Early Prediction of Mental Health Disorder Among Higher Education Students Using Machine Learning

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Article Information

Received: 21-11-2024
Revised: 28-11-2024
Published: 05-12-2024

Keywords
Mental Health, Machine Learning, Decision Tree, Prediction

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Abstract
In spite of the fact that mental health illnesses are quite common among students in higher education, early detection continues to be a difficult task. This study seeks to determine the use of machine learning to forecast the occurrence of mental health issues in this group. Various machine learning methods were explored to analyze the data collected from higher education students and to identify potential risk factors associated with mental health issues. Through the development of a model that is capable of accurately predicting the risk of mental health illnesses, the project intends to facilitate early intervention and improve the overall well-being of their student population.

1. Introduction

Mental health disorders are a significant challenge for students worldwide, adversely impacting their academic performance, social relationships, and overall well-being. Conditions such as anxiety and depression are prevalent among this demographic, often going unnoticed due to limitations in traditional screening methods like self-report questionnaires and clinical evaluations. These methods, while useful, may not always be accessible or efficient in detecting early signs of distress. To address this, machine learning (ML) offers a transformative solution by analyzing large datasets of academic, psychological, and behavioral factors to identify patterns and risks associated with mental health disorders. This approach enables early identification and personalized interventions, such as cognitive-behavioral therapy and enhanced mental health services, helping to improve mental health outcomes in educational settings. By integrating ML into mental health strategies, institutions can create a more supportive and proactive environment that promotes student well-being and academic success.

1.1 Literature Review

Mental health disorders among students have become a pressing global concern, with many struggling with conditions such as depression, anxiety, stress, suicidal thoughts, eating disorders, and addiction. These issues significantly impact academic performance, social relationships, and overall well-being, making timely intervention essential (Mutalib et al., 2021; Sun & Zhao, 2024). In Malaysia, depression, anxiety, and stress are the most prevalent disorders among students, often driven by academic pressures, lack of social support, financial challenges, and family problems. Female students and those navigating peer relationships or balancing academic demands with personal responsibilities are particularly at risk. Stigma and fear of discrimination further exacerbate the problem by discouraging help-seeking behaviors, underscoring the need for mental health education and awareness to reduce stigma and promote early intervention (Mohd Shafiee & Mutalib, 2020; Alkilani & Nusir, 2022).

Machine learning has emerged as a powerful tool for addressing mental health challenges, providing data-driven insights for early prediction and intervention. Machine learning focuses on enabling computers to learn from data without explicit programming and can be categorized into supervised, unsupervised, semi-supervised, and reinforcement learning (Wang & Yang, 2023). Among these, supervised learning is widely used for mental health prediction, with algorithms like Support Vector Machine (SVM), Decision Tree, and Neural Network achieving high accuracy rates above 70% while minimizing the risk of overfitting (Mutalib et al., 2021). These algorithms excel in identifying patterns and classifying mental health issues, offering practical solutions for detecting at-risk students and supporting proactive interventions.

The application of machine learning in mental health prediction involves several critical steps. Data is collected, cleaned, and transformed to ensure quality, followed by feature extraction for model training. Algorithms are then applied to learn patterns in the data, with models being fine-tuned to optimize predictive accuracy. Performance evaluation metrics such as accuracy, precision, recall, and F1 score are used to validate the models' effectiveness. Techniques like SVM and Neural Networks are particularly effective for identifying complex patterns in data, making them suitable for predicting conditions like depression, anxiety, and stress (Hardonag, 2024; Mahesh, 2018). These iterative processes allow for continuous improvement in model performance, ensuring reliability and accuracy in mental health prediction.

Specific algorithms like the Chi-squared Automatic Interaction Detection (CHAID) decision tree have been applied effectively in mental health prediction. CHAID uses chi-square statistics to identify significant predictor variables and determine optimal data splits, making it suitable for handling categorical and continuous variables. In mental health contexts, it has been used to classify students into different risk categories for stress, depression, and anxiety based on relevant factors (Mohd Shafiee & Mutalib, 2020). By providing a clear visual representation of predictor relationships and outcomes, CHAID offers interpretable and actionable insights, enabling universities and policymakers to implement targeted mental health support strategies (Mutalib et al., 2021). Machine learning approaches like these highlight the potential for innovative, data-driven solutions to improve student mental health outcomes.

