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LEVERAGING MACHINE LEARNING FOR EARLY DETECTION OF MENTAL HEALTH ISSUES AMONG HIGHER EDUCATION STUDENTS

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Abstract:

Mental health disorders among higher education students have become a pressing global concern, with anxiety, depression, and stress significantly impacting academic performance, social relationships, and overall well-being. Early detection and intervention are critical to mitigating these challenges, yet traditional screening methods often fall short due to limited scalability, accessibility, and sensitivity to early signs of distress. This study explores the potential of machine learning (ML) to address these gaps by developing predictive models for identifying students at risk of mental health issues. The research utilized two datasets: a publicly available dataset from Kaggle and a custom dataset collected through an online survey administered to 212 university students. The survey captured diverse dimensions, including demographic, academic, psychological, and social factors, ensuring a comprehensive understanding of the variables influencing mental health. Multiple ML algorithms, including Decision Trees, Support Vector Machines, and Neural Networks, were applied to analyze the data and identify key predictors of mental health risks. The resulting predictive model demonstrated

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commendable accuracy, highlighting its potential utility for early intervention in educational settings.

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Keywords:

Higher Education Students, Machine Learning Models, Mental Health Prediction, Predictive Model, Risk Factor Analysis

Introduction

Mental health disorders represent a growing global concern, with students in higher education institutions being particularly vulnerable. Anxiety, depression, and other mental health conditions are increasingly prevalent among this demographic, adversely affecting academic performance, social relationships, and overall quality of life (Deshmukh et al., 2023). The transition to higher education often brings unique stressors, including academic pressure, financial burdens, and social adjustments, which can worsen mental health challenges. Early identification and intervention are critical for mitigating these issues and fostering student well-being (Sofianita, 2020). However, traditional methods of mental health screening, such as self-report questionnaires and clinical evaluations, often fall short due to their limited scalability, accessibility, and sensitivity to early signs of distress.

The limitations of conventional approaches have spurred interest in leveraging advanced technologies to address this pressing issue. Machine learning (ML), a subset of artificial intelligence, has emerged as a promising tool for developing automated and scalable solutions for early detection of mental health disorders. ML algorithms can analyze vast datasets comprising academic, psychological, and behavioral factors to identify patterns indicative of mental health risks (Baba & Bunji, 2023). For instance, variables such as academic performance, social media activity, and sleep patterns can serve as valuable predictors of mental health outcomes. Despite the potential of ML, significant gaps remain in its application within educational settings. Existing studies have primarily focused on specific populations or narrow datasets, leaving broader questions about generalizability and practical implementation unanswered (Sofianita, 2020).

This study aims to bridge these gaps by developing a machine learning model capable of predicting the risk of mental health disorders among higher education students. The primary objectives include selecting relevant data sources—such as anonymized surveys, academic records, and social media activity—and preprocessing these datasets for analysis. A key focus will be on understanding the factors that most significantly contribute to the model's predictions, thereby enhancing interpretability and trustworthiness. While the project acknowledges certain limitations, such as data availability and predictive accuracy, it seeks to lay the groundwork for future refinements and applications.

The contributions of this study are threefold. First, it introduces an innovative approach to early detection of mental health issues, enabling timely interventions that could improve student outcomes. Second, it provides insights into the key predictors of mental health risks, informing preventive strategies and resource allocation within educational institutions. Finally, it highlights ethical considerations and outlines potential directions for integrating ML models into practical applications. By addressing these aspects, the study seeks to revolutionize how mental health is managed in higher education settings.

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The remainder of this paper is structured as follows: Section 2 reviews the existing literature on mental health issues among students and the role of machine learning in healthcare. Section 3 details the methodology, including data gathering, model development and model training and testing. Section 4 presents the results, followed by Section 5 that concludes the paper by summarizing the key findings and their significance for educational institutions and student well-being along with the strength, limitations, and future research directions of this study.

Literature Review

This section discussed on the literature of mental health disorder, machine learning and related works.

