pre-processing to ensure accuracy, consistency, and optimal compatibility with machine learning models [18,19]. The following steps were taken:

• Normalization and Encoding: As all questions in the questionnaire were mandatory, no missing values were present. Categorical variables were label-encoded to convert them into numerical values, ensuring compatibility with machine learning algorithms. Continuous variables were normalized using standard scaling, a critical step to ensure that features with varying scales do not disproportionately influence the model's performance [23,28]. This process standardizes the dataset and enhances the model's ability to identify meaningful patterns in the data.

• Scoring and Target Variable Categorization: A cumulative mental health risk score was calculated based on responses to 20 structured questions designed to evaluate Personal Well-being, Emotional and Psychological Health, Social Behaviour and Support, Coping Mechanisms, Support Systems, and Lifestyle Choices.

The Likert Scale (e.g., "Never," "Sometimes," "Always") was employed as the primary response format for most questions. This scale is widely recognized in psychological and behavioural research for its ability to quantify subjective perceptions and experiences [29,30]. Assigning numeric values (0-4) to responses ensures a standardized scoring framework that reflects the severity or frequency of each factor influencing mental health. For example:

• A response of "Always" to feeling overwhelmed by academic workload received the highest score (4 points), as it indicates a severe and persistent mental health challenge [3,5].

• Similarly, questions related to physical activity or substance use followed a scaled scoring system, where lower engagement in healthy behaviours or higher engagement in risky behaviours led to higher scores [20,28].

Point System and Risk Categorization: The cumulative scoring system allowed for the categorization of students into three distinct mental health risk groups: Low risk: Overall scores below 30; Medium risk: Scores between 30 and 50; and High risk: Scores above 50. These thresholds were derived from the distribution of responses, ensuring balanced segmentation across risk categories. The classification aligns with methodologies in mental health research that use multi-tiered risk frameworks to assess varying intensities of mental health challenges [9,10]. For instance, Low Risk reflects students with minimal indicators of mental health issues, often attributed to effective stress management and strong social support [25,26]. Medium Risk captures students showing moderate mental health challenges, requiring monitoring and potential interventions. High Risk indicates students with significant mental health risks, necessitating immediate attention and targeted interventions [31,32].

The scoring system captures the cumulative effect of diverse factors impacting mental health. For example, questions on Personal Well-being evaluate stress and exhaustion levels, which are established predictors of academic burnout [2,33]. Similarly, questions on Social Connections and Lifestyle Choices explore the buffering effects of social support and healthy habits against mental health risks [29,31].

Feature Selection Using Lasso Regularization

To enhance model performance and interpretability, Lasso (L1) regularization was applied for feature selection. This method penalizes less important features by shrinking their coefficients to zero, thereby identifying only the most relevant predictors of mental health risk. The choice of Lasso regularization is particularly suited for datasets with potentially high-dimensional features, as it effectively addresses multicollinearity and eliminates redundant predictors, leading to a more parsimonious and interpretable model [34-35].

The strength of the regularization in Lasso is controlled by a parameter called alpha. A higher alpha value increases the regularization strength, resulting in more feature coefficients being shrunk to zero, thereby retaining only the most impactful predictors. In this study, Lasso regularization was performed with different alpha values, and the results for alpha values of 0.05 and 0.1 are presented. With an alpha value of 0.05, nine features were selected, while an alpha of 0.1 resulted in the selection of five features. These features, identified as key predictors for the machine learning models, included variables such as exhaustion, sadness/hopelessness, and social connection, which are critical to understanding mental health risks.

The application of Lasso regularization aligns with its demonstrated utility in healthcare and psychological studies, where selecting influential predictors is crucial for actionable insights [22,36]. Its ability to enhance model generalizability by reducing overfitting makes it highly applicable in mental health research, where datasets often include correlated features such as emotional, social, and behavioral indicators. Furthermore, studies have highlighted Lasso's effectiveness in handling complex data structures, as shown in applications like cervical cancer prediction and depression course prediction [19].

In this study, Lasso regularization enabled a nuanced understanding of key mental health risk factors, balancing model interpretability with performance. The dual-alpha approach provided flexibility: alpha = 0.05 offered a broader feature set for deeper analysis, while alpha = 0.1 simplified the model, making it suitable for general applications. By identifying predictors most relevant to mental health risks, Lasso regularization ensured the framework remained interpretable and robust, supporting its integration into machine learning models for predictive analytics.

Machine Learning Algorithms

The selected features were used as inputs for four machine learning algorithms to predict mental health risk levels. The machine learning algorithms used in this study were selected based on their demonstrated effectiveness in healthcare applications and their unique strengths in handling mental health prediction tasks. The rationale for choosing these specific algorithms is rooted in both practical and theoretical considerations, as well as their varying capacities to handle complex, multi-dimensional data.

• Logistic Regression: LR is a powerful yet interpretable algorithm widely used in binary classification problems. It has been proven effective in predicting mental health disorders due to its ability to quantify the relationship between various mental health indicators (such as stress, anxiety, and emotional stability) and the likelihood of mental health risk. By providing clear coefficients, LR helps in understanding the influence of each predictor, which is particularly valuable when studying sensitive areas like mental health, where interpretability is crucial [19].