2. Research Methods

The sampling process is crucial for ensuring the dataset represents the diversity of higher education students for building a predictive mental health model. This study targets students from various universities, covering diverse backgrounds, disciplines, and demographics. A stratified random sampling method will be used to include different groups, such as academic years, socio-economic statuses, and genders. This approach ensures a comprehensive understanding of factors influencing mental health across student subgroups as shown in Figure 1, as well as increasing the model's generalizability to diverse educational settings.

Factor
Lack of Social Support
Financial Problem
Learning Environment
Being Female
Family Problem
Peer Relationship

Fig. 1 Some Factor that Contribute to Mental Health Predictive Model

Data collection for this study is conducted using two primary sources: pre-existing datasets from Kaggle and customized online surveys targeting higher education students. The Kaggle datasets provide valuable information, including demographic data, mental health survey responses, and academic performance indicators, forming a robust foundation for identifying relevant patterns and correlations. The online surveys are specifically designed to capture real-time, context-specific data on psychological factors, lifestyle habits, academic pressures, and socio-economic conditions. This approach ensures efficient and diverse data collection. By integrating historical data from Kaggle with the real-time responses obtained through the surveys, a comprehensive and enriched dataset will be developed for analysis. Sample of surveys conducted is depicted in Figure 2.

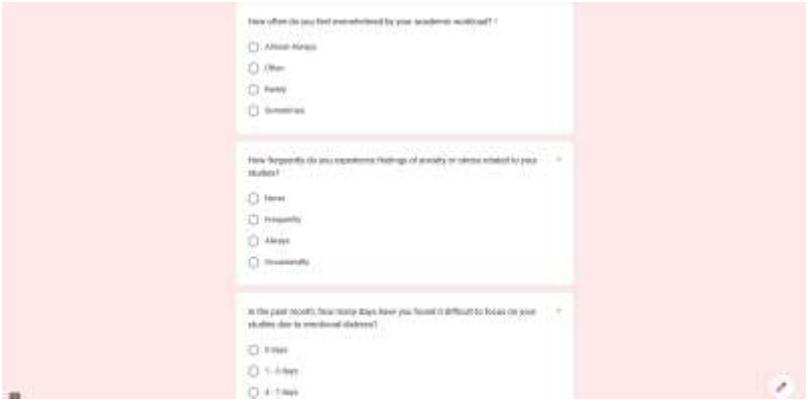

Fig. 2 Online Survey Question

To ensure the accuracy and validity of the mental health predictions, the measurement of mental health and related factors is based on standardized and validated scales. The online survey includes questions designed to assess various psychological conditions, such as depression, anxiety, and stress, using well-established mental health assessment tools. Additionally, academic performance indicators, socio-economic data, and lifestyle factors will be measured using reliable metrics to capture the broad range of variables that may influence student mental health. Data been through a preprocessed stage to handle missing values, outliers, and inconsistencies, ensuring the dataset is suitable for machine learning analysis. By relying on validated measurement tools and comprehensive data cleaning, the study ensures reliable results and strengthens the predictive model's performance.

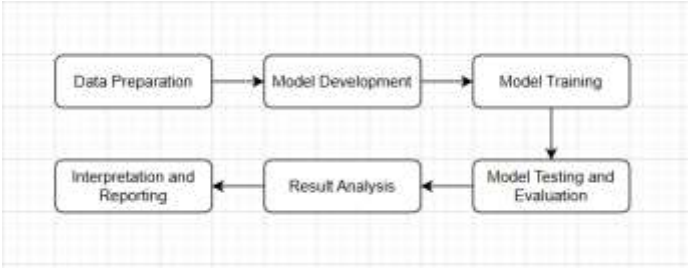

Fig. 3 Process Flowchart

Data preparation is a critical step to ensure the dataset is suitable for machine learning analysis. This phase includes data cleaning, transformation, and normalization to address any inconsistencies or irregularities. Missing values and outliers will be handled through imputation or removal to maintain data integrity. Categorical variables will be encoded, and continuous variables will be normalized to place all features on a comparable scale. Additionally, irrelevant or redundant features will be eliminated to enhance the model's efficiency and accuracy. Once the dataset is prepared, it will be divided into training and testing sets using two distinct ratios: 70-30 and 80-20. These splits provide a robust evaluation framework to assess the model's performance under varying training conditions. The Random Tree algorithm in Weka will then be applied to the pre-processed data to classify mental health outcomes among students. This method ensures accurate predictions while enabling the model to generalize effectively to new, unseen data. The process flow is shown in Figure 3.