Mental Health Disorder

Mental health disorders among students have emerged as a critical global concern, with alarming rates of depression, anxiety, suicidal ideation, eating disorders, and addiction reported across college campuses worldwide. These conditions not only impair academic performance but also disrupt social relationships and diminish overall well-being, underscoring the urgent need for effective interventions (Mutalib et al., 2021; Sun & Zhao, 2024). Despite their prevalence, mental health issues often remain unaddressed due to pervasive stigma, which discourages students from seeking help and exacerbates the severity of their conditions.

Efforts to combat this stigma and promote mental health awareness are essential for fostering supportive environments where students feel empowered to seek assistance. Mental health literacy programs have demonstrated significant potential in improving knowledge, attitudes, and help-seeking behaviors among students. For instance, studies have shown that such initiatives can enhance students' understanding of mental health issues, reduce misconceptions, and encourage proactive engagement with available support systems, ultimately leading to better mental health outcomes (Alkilani & Nusir, 2022).

In Malaysia, mental health challenges among students are predominantly characterized by depression, anxiety disorders, and stress. Anxiety disorders manifest as overwhelming worry and fear, particularly when individuals face decision-making or problem-solving situations. Depression, on the other hand, is marked by persistent sadness, loss of interest in activities, feelings of guilt, disturbed sleep patterns, and chronic fatigue. Stress, a common precursor to both anxiety and depression, often stems from biological, psychological, and environmental factors, including academic pressures, financial instability, and interpersonal conflicts (Mohd Shafiee & Mutalib, 2020).

Higher education students are particularly vulnerable to these mental health challenges due to a confluence of risk factors. These include insufficient social support, financial difficulties, an unsupportive learning environment, gender disparities (with female students being more susceptible), family-related stressors, and strained peer relationships (Mutalib et al., 2021). The pressure to balance academic responsibilities with personal obligations further compounds stress levels, especially during peak periods such as the end of the semester. To address these issues, universities must adopt comprehensive strategies that normalize help-seeking behaviors and provide accessible, stigma-free mental health services. Unfortunately, many students remain reluctant to utilize these resources due to fears of judgment or discrimination, highlighting the need for systemic changes in how mental health is perceived and addressed within educational institutions (Mohd Shafiee & Mutalib, 2020).

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Machine Learning

Machine learning (ML) is a scientific discipline that focuses on enabling computers to learn from data without being explicitly programmed, thereby providing them with the ability to improve performance through experience (Wang & Yang, 2023). This field has gained significant traction in recent years due to its versatility and applicability across diverse domains, including healthcare, finance, and education. Within healthcare, ML has shown particular promise in addressing complex challenges such as the classification and prediction of mental health disorders. ML can be broadly categorized into four primary paradigms: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Among these, supervised learning has emerged as the most widely adopted technique for solving classification problems related to mental health issues. Commonly used algorithms include Support Vector Machines (SVM), Decision Trees, and Neural Networks, all of which have demonstrated high accuracy rates—often exceeding 70%—and robust generalization capabilities that mitigate the risk of overfitting (Mutalib et al., 2021).

The structure of ML models involves several key components that work in tandem to generate predictive insights. The process begins with data collection, followed by preprocessing steps such as cleaning, transformation, and normalization to ensure the quality and usability of the dataset. Feature extraction is then performed to identify relevant variables that contribute to the model's predictive power. These features are fed into an algorithm or a combination of algorithms, which learns patterns and relationships within the data during the training phase. During this phase, the model iteratively adjusts its parameters to minimize prediction errors. Once trained, the model is evaluated using separate validation or test datasets to assess its ability to generalize to unseen data. Performance metrics such as accuracy, precision, recall, and the F1 score are commonly employed to quantify the model's effectiveness. Finally, the trained model is deployed in real-world applications to make predictions or support decision-making processes. This workflow is inherently iterative, often requiring fine-tuning, retraining, and optimization to enhance performance over time as in Figure 1 (Hardonag, 2024; Mahesh, 2018).