• Support Vector Machine: SVM is particularly suited for high-dimensional data and excels in creating decision boundaries between classes, making it ideal for multi-class classification problems such as mental health risk prediction. SVM's strength lies in its ability to model non-linear relationships, a useful characteristic for identifying subtle patterns in emotional or behavioural data. It is frequently used in healthcare for distinguishing complex relationships, making it well-suited for this study [20].

• K-Nearest Neighbours: KNN is a simple and effective algorithm that classifies data points based on proximity to existing labelled examples. Its non-parametric nature allows it to operate without assumptions about data distribution, making it useful in contexts like mental health, where patterns may not follow standard distributions. Although KNN can be limited by larger datasets, it performs well on smaller or moderately sized datasets, which is appropriate for the student mental health dataset used in this research [21].

• Random Forest: RF is an ensemble learning method that aggregates predictions from multiple decision trees, making it robust against overfitting and suitable for complex datasets with many variables. It also provides built-in feature importance scores, making it a complementary tool alongside the Lasso feature selection method used in this study. RF's versatility and capacity to handle large, noisy datasets make it ideal for mental health prediction, where various factors interact in complex ways [10].

Model Training and Evaluation

The dataset was split into 80% for training and 20% for testing. To assess the performance of the machine learning models, several evaluation metrics were employed:

• Accuracy: Measures the proportion of correctly predicted instances out of the total instances.

• Precision: Indicates the proportion of true positive predictions out of the total predicted positives, highlighting the model's ability to avoid false positives.

• Sensitivity (Recall): Reflects the model's ability to correctly identify true positives.

• Specificity: Represents the model's ability to correctly identify true negatives, ensuring false negatives are minimized.

• F1-Score: Represents the harmonic mean of precision and recall, providing a balanced evaluation of the model's performance when dealing with imbalanced classes.

Additionally, ROC curves and confusion matrices were utilized to gain further insights into the trade-offs between true positive and false positive rates. These results will be discussed in detail in the Results section of this paper.

Results And Discussion

The experimental study was conducted using a mental health dataset comprising student responses collected via a structured questionnaire. The dataset was pre-processed by separating features from the target variable and scaling the features using StandardScaler. Lasso (L1) regularization was applied to perform feature selection, reducing the feature set by identifying the most influential variables using alpha values. The selected features were then used to train LR, SVM, KNN, and RF classifiers. The dataset was split into 80:20. All experiments were executed on Python 3.11 (64-bit) using a Windows 10 environment with an Intel Core i5 (11th Gen) processor and 8 GB RAM. Scikit-learn, NumPy, pandas, and matplotlib were used.

In this section, we present the results from applying Lasso regularization for feature selection, followed by the evaluation of various machine learning algorithms in predicting mental health risks among students using the proposed SHRE Model. The dataset used for this analysis consists of 253 instances and 20 parameters, collected through a questionnaire distributed to students. Lasso regularization was employed to select the most relevant features, and machine learning models were evaluated based on metrics like accuracy, precision, sensitivity (recall), specificity, and F1-score.

Lasso regularization for feature selection

In Lasso regularization, selecting the alpha value is a crucial step that impacts both the performance of the model and the number of features retained. The alpha value controls the strength of the regularization, where higher values impose a stronger penalty, leading to fewer features being selected, while lower values allow more features to be retained [22,36]. This study explores how varying the alpha value can influence the model's ability to predict mental health risks among students.

After experimenting with multiple alpha values ranging from 0.01 to 0.2, the values of 0.05 and 0.1 were chosen for a deeper examination. These values were selected based on their balance between retaining enough features for interpretability and maintaining strong model performance. Lower values like 0.05 allow for a more detailed exploration of predictors, while a slightly higher value like 0.1 reduces complexity by eliminating less impactful features. This dual-alpha approach enables us to examine how feature selection impacts both model performance and interpretability in the context of mental health risk prediction.

• Alpha = 0.05: This value identified the following features as significant predictors of mental health risks:

○ Exhaustion: Coefficient = −0.044

○ Sadness/Hopelessness: Coefficient = −0.080

○ Concentration Difficulty: Coefficient = −0.032

○ Social Connection: Coefficient = −0.117

○ Comfort in Discussing Mental Health: Coefficient = 0.025

○ Family-Related Stress: Coefficient = −0.008

○ Physical Activity: Coefficient = −0.041

○ Substance Use: Coefficient = 0.041

○ Goal Review Frequency: Coefficient = −0.035

A total of nine features were selected from the original set of 20. These coefficients reflect the relative importance and direction of the relationship between each feature and the mental health risk. Negative coefficients, such as those for Exhaustion or Social Connection, do not imply a protective effect but rather indicate that higher values of these features are inversely associated with the target variable after adjusting for all other predictors. This phenomenon arises due to the interdependence of features and the regularization process, which optimizes the overall model fit. Figure 3 illustrates the feature importance graph for alpha = 0.05.