This study aims to compare the performance of three predictive model, Decision Tree (Random Tree), Support Vector Machine (SVM) using SMO, and Naive Bayes in identifying mental health risks among students. Each model will be trained and tested using preprocessed data split into two configurations: 70-30 and 80-20 ratios. Evaluation metrics such as accuracy, precision, recall, and F1-score will be used to assess and compare the effectiveness of each model. The Random Tree algorithm is chosen for its interpretability, while SVM is included for its ability to handle high-dimensional data and Naive Bayes for its simplicity and efficiency. By analyzing the results, the study will determine the most suitable model for predicting mental health disorders in higher education students, ensuring robust and reliable outcomes for practical applications.

To effectively compare the performance of the predictive models, various data visualization techniques will be employed using Weka's built-in tools. The evaluation results, including accuracy, precision, recall, and F1-score, will be represented in tabular and graphical formats for clearer insights. Confusion matrices for each model os used to visualized to illustrate how well each algorithm distinguishes between classes. This confusion matrix is illustrated in Figure 4 below. Additionally, ROC (Receiver Operating Characteristic) curves will be generated to compare the trade-offs between true positive and false positive rates across models. By visualizing these metrics, a comprehensive understanding of each model's strengths and weaknesses will be obtained, facilitating an informed decision on the most suitable predictive approach for early mental health disorder detection among students.

Confusion Matrix

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Fig. 4 Confusion Matrix

3. Result and Discussion

Table 1 below presents the performance comparison of three predictive models Random Tree, Support Vector Machine (SVM), and Naive Bayes evaluated using the 70-30 training and testing split. The metrics used for the comparison include accuracy, precision, recall, and F1 score, which provide a comprehensive understanding of each algorithm's effectiveness in predicting mental health outcomes among higher education students. This evaluation aims to identify the most suitable model for early mental health risk prediction, ensuring reliability and generalizability in diverse educational contexts.

Table 1. Comparison for Each Algorithm (70-30)

Algorithm	Accuracy	Precision	Recall	F1-Score
Random Tree	87.5	0.85	0.875	0.856
SVM	81.25	0.813	0.813	0.813
Naïve Bayes	78.125	0.803	0.781	0.791

The results from the performance comparison of the Random Tree, SVM, and Naive Bayes algorithms reveal notable differences in their predictive capabilities. The Random Tree algorithm outperformed the other models with the highest accuracy of 87.5%, indicating its robustness in correctly classifying mental health outcomes. Its precision (0.85) and recall (0.875) further highlight its ability to accurately identify true positive cases while minimizing false negatives. This balance between precision and recall is reflected in its F1 Score of 0.856, which indicates the model's overall reliability and effectiveness in prediction. These results suggest that the Random Tree algorithm is particularly suited for this study due to its ability to handle diverse datasets and provide consistent predictions.

In comparison, the SVM algorithm showed moderate performance with an accuracy of 81.25% and a consistent precision, recall, and F1 score of 0.813. While it demonstrates reliability, its slightly lower metrics compared to Random Tree suggest it may struggle to generalize complex patterns within the dataset. Meanwhile, Naive Bayes achieved an accuracy of 78.125%, with a precision of 0.803, recall of 0.781, and an F1 Score of 0.791. While this model is efficient and fast, its lower performance metrics indicate limitations in capturing the intricate relationships between variables. Overall, the results emphasize that the Random Tree algorithm is the most effective choice for developing a reliable predictive model for mental health issues among higher education students.

4. Conclusions

In conclusion, this project illustrates the effective application of machine learning techniques to predict mental health issues among higher education students, aiming to identify at-risk individuals and provide timely interventions. By leveraging the Random Tree, SVM, and Naive Bayes algorithms, the study demonstrates the potential of predictive models in addressing mental health challenges within academic environments. The data collection process, utilizing both pre-existing datasets and primary survey data, ensures a comprehensive understanding of the factors contributing to mental health outcomes. The results highlight the superior performance of the Random Tree model, suggesting its efficacy in predicting mental health risks. This research emphasizes the importance of incorporating machine learning into mental health support systems in universities, offering a promising approach for early detection and intervention to promote student well-being and academic success.

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