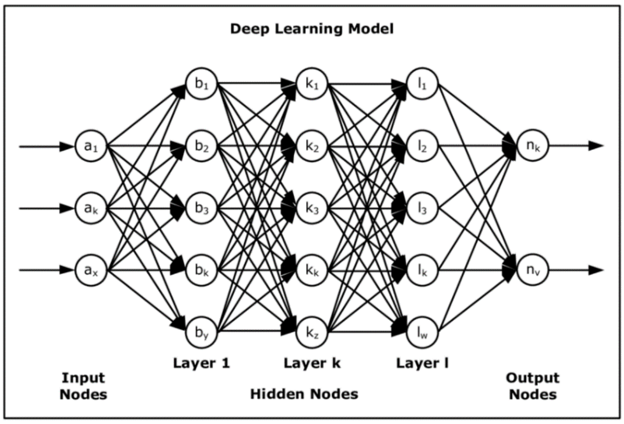

Figure 1: Deep Learning Model

In the context of mental health research, ML offers transformative potential by enabling the analysis of large-scale, heterogeneous datasets to identify early warning signs of mental health disorders. For instance, models trained on data encompassing academic performance, social media activity, and physiological indicators can predict the likelihood of conditions such as depression or anxiety before they manifest clinically. This capability underscores the

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importance of continued advancements in ML methodologies and their integration into healthcare systems to address pressing public health challenges.

Machine Learning Technique Rural Tourism

ML algorithms have gained significant traction in diverse fields, including the prediction and classification of mental health disorders. Among the most widely utilized algorithms are Decision Trees, Support Vector Machines (SVM), and Neural Networks, each offering unique strengths for addressing complex challenges in mental health research. Decision Trees, a supervised learning technique, employ a hierarchical tree-like structure to classify mental health conditions such as stress, depression, and anxiety. This algorithm is particularly effective in identifying the most influential factors contributing to these conditions, enabling the prediction of students' susceptibility to mental health issues with high interpretability (Jage et al., 2023; Mahalakshmi & Sujatha, 2023). Its transparency and ease of visualization make it a valuable tool for both researchers and practitioners.

Support Vector Machines (SVM) and Neural Networks are also prominent in mental health prediction. SVM operates by constructing a hyperplane that separates data points into distinct classes, making it highly effective for identifying patterns in datasets. This algorithm has been successfully applied to predict conditions such as depression and anxiety, demonstrating robust performance in handling high-dimensional data (Wang & Yang, 2023). Neural Networks, inspired by the human brain's architecture, utilize interconnected nodes to process and classify complex data. Their ability to model intricate relationships within datasets makes them particularly suited for predicting nuanced mental health outcomes, such as stress and depression, where multiple interacting factors may be at play (Wang & Yang, 2023).

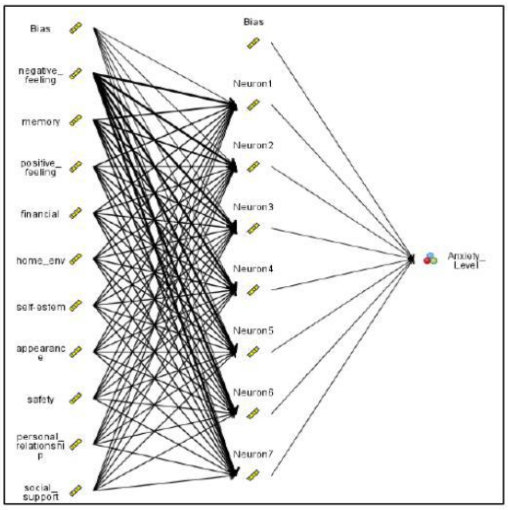

Figure 2: Example of Mental Health Model Using Neural Network

Another notable algorithm in this domain is the Chi-squared Automatic Interaction Detection (CHAID) decision tree, which has proven effective in mental health prediction models. CHAID employs chi-square statistics to identify the most significant predictor variables and determine optimal splits in the decision tree. This technique excels in handling both categorical and continuous variables, making it versatile for analyzing diverse datasets (Mohd Shafiee & Mutalib, 2020). In mental health applications, CHAID has been used to classify students into categories of stress, depression, and anxiety based on various predictors. The algorithm

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recursively partitions the data using the predictor variable that maximizes the chi-square statistic, continuing until no further meaningful splits can be made or a predefined stopping criterion is reached. The resulting decision tree provides a clear, interpretable representation of the relationships between predictors and mental health outcomes, facilitating practical implementation in educational and clinical settings (Mutalib et al., 2021).