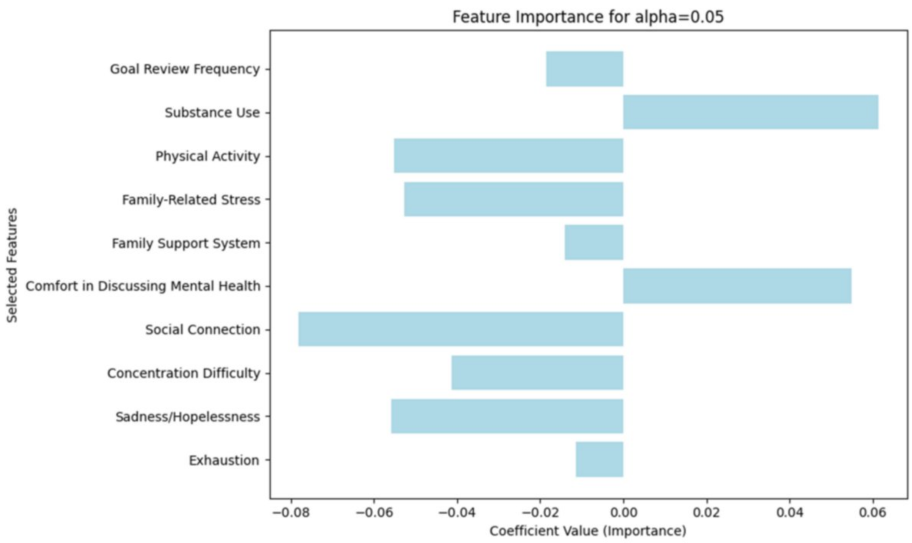

FIGURE 3: Feature importance graph for alpha = 0.05

● Alpha = 0.1: This value identified the following features as significant predictors of mental health risks:

○ Exhaustion: Coefficient = −0.016

○ Sadness/Hopelessness: Coefficient = −0.060

○ Concentration Difficulty: Coefficient = −0.011

○ Social Connection: Coefficient = −0.082

○ Physical Activity: Coefficient = −0.002

This configuration resulted in a reduction to five features, indicating a simpler model. Figure 4 illustrates the feature importance graph for alpha = 0.1.

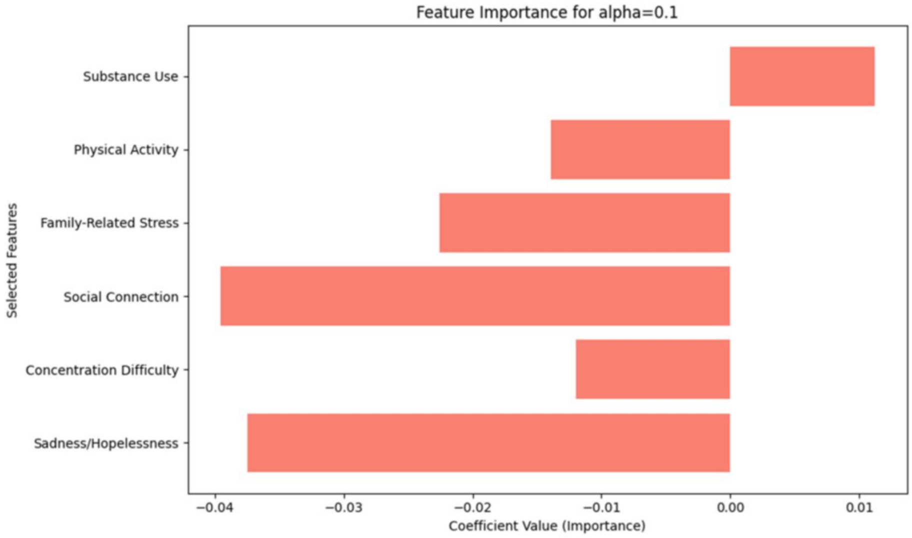

FIGURE 4: Feature importance graph for alpha = 0.1

In the context of Lasso regularization, negative coefficients indicate an inverse relationship with the target variable (mental health risk), holding all other variables constant. For instance, Social Connection has a negative coefficient because better social connections may correlate with lower mental health risk. Exhaustion may show a negative coefficient in this model due to overlapping effects with other predictors like Sadness/Hopelessness. Positive coefficients suggest a direct association. For instance, Comfort in Discussing Mental Health has a positive coefficient, implying that higher comfort levels may correlate with higher awareness or reported risk due to increased openness.

These results align with findings in prior studies that highlight the complexity of mental health predictors, where factors interact in multi-dimensional ways. Negative coefficients reflect not a contradiction but a nuanced model outcome shaped by multicollinearity and feature regularization.

This study selected the alpha values of 0.05 and 0.1 after testing a range of alpha values. The choice of these two values is grounded in balancing model complexity and interpretability with predictive performance.

- Alpha = 0.1: This value introduces stronger regularization, reducing the number of features to five. The selected features represent the most critical factors in predicting mental health risk, with the model delivering high accuracy (94.12%) and a reduced mean squared error (0.4078). This alpha value is ideal for settings where simpler models are preferred to avoid overfitting while retaining strong predictive power.