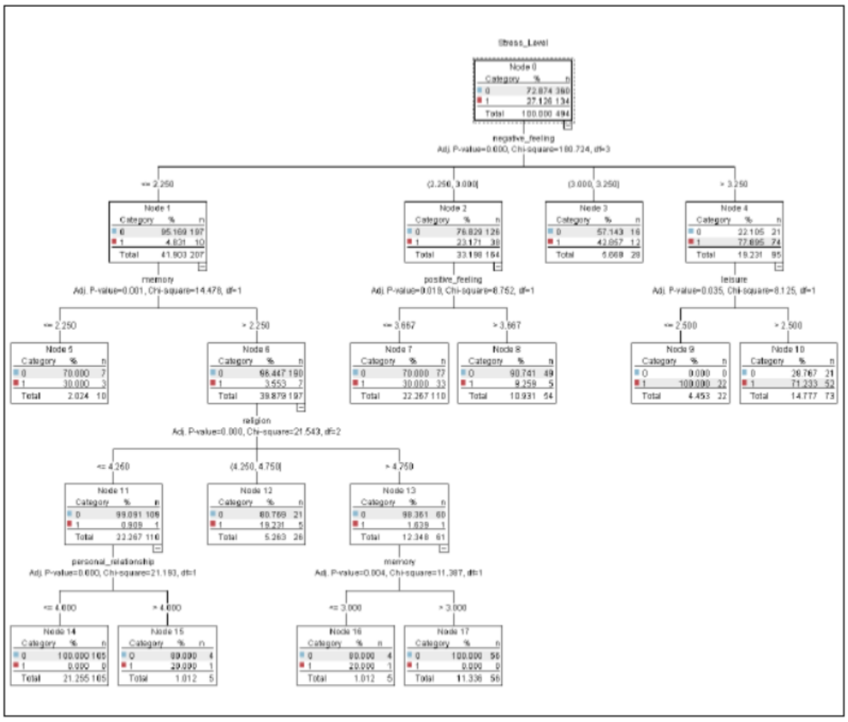

Figure 3: Example of Mental Health Model Using CHAID Decision Tree

These ML techniques collectively offer powerful tools for advancing mental health research and practice. By leveraging their unique capabilities, researchers can develop predictive models that not only identify at-risk individuals but also provide actionable insights into the underlying factors contributing to mental health disorders. Such advancements hold immense potential for transforming early detection and intervention strategies in higher education and beyond.

Related Works

Recent studies have identified key factors contributing to mental health challenges, such as lack of social support, financial stress, academic pressures, and biological influences (Mutalib et al., 2021). Researchers have explored the potential of ML algorithms to classify students into categories of stress, depression, and anxiety, with Decision Trees, Support Vector Machines (SVM), and Neural Networks demonstrating high accuracy in these tasks. These models highlight the importance of developing comprehensive prediction systems capable of identifying at-risk students early, enabling timely interventions to improve their well-being (Mutalib et al., 2021).

Another significant area of research involves leveraging social media data and behavioral patterns to detect depression among college students. For instance, Ding et al. (2020) employed a deep integrated support vector machine (DISVM) model to analyze Weibo posts, achieving high accuracy in identifying depression-prone individuals based on language style, emoji usage, and network behavior. Similarly, Wang and Yang (2023) utilized advanced ML

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techniques to uncover correlations between mental health status and factors such as gender, academic year, and personal background. Their findings emphasize the need for tailored interventions that address the unique needs of diverse student populations, ultimately enhancing both academic performance and personal development.

Recent advancements have also focused on integrating natural language processing (NLP) and data mining techniques to evaluate students' psychological states comprehensively. Ren et al. (2024) proposed analyzing social network behavior, online search records, and linguistic patterns to identify potential mental health issues early. Additionally, hybrid ML models combining multiple classifiers have achieved remarkable accuracy in predicting depression (99%) and anxiety (97%), surpassing traditional methods like logistic regression and K-nearest neighbors (Rahman et al., 2023). Mahalakshmi and Sujatha (2023) further demonstrated the efficacy of ML approaches such as KNN, which achieved 87.2% accuracy in predicting stress levels among students. These studies collectively underscore the potential of ML to revolutionize mental health interventions by providing scalable, personalized solutions.

Table 1: Summary of Related Study

Authors	Issues	ML Techniques Applied
Ding et al. (2020)	Depression detection using social media data (Weibo)	Deep Integrated Support Vector Machine (DISVM)
Mutalib et al. (2021)	Lack of social support, financial stress, academic pressures, biological influences	Decision Trees, Support Vector Machines (SVM), Neural Networks
Wang & Yang (2023)	Correlation between mental health and factors like gender, academic year, personal background	Advanced ML techniques
Mahalakshmi & Sujatha (2023)	Predicting stress levels among students (87.2% accuracy)	K-Nearest Neighbors (KNN)
Rahman et al. (2023)	Predicting depression (99% accuracy) and anxiety (97% accuracy)	Hybrid ML models, surpassing logistic regression & KNN
Ren et al. (2024)	Psychological state analysis via social network behavior, search records, and linguistic patterns	NLP, Data Mining, Hybrid ML Models

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Methodology

The methodology of this study encompasses data gathering, preprocessing, model development, model training and testing to ensure the accuracy and reliability of the mental health prediction model.

Data Gathering

The data gathering phase involved collecting information from multiple sources to ensure a comprehensive and diverse dataset. A primary source was Kaggle, a well-known platform for data science datasets, which provided pre-existing datasets related to student mental health. These datasets typically included variables such as demographic information, mental health survey responses, academic performance indicators, and other relevant factors. Such historical data served as a foundation for identifying patterns and correlations between various predictors and mental health outcomes. In addition to leveraging Kaggle datasets, an online questionnaire was designed and administered to higher education students to gather current, context-specific data. The survey incorporated standardized and validated scales to measure mental health and related parameters, ensuring the reliability and validity of the results.

The online questionnaire captured a wide range of factors, including psychological, lifestyle, academic, and socio-economic elements. Questions addressed aspects such as stress levels, academic workload, emotional distress, support systems, and satisfaction with institutional mental health resources. Examples of survey items included frequency of anxiety or stress, coping mechanisms, and the impact of financial issues on mental well-being. Combining Kaggle's historical data with self-reported survey responses enriched the dataset, enabling a more nuanced understanding of factors influencing student mental health. Rigorous data cleaning and preparation steps were undertaken to handle missing values, outliers, and inconsistencies, ensuring the dataset's quality and suitability for ML applications. This systematic approach to data collection laid a robust foundation for developing an accurate predictive model for early detection of mental health issues among higher education students.

Designing Student Mental Health Prediction Model

Designing a student mental health prediction model utilizing the decision tree approach in WEKA entails numerous systematic stages to assure the establishment of an accurate and interpretable model. The first step is to prepare the cleaned dataset to be import into WEKA, ensuring that it is in an appropriate format such as ARFF (Attribute-Relation File Format) or CSV. Once the dataset is put into WEKA, the next step is to select the decision tree algorithm, such as J48, which is WEKA's implementation of the C4.5 algorithm. Decision trees are chosen for their simplicity and ability to handle both numerical and categorical data, making them excellent for identifying the contributing elements to mental health concerns.

Model Training and Testing

Once the dataset is partitioned, the J48 method is performed to the training set within the WEKA environment. The training procedure comprises the algorithm examining the training data, generating a decision tree by recursively separating the data based on attribute values that best divide the classes. After the model is trained, it is next tested on the 20% testing set. WEKA delivers a thorough evaluation report, containing metrics such as accuracy, precision, recall, and the F-measure, which help judge the success of the model. The findings from this evaluation indicate whether the model is overfitting or underfitting the data, leading further tuning and optimization of the model parameters.

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To ensure the robustness and dependability of the model, a second split of the dataset is done, this time with a 70/30 ratio—70% for training and 30% for testing. This variance in the training/testing split provides an additional layer of validation, revealing insights into the model's consistency across diverse data distributions. 33

The training process is repeated on the 70% training set, followed by testing on the 30% testing set. By comparing the evaluation metrics from both the 80/20 and 70/30 splits, researchers can better understand the model's stability and performance. This extensive training and testing approach assure that the final decision tree model is both accurate and generalizable, capable of efficiently predicting mental health risks among higher education students based on the features extracted from the collected data.