- Alpha = 0.05: With a lower regularization strength, the model includes a broader set of nine features, offering deeper insights into the factors contributing to mental health risk. Despite retaining more features, the model's accuracy remained high (94.12%), and the mean squared error (0.4278) only marginally increased compared to alpha = 0.1. This suggests that while additional features provide more granularity, they do not significantly improve predictive performance, thus offering diminishing returns in terms of model complexity.

The decision to use these two alpha values highlights the need to strike a balance between feature richness and model simplicity. Alpha = 0.1 provides a more streamlined model for general use, while alpha = 0.05 gives a more detailed understanding of the contributing factors, which may be especially valuable in educational or clinical settings, where a broader range of predictors could offer more actionable insights.

This dual-alpha approach, by offering both simplicity and depth, allows for flexibility in the deployment of the predictive model depending on the specific needs of the user - whether it be for a more interpretable model or a more nuanced analysis of mental health predictors.

Machine learning model performance

The performance of various machine learning algorithms was evaluated using the features selected from both alpha values. The results, including key performance metrics, are presented in the following tables and graphs. Table *2* highlights the accuracy scores achieved by applying LR, SVM, KNN, and RF algorithms to the selected features for both alpha values, and Figure *5* is its graphical representation.

Model	Alpha = 0.05	Alpha = 0.1
LR	94.12%	94.12%
SVM	94.12%	90.20%
KNN	92.16%	88.24%
RF	92.16%	82.35%

TABLE 2: Results obtained for accuracy parameter

LR, Logistic Regression; SVM, Support Vector Machine; KNN, K-Nearest Neighbors; RF, Random Forest

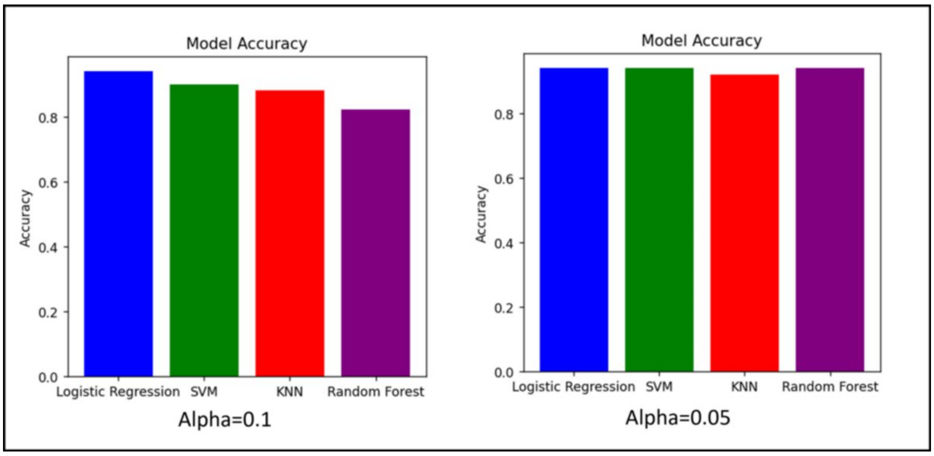

FIGURE 5: Comparison of accuracy of machine learning algorithms for alpha = 0.1 and alpha = 0.05

SVM, Support Vector Machine; KNN, K-Nearest Neighbors

The LR model exhibited the highest accuracy at 94.12% for both alpha values, along with comparable precision and sensitivity metrics. The SVM model also performed well for alpha = 0.05, but showed a drop in accuracy at alpha = 0.1. The KNN and RF models exhibited a similar trend, indicating that increasing the alpha value could result in reduced model performance due to the exclusion of significant predictors.

Model	Precision (Alpha = 0.05)	Precision (Alpha = 0.1)
LR	93.97%	94.55%
SVM	94.55%	91.34%
KNN	92.84%	89.17%
RF	92.84%	81.87%

TABLE 3: Precision for alpha = 0.05 and alpha = 0.1

LR, Logistic Regression; SVM, Support Vector Machine; KNN, K-Nearest Neighbors; RF, Random Forest

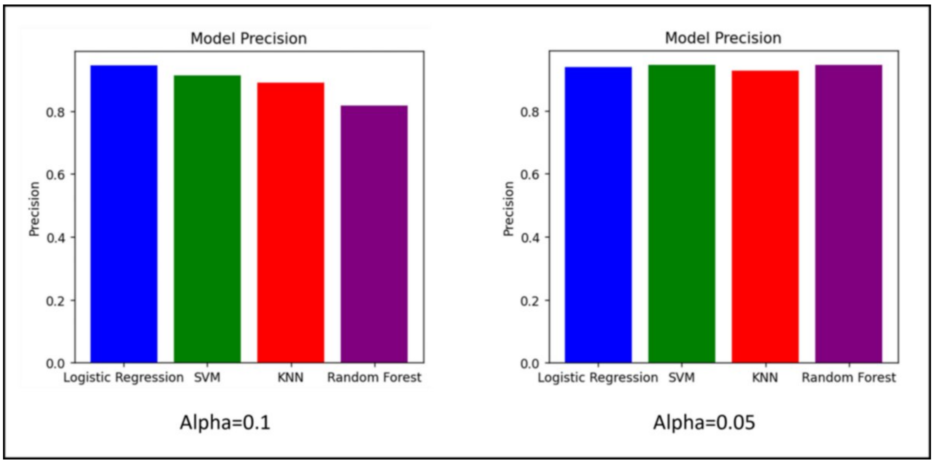

FIGURE 6: Comparison of precision of machine learning algorithms for alpha = 0.1 and alpha = 0.05

SVM, Support Vector Machine; KNN, K-Nearest Neighbors

The precision results in Table 3 show that LR and SVM achieved the highest precision for both alpha values, indicating strong performance in correctly identifying true positives across the dataset, as shown through Figure 6. The RF model performed comparatively lower when using the features selected by alpha = 0.1, while KNN showed a moderate drop in precision as alpha increased.