Model Comparison

The Model Comparison stage involves a detailed evaluation of the performance of three ML algorithms, namely Decision Tree, Support Vector Machine (SVM), and Naïve Bayes. It assures all-inclusive throws-on-the-ground assessments of each of the predictive power indicators specific to recognizing mental health risks in children-focused on important performance indicators like accuracy, precision, recall, and F1 score.

In terms of preserving objectivity in the evaluation procedure, a uniform training data is allocated to the algorithm and the performance is subsequently assessed through an exclusive testing dataset. For the offer of total insight into the prediction outputs in the form of true positives, true negatives, false positives, and false negatives, it is prepared much confusion matrix with every model. The knowledge of the advantages and disadvantages of each model is typically inferred from these values, which are the grounds for establishing the evaluation measures.

This particular stage brings the advantages of in-depth comparisons among the Decision tree, SVM, and Naïve Bayes algorithms that would ensure selection of models according to the best performance capacity in meeting all legitimacy and usefulness requirements. Such a process of study is very rigorous and resourceful in the development of a reliable yet effective predictive model for early student mental health intervention.

Result and Discussion

Dataset of Survey Feedback

This study utilized two datasets: one publicly available dataset from Kaggle and a custom dataset collected through an online questionnaire designed to explore factors contributing to mental health issues among higher education students. Combining these datasets ensured a wide range of variables and patterns, enhancing the robustness of the predictive models for mental health disorders.

The custom dataset was collected via an online survey distributed through Google Forms, targeting university students as primary respondents. A total of 212 valid responses were gathered, ensuring a sufficient sample size for analysis. The questionnaire covered multiple dimensions—demographic, academic, psychological, and social—to provide a comprehensive understanding of factors influencing mental health. These dimensions included age, gender,

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current CGPA, feelings of being overwhelmed by academic workload, frequency of anxiety or stress, difficulty concentrating, engagement in stress-relief activities, emotional well-being, availability of support systems, satisfaction with counseling services, financial stress, and physical symptoms of stress. This diverse set of 13 attributes captured both individual and environmental factors, enabling a holistic approach to predictive modeling for mental health challenges among university students. Table 2 provides detail description of each attribute.

Table 2: Dataset of Attributes

Attribute Name	Description
Age	The age of the respondent
Gender	The gender of the respondent
Current CGPA	The respondent's current Cumulative Grade Point Average
Academic Overwhelmed	Whether the respondent feels overwhelmed by academic responsibilities.
Anxiety Frequency	Frequency of experiencing anxiety symptoms
Focus Difficulty	Challenges faced by the respondent in maintaining focus on academic tasks.
Support System Availability	Availability of a support system for the respondent
Physical Symptoms	Physical manifestations of mental health issues
Counselling Satisfaction	The level of satisfaction with counselling services received, if any
Stress Management Activity	Participation in activities designed to manage stress
Sadness Experience	The frequency with which respondents experience feelings of sadness.
Financial Issues	Whether the respondent experiences financial difficulties.
Mental Health	The mental health status of the respondent

These attributes form the basis for constructing ML models, performing analysis on their impact on mental health hazards, and hunting down key predictors. Merging the insight derived from the Kaggle dataset and deep, context-relevant details from the custom questionnaire ensures the analysis is quite comprehensive and robust

Predictive Model Result

This section presents results from experiments involving three ML algorithms namely Decision Tree, Support Vector Machine (SVM), and Naïve Bayes with regard to the detection of mental health risk in university students. Each model was evaluated based on how well it performed through measures of accuracy, precision, recall, and F1 score. The findings evaluate how well these models have performed in identifying the student’s risk.

The evaluation of Decision Tree, Support Vector Machine (SVM), and Naïve Bayes models relies on key performance metrics such as accuracy, precision, recall, and F1 score. These metrics are directly influenced by the confusion matrix, which provides insight into how well each model classifies students at risk of mental health issues.

- True Positives (TP): Represents students correctly identified as at risk of mental health issues. A high recall value indicates that the model is effectively detecting most of these cases.