Model	Sensitivity (Alpha = 0.05)	Sensitivity (Alpha = 0.1)
LR	94.12%	94.12%
SVM	94.12%	90.20%
KNN	92.15%	88.23%
RF	92.15%	82.35%

TABLE 4: Sensitivity for alpha = 0.05 and alpha = 0.1

LR, Logistic Regression; SVM, Support Vector Machine; KNN, K-Nearest Neighbors; RF, Random Forest

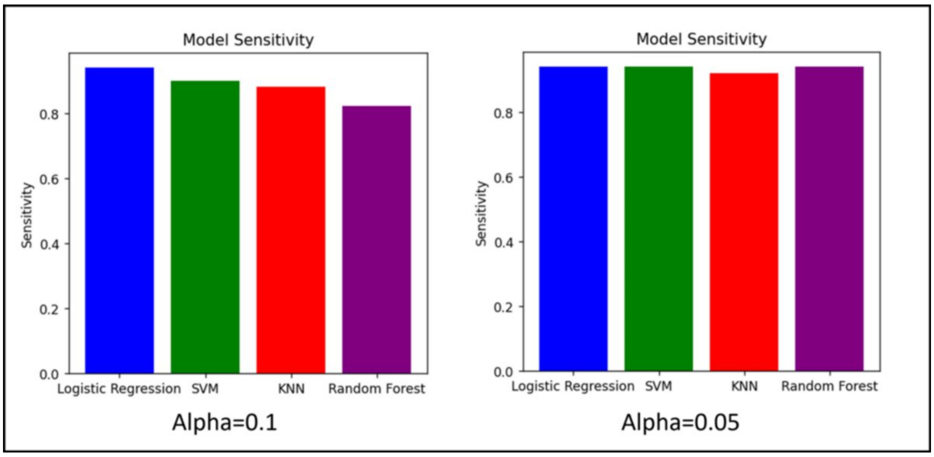

FIGURE 7: Comparison of sensitivity of machine learning algorithms for alpha = 0.1 and alpha = 0.05

SVM, Support Vector Machine; KNN, K-Nearest Neighbors

Sensitivity scores, as shown in Table *4*, reveal that LR and SVM consistently maintain high sensitivity for both alpha values, with LR performing slightly better, as depicted through Figure *7*. The RF model, however, shows a significant decrease in sensitivity at alpha = 0.1, indicating a drop in the ability to correctly classify students at risk. KNN also demonstrated slightly reduced sensitivity at alpha = 0.1 compared to alpha = 0.05.

Model	Specificity (Alpha = 0.05)	Specificity (Alpha = 0.1)
LR	94.08%	92.31%
SVM	92.31%	87.18%
KNN	91.60%	86.47%
RF	91.60%	84.09%

TABLE 5: Specificity for alpha = 0.05 and alpha = 0.1

LR, Logistic Regression; SVM, Support Vector Machine; KNN, K-Nearest Neighbors; RF, Random Forest

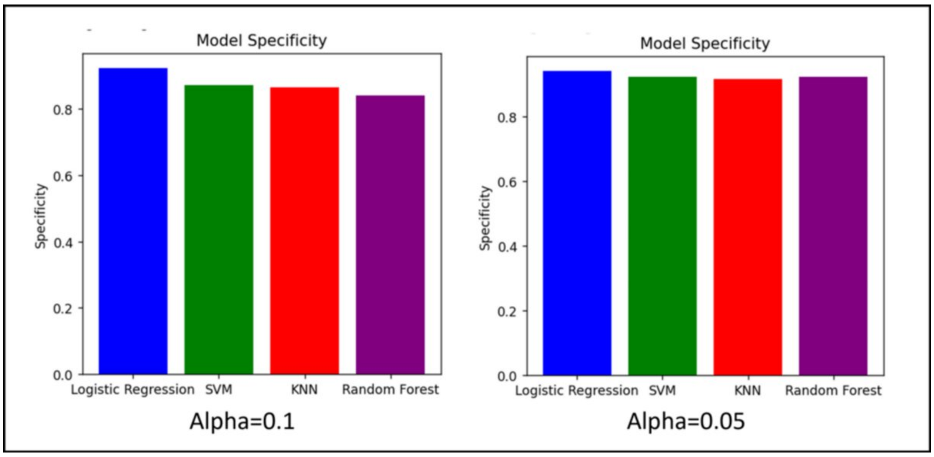

FIGURE 8: Comparison of specificity of machine learning algorithms for alpha = 0.1 and alpha = 0.05

SVM, Support Vector Machine; KNN, K-Nearest Neighbors

The specificity results, as shown in Table 5, demonstrate that LR maintains high specificity across both alpha values, with a slight decrease at alpha = 0.1. The SVM and KNN models also show declining specificity as alpha increases, with the RF model showing the most significant drop, particularly at alpha = 0.1, as depicted through Figure 8.

Model	F1-Score (Alpha = 0.05)	F1-Score (Alpha = 0.1)
LR	93.98%	93.84%
SVM	93.64%	89.24%
KNN	91.78%	87.41%
RF	91.78%	82.06%

TABLE 6: F1-score for alpha = 0.05 and alpha = 0.1

LR, Logistic Regression; SVM, Support Vector Machine; KNN, K-Nearest Neighbors; RF, Random Forest

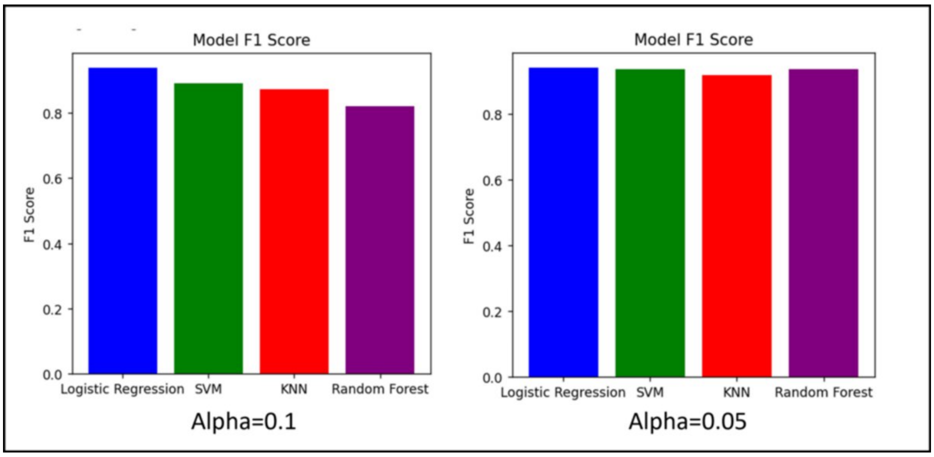

FIGURE 9: Comparison of F1-score of machine learning algorithms for alpha = 0.1 and alpha = 0.05

SVM, Support Vector Machine; KNN, K-Nearest Neighbors

The F1-score (Table 6) reflects the balance between precision and sensitivity, with LR again leading with stable performance across both alpha values. SVM maintains a strong F1-score for alpha = 0.05 but shows a notable reduction when using alpha = 0.1. KNN and RF models also experience a drop in performance as the alpha value increased. In case of RF, the most considerable decline can be seen in F1-score at alpha = 0.1, as depicted through Figure 9.

To further analyze the performance of the machine learning algorithms, receiver operating characteristic (ROC) curves and confusion matrices were plotted for all the models using the chosen features with alpha = 0.05. The ROC curve is a plot utilized to measure the diagnostic capability of a multi-class or binary classification system. It draws the True Positive Rate (TPR), or sensitivity or recall, against the False Positive Rate (FPR) at different threshold values, giving an overall picture of the mutual relationship between true positive detection and false alarms. The more that the ROC curve hugs the left-hand border and then the top border of the plot, the more accurate the model is. An ideal classifier would be one where an ROC curve passes through the top-left corner of the plot, reflecting a high TPR with a low FPR.

Though features chosen with alpha = 0.1 were also examined, the fewer number of features (5 vs. 9 for alpha = 0.05) resulted in lower model performance since important predictive features were omitted. Hence, ROC curves and confusion matrices were plotted only for alpha = 0.05 since it was the best trade-off between feature selection and model performance.

ROC curves were drawn between three classes for all machine learning classifiers LR, SVM, KNN, and RF, as presented in Figure 10. Besides the ROC curves, area under the curve (AUC) was also calculated, which is a scalar value that represents the performance of the classifier as a whole. AUC ranges from 0 to 1, where 1 signifies optimal classification and 0.5 implies random guessing. A model's high discriminative capability is indicated by an AUC value that is closer to 1.

The ROC curves show that LR and SVM had almost perfect classification for Class 0 (AUC = 1.0), indicating their capacity to categorically separate between positive and negative instances for this class. The performance of Classes 1 and 2 is also good with AUC values near 1.0, which further indicates their utility in separating among various levels of risks. RF also shows very good performance, with AUC values close to 1.0 for all three classes, reflecting a high degree of predictive accuracy. While KNN had lower AUC values compared to the other models, particularly for Class 2, but still did quite well for Class 0.

These findings reflect that all four models have very strong ability to classify between the various classes based on AUC values, with LR, SVM, and RF performing the best. This reflects that overall, these models have high predictive capacity and perform well in differentiating various mental health risk categories in the dataset. The ROC analysis when viewed together with confusion matrices can give a complete picture of model performance. It emphasizes the trade-off between sensitivity and specificity, strengthening the capability of such algorithms to perform multi-class classification tasks.