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- False Positives (FP): Cases where students are incorrectly classified as at risk when they are not. A high precision value suggests a lower number of false positives, ensuring that fewer students are unnecessarily flagged.
- True Negatives (TN): Students correctly classified as not at risk. This contributes to the model's overall accuracy, confirming that it correctly distinguishes those who do not require intervention.
- False Negatives (FN): Instances where students at risk were misclassified as not at risk. A low false negative rate is crucial to ensuring that those who need support are correctly identified.

The balance between precision and recall is represented by the F1 score, which ensures that the model maintains both high sensitivity (low false negatives) and specificity (low false positives). These factors collectively contribute to determining the most reliable predictive model for identifying mental health risks among university students.

Decision Tree

The application of the Decision Tree model for predicting mental health risks among university students was evaluated on using two distinct dataset splits, namely 70-30 and 80-20. The 70-30 classification shows an accuracy of 89.06% with an F1 score that reaches 0.881; the model also earned a precision of 0.879, while the recall was 0.891. These measures determine how well the Decision Tree identifies students most likely to be at risk of developing mental health issues.

The performance improved a little with the 80-20 division, achieving an accuracy of 90.47 percent, precision and recall rate of 0.905, and F1-score of 0.905. The improvement, as suggested, was brought about by the increased training set to the model package hence, making the model more robust with increased training data.

Table 3 illustrates performance metrics of the Decision Tree model for the dataset split at 70-30 and 80-20. The focus of such model evaluation is in terms of important measures like accuracy, precision, recall, and F1 score, which provide a complete view to ascertain the actual utility of a model in predicting mental health risks among university students.

Table 3: Summary of Decision Tree Model

Metric	70-30 Split	80-20 Split
Accuracy	89.06%	90.47
Precision	0.879	0.905
Recall	0.891	0.905
F1 Score	0.881	0.905

In general, the results suggest that the model performs satisfactorily in both scenarios, with slightly superior results in the 80-20 split. The model's predictive performance is enhanced by the increase in accuracy from 89.06% to 90.47%, as well as the enhancement in precision, recall, and F1 score. This trend illustrates the significance of a large enough training dataset in improving the consistency and reliability of the Decision Tree model

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SVM

Prediction performance was also tested using two splits (70-30 and 80-20) for the Support Vector Machine (SVM) model in predicting college students' mental health risks. The 70-30 split gave an accuracy of 92.18%, F1 score of 0.909, precision of 0.928, and recall of 0.922. Highly precise and recall value of the model demonstrates its ability to forecast mental health problems.

While the model performed well when using the 80-20 split, with an accuracy of 88.09%, the precision it obtained was 0.873, the recall was 0.881, and the F1 score calculated as 0.876. All of these translate into a slight fall in performance. It implies that the size of the training dataset does make the model performance differ, with a smaller training set resulting in the SVM showing slightly diminished results.

Table 4 illustrates performance metrics of the SVM model for the dataset split at 70-30 and 80-20. The focus of such model evaluation is in terms of important measures like accuracy, precision, recall, and F1 score, which provide a complete view to ascertain the actual utility of a model in predicting mental health risks among university students.

Table 4: Summary of SVM Model

Metric	70-30 Split	80-20 Split
Accuracy	92.18%	88.09
Precision	0.928	0.873
Recall	0.922	0.881
F1 Score	0.909	0.876

These findings indicate that the training-to-testing ratio has an impact on the model's efficacy, and a larger training set does not necessarily result in improved performance. In both situations, the SVM model showed a high degree of predictive power, confirming its dependability for classifying students' mental health risks.

Naïve Bayes

The findings examined the predictive performance of the Naïve Bayes model on mental health risk prediction for university students using both 70-30 and 80-20 splits in the datasets. The 70-30 split yields an accuracy of 90.62%, precision of 0.915, recall of 0.906 and F1 score of 0.885 for the model. Quite rightly, these metrics indicate a fair performance for the Naïve Bayes classifier in the detection of mental health risk with fairly high precision and recall values and scope for improvement on the F1 score.

When assessed with the 80-20 split, the performance of the model improved to reach an accuracy of 92.85%, with precision at 0.934, recall at 0.929, and an F1 score of 0.918. This indicates that the Naïve Bayesian model performs better when trained with a larger dataset, improving all performance measures.