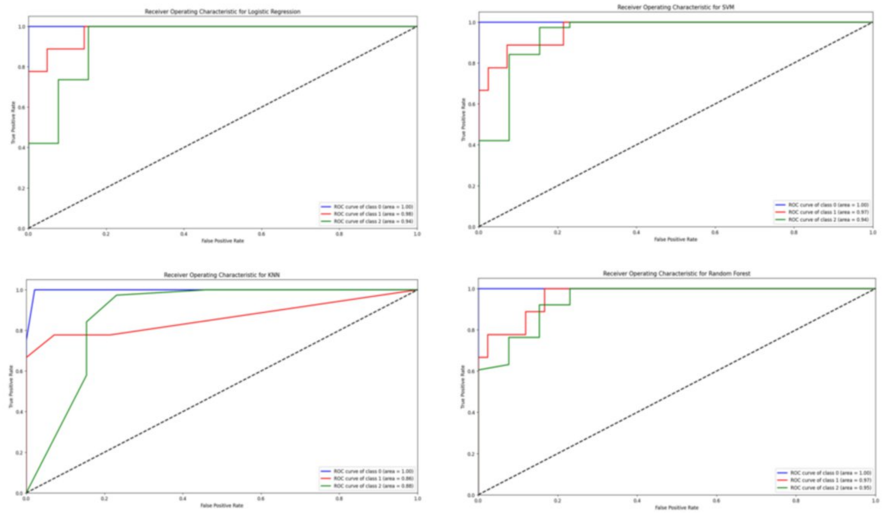

FIGURE 10: ROC curves for machine learning algorithms (alpha = 0.05)

The confusion matrix is another metric that can be used to evaluate model performance. Confusion matrices can be helpful in providing insights into the number of correct and incorrect predictions made for each class offering a more precise view as compared to metrics like accuracy or precision. The confusion matrices for the LR, SVM, KNN, and RF models are presented in Figure *11*. These matrices give a detailed view based on the testing set of the data to classify accuracy of each model across the high, medium, and low mental health risk categories.

The metrics accuracy, precision, F1-score, sensitivity, and specificity have indicated that LR offers the best overall performance. The confusion matrix results provide additional insights into class-specific performance. As can be seen in Figure *11*, RF can correctly classify medium-risk instances with 38 correct classifications and no misclassifications in this category, even though it does not offer the highest accuracy. It can also be seen that LR and RF showed low misclassification rates for other classes. SVM and KNN also performed well but had minor misclassifications particularly for the high-risk category. These results demonstrate that different models may be better suited for specific classes, and the choice of model may depend on which class predictions (e.g., medium risk) are most critical in the application.

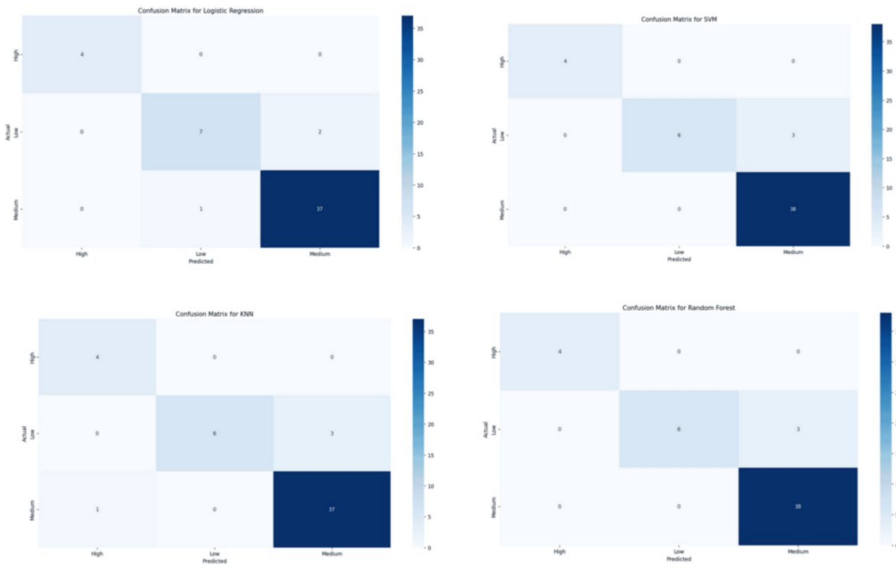

FIGURE 11: Confusion matrices for machine learning algorithms (alpha = 0.05) for the testing set

SVM, Support Vector Machine; KNN, K-Nearest Neighbors

Discussion

This study's findings prove that AI-powered predictive analytics can be helpful in addressing mental health risks among students particularly through the application of the SHRE Model. The usage of Lasso regularization in SHRE Model helps in identifying the key factors influencing students' mental health. It identified Exhaustion, Sadness/Hopelessness, and Social Connection across both alpha values that showed their vital significance in predicting and understanding mental health hazards among students. They can prove useful in boosting resilience and coping mechanisms in students.

These chosen features also relate to known mental health models, providing insight into their prediction capabilities. For instance, Maslach's Burnout Inventory also indicates exhaustion is a key indicator of burnout where exhaustion reflects prolonged exposure to stress. Exhaustion can affect both emotional well-being and academic performance of students, making it a significant predictor of mental health risks [32,33,37].

Similarly, Sadness/Hopelessness is a central feature of depression according to Beck’s Cognitive Triad Theory. It links negative views about the self, the world, and the future with depressive symptoms [31,38].

Social Connection also plays a crucial role validated by the Buffering Hypothesis. Social support may buffer the adverse effects of stress [25,26,30]. Students who are more socially connected tend to be more resilient against mental health issues.

Other features studied, such as Family-Related Stress, Physical Activity, and Substance Use, are consistent with findings in [39]. Family-related stress can increase existing mental health challenges, while physical activity can help in reducing symptoms of depression and anxiety. Substance use, often a coping mechanism, is frequently associated with unmanaged stress or mental health issues. These predictors align well with existing mental health models, strengthening the interpretability and relevance of the SHRE model.

The ROC curves and confusion matrices validate the excellent performance of the LR model in the SHRE framework, as indicated by its applicability in multi-class classification tasks. The ROC curves gave a close-up view of the TPR vs. FPR trade-off in each of the models, illustrating the ability of each algorithm to discriminate among various categories of mental health risk. AUC values near 1.0 for LR, SVM, and RF represent that these models provide good predictive performance across all the risk categories. LR's almost perfect discrimination in Class 0 (AUC = 1.0) and good performance in all other classes demonstrate that it is extremely effective in discriminating among different mental health risks in the SHRE model.

Also, the confusion matrices revealed the misclassification rates for the high-, low-, and medium-risk categories, and this offered a finer breakdown of each model's performance in terms of the SHRE model. While RF and LR showed a good number of correct classifications in the medium-risk category, LR performed best as the most reliable one using overall accuracy, precision, and recall measures. SVM presented competitive outcomes, characterized by low rates of misclassification, which further attest to its position in the SHRE approach to predicting mental health risk.

The use of results from both alpha values (0.05 and 0.1) depicts the trade-offs of feature selection. Although alpha = 0.05 gave a more elaborate set of features, allowing the models to pick up more subtle patterns in the data, alpha = 0.1 resulted in an optimized SHRE framework, which had the potential to minimize the threat of overfitting. It can guide the future studies in selecting the optimal alpha value based on the specific dataset and research objectives.

The outcomes of this study can assist mental health practitioners and educational institutions. The SHRE framework helps to identify students at risk and allows for early intervention strategies. By using machine learning models and recognizing their trade-offs through metrics such as ROC and confusion matrices, stakeholders can make personalized interventions a priority based on accurate predictions.

Nevertheless, this study is limited by its relatively small, self-reported dataset from a single context, which may introduce subjectivity and restrict generalizability. Future work will therefore prioritize larger cross-institutional datasets, external validation through clinical or longitudinal data, stronger psychological justification for selected features, and careful attention to ethical considerations in deploying predictive mental health frameworks.

Conclusions

This research introduces the SHRE framework, an AI-powered predictive analytics system designed to assess mental health risks among students effectively. The framework identifies the key predictors of mental health risk by integrating Lasso regularization for feature selection and employing machine learning models such as LR, SVM, KNN, and RF. Compared to these, LR achieved the highest accuracy of 94.12% and excelled in evaluation metrics such as precision, sensitivity, and F1- score. The ROC curves and confusion matrices proved that the framework worked well in identifying different levels of mental health issues. The study using Lasso regularization feature selection technique found that features such as feeling exhausted, sad or hopeless, and lacking social connection highlighted some important signs that can help predict mental health risks in students. These findings can help teachers, counsellors, and mental health professionals to understand what students might be going through and take early intervention steps. The SHRE Framework is adaptable and can be integrated with the Management Information Systems of colleges or universities, with the potential for further application of learning analytics.

SHRE framework presents a number of directions for further development and elaboration. In this research, 20 questions were used, and out of them, on using Lasso regularization, only 9 and 5 were important at alpha levels of 0.05 and 0.1, respectively. For future study, the questionnaire could be made more precise to keep only the most effective features. Statistical and clinical testing can also help to ensure that the features kept are representative of the mental health requirements of diverse student populations. In conclusion, the SHRE Framework not only proves strong predictive power but also provides the foundation for high-impact use in classroom environments. Through its potential for ongoing refinement and modifiability, the framework offers a major stride towards responding to increasing mental health issues among students, enabling institutions to create healthier and more nurturing learning spaces.

Appendices

The dataset used in this study consists of 253 responses collected via a questionnaire distributed to students from various colleges and universities. The Excel sheet containing the responses is available at the following Google Drive link: https://docs.google.com/spreadsheets/d/1dHMzMdP2ZxNyg2zMS-8K4zxPV7Ny1f1g/edit?usp=sharing&ouid=117533896895979070221&rtpof=true&sd=true

Link of the codes developed for SHRE model (for ML Comparison and Feature Selection): https://docs.google.com/document/d/1rytPlTW4ypu5Dm8py2IeQynihHQNlE1weEdBz5tz1f8/edit?usp=sharing

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Disclosures

Human subjects: Consent was obtained or waived by all participants in this study. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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