Table 5 provides a detailed comparison of the Naïve Bayes model's performance across the two dataset splits. These performance metrics illustrate the effectiveness of Naïve Bayes in predicting mental health risks, with notable improvements when using a larger training dataset.

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Table 5: Summary of Naïve Bayes Model

Metric	70-30 Split	80-20 Split
Accuracy	90.62%	92.85
Precision	0.915	0.934
Recall	0.906	0.929
F1 Score	0.885	0.918

These findings demonstrate how consistently the Naïve Bayes model performs on tasks involving mental health prediction. The model's ability to learn from data is demonstrated by the improvement in performance with a bigger training set, which makes it a serious candidate for predictive analysis in this field.

Predictive Model Comparison

Comparative analysis of many predictive models is important to derive the best criteria to identify mental health risks among students. The section compares the Decision Tree, SVM, and Naive Bayes models with respect to the performance metrics such as accuracy, precision, recall, and F1 score. Understanding these evaluations would enable the identification of strength and weaknesses of each model for better insightful considerations on their use as far as mental health prediction is concerned. Table 6 show the different of accuracy, precision, recall and F1 Score for Decision Tree, SVM and Naïve Bayes.

Table 6: Predictive Model Comparison

Model	Split	Accuracy (%)	Precision	Recall	F1 Score
Decision Tree	70-30	89.06	0.879	0.891	0.881
	80-20	90.47	0.905	0.905	0.905
SVM	70-30	92.18	0.928	0.922	0.909
	80-20	88.09	0.873	0.881	0.876
Naïve Bayes	70-30	90.62	0.915	0.906	0.885
	80-20	92.85	0.934	0.929	0.918

It has been observed that all the three prediction models exhibit different behavioral trends. The Decision Tree model can be considered as the most reliable among all those for predicting mental health problems since it regularly shows accuracy while maintaining an optimal balance of precision and memory. However, as far as fluctuating overall measures are concerned, they did not outperform any of the other models.

SVM has proven to be capable of handling complicated relationships within the data with the maximum accuracy of 92.18% at the 70-30 split; however, its performance in the 80-20 set decreased to 88.09%, possibly indicating sensitivity to smaller training sets. In spite of this, SVM retained its competitive precision and recall values.

Naïve Bayes is quite good in general and has achieved maximum accuracy (92.85%) in the 80-20 split. This shows that it is rather efficient in dealing with the probabilistic relations present in the data: in all cases, it has outshone the precision, recall, and of course, F1 measures of the Decision Tree.

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Conclusion

This study successfully achieves its primary objective of developing a machine learning model to predict mental health risks among higher education students. By utilizing a robust dataset comprising 212 valid survey responses alongside supplementary data from Kaggle, the research effectively identifies key factors influencing mental well-being, including academic workload, emotional distress, social support, financial stress, and physical symptoms. Through the application of multiple ML algorithms, the model demonstrates commendable predictive accuracy, enhancing interpretability and trustworthiness. These findings contribute to the existing literature by addressing the unique challenges faced by university students and providing a strong foundation for early intervention strategies and future model refinements.

Despite its strengths, the study has certain limitations that need to be considered. The reliance on a single dataset may limit the generalizability of the findings, as it may not fully capture the diversity of higher education students. Additionally, the focus on specific ML algorithms, while effective, leaves room for exploration of other techniques such as deep learning or ensemble methods that could enhance predictive performance. Furthermore, the cross-sectional design restricts the ability to establish causal relationships between identified risk factors and mental health outcomes, highlighting the need for longitudinal studies to track changes over time.

Looking ahead, future research should aim to address these limitations by integrating diverse data sources, such as socio-economic and environmental factors, to create more comprehensive models. Exploring advanced ML techniques and collaborating with mental health professionals could further refine predictive accuracy and ensure practical applicability. Developing user-friendly tools for educational institutions to monitor student mental health and evaluate intervention effectiveness is another critical step. Expanding the scope of research to include other populations, such as high school or non-traditional students, would also enhance the generalizability of the findings. By addressing these gaps, future studies can build on this work to create scalable, impactful solutions for improving mental health outcomes across educational settings.

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