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Early Mental Health Detection with Machine Learning: A Practical Approach to Model Development and Implementation

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ABSTRACT

Mental health, encompassing emotional, psychological, and social well-being, plays a pivotal role in individuals' academic and personal success. Among undergraduate students, the prevalence of mental health disorders such as anxiety, depression, and stress has escalated in response to academic pressures, lifestyle transitions, and socioeconomic factors. Early detection is vital for mitigating severe repercussions, including diminished academic performance and increased risk of self-harm. Leveraging the Depression, Anxiety, and Stress Scale-42 (DASS-42), this study employs machine learning (ML) methods—specifically Support Vector Machine (SVM) and Random Forest (RF)—to analyze mental health patterns under a two-class scenario ("Good" vs. "Counseling"). A balanced dataset was obtained through the Synthetic Minority Over-Sampling Technique (SMOTE), ensuring fairer representation of minority "Counseling" cases. The results demonstrate that both SVM and RF excel in detecting depression, each achieving near-perfect accuracy, precision, and recall (0.97). This performance suggests that the discriminative power of the features for depression is sufficiently robust to enable clear classification boundaries with minimal misclassification. For anxiety, SVM attains a slightly higher accuracy (0.91) compared to RF (0.90), largely driven by SVM's superior precision (0.94) when identifying "Good" cases. In stress prediction, SVM again outperforms RF (0.95 vs. 0.93 accuracy), although RF showcases near-perfect precision and recall for "Counseling." Despite these successes, both models occasionally falter when distinguishing borderline cases, indicating that feature overlap and remaining class imbalance still pose challenges. In conclusion, SVM and RF provide promising avenues for early mental health detection in university settings, highlighting the potential of ML-driven tools to inform targeted interventions. Future research should focus on expanding feature sets (e.g., integrating behavioral or physiological data) and refining sampling strategies to enhance minority-class detection.

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1. INTRODUCTION

Mental health, a cornerstone of overall well-being, significantly impacts individuals' emotional, psychological, and social functioning. Among undergraduate students, the prevalence of mental health disorders, including anxiety, depression, and stress, has increased due to academic pressures, lifestyle changes, and socioeconomic challenges [1]. Early identification and intervention are crucial to mitigate severe consequences [2]. The Depression, Anxiety, and Stress Scale-42 (DASS-42) is a widely used self-report measure to assess these conditions. Machine learning (ML) offers a promising approach to analyzing large-scale mental health data, enabling the identification of patterns and the development of predictive models [3]. ML models can process vast amounts of data from self-reported surveys like the DASS-42 to behavioral metrics and provide unparalleled insights for targeted mental health interventions in academic settings [4]. Machine learning algorithms have emerged as powerful tools for classifying mental health disorders, predicting risk factors, and identifying potential intervention strategies. Popular techniques like Random Forest, Support Vector Machines (SVM), and Logistic Regression have demonstrated significant accuracy in detecting stress, anxiety, and depression [5]. In particular, SVM has achieved impressive accuracy rates exceeding 90% in predicting anxiety levels [6]. Machine learning models can enhance their predictive capabilities by integrating behavioral data, such as sleep patterns, physical activity, and social interactions, leading to more precise and timely interventions [7]. For instance, models that incorporate lifestyle factors alongside psychological surveys like DASS-42 have successfully predicted depression and stress levels in students [8]. However, several challenges hinder the broader application of ML in mental health analysis.

Data quality remains a significant issue, with many datasets limited by sample size, demographic diversity, and the accuracy of self-reported data [9]. Ethical concerns, including data privacy and potential algorithmic bias, necessitate the establishment of rigorous regulatory frameworks to protect individuals' rights [10]. Additionally, the interpretability of ML models poses significant challenges. While advanced models like Neural Networks provide high accuracy, their "black-box" nature limits their adoption in clinical and educational settings [11]. Therefore, explainable AI systems are necessary to ensure transparency in decision-making processes. To address these issues, future research must prioritize the development of standardized datasets encompassing diverse populations and longitudinal data. Collaborative efforts among universities, healthcare providers, and technology developers can facilitate the creation of robust data repositories [12]. Moreover, advancements in algorithmic transparency and fairness are essential. Explainable AI (XAI) methodologies can improve interpretability, ensuring that mental health predictions are accurate and understandable to stakeholders [13]. Interdisciplinary research involving psychologists, data scientists, and ethicists will further enhance the ethical deployment of ML technologies in mental health [14].

The application of machine learning in mental health analysis has the potential to revolutionize mental health management for university students. By leveraging predictive models and validated tools like DASS-42, universities can proactively address mental health challenges and foster supportive academic environments. However, overcoming challenges related to data quality, ethical concerns, and interpretability will be crucial to unlocking the full potential of these technologies. This study contributes to the growing knowledge of ML-driven mental health analysis, advocating for collaborative, transparent, and ethically sound approaches.

While the application of Support Vector Machines (SVM) in mental health prediction has gained momentum in recent years, several critical limitations persist in the existing body of research. These gaps highlight the need for more practical, equitable, and scalable approaches to early mental health detection. Many recent studies utilize complex datasets containing physiological signals, neuroimaging data, or extensive psychological assessments. For example, [15] applied multi-class SVMs to classify mental states using EEG signals, while [16] introduced an ensemble of weighted random SVMs for detecting mild cognitive impairment using fMRI. Although technically advanced, these approaches rely on high-cost data acquisition methods that are unsuitable for deployment in typical educational or community environments.

Similarly, SVMs have been shown to be effective in medical image classification and genomic-based psychiatric diagnostics [17][18], but these models again depend on data that are rarely available outside clinical or research settings. Recent attempts to make SVM more accessible have been promising, but still fall short in addressing key performance limitations. For instance, [19] achieved high accuracy using SVM with tuned kernel parameters and feature scaling, yet did not compare performance against other machine learning models or report on class-specific performance such as recall for high-risk individuals. Similarly, [20] concluded that SVM outperformed other algorithms in predicting mental illness, but their study lacked focus on minimal-input models suitable for constrained settings.

A few studies have moved toward educational contexts. For example, [21] used SVM to classify final-year students' stress levels and achieved promising results (93.3% accuracy). However, their study did not emphasize class imbalance or real-world deployment feasibility, and still relied on relatively curated data inputs. Furthermore, none of the reviewed studies performed targeted evaluations on minority class detection—such as students with urgent counseling needs—which is critical for fair and actionable early intervention. From a theoretical standpoint, SVMs are well-suited for small, imbalanced, and high-dimensional datasets due to their ability to maximize margin separation and employ kernel tricks for non-linear classification. However, the full potential of SVM in low-data, real-world applications remains underexplored. Comparative analysis with interpretable and ensemble-based models like Random Forest is also rarely addressed, despite its importance in model selection for mental health deployment scenarios.

2. RESEARCH METHOD

This study employed a rigorous quantitative, cross-sectional research design to investigate mental health patterns among university students using self-reported data. The study aimed to explore relationships between demographic variables, academic factors, and mental health outcomes, including depression, anxiety, and stress. The research methodology is detailed in terms of population, sampling, data collection, instruments, and analysis techniques, demonstrating the thoroughness and validity of the study.

2.1. Population and Sample

The study targeted undergraduate students enrolled in various academic programs at a university, aiming to capture a diverse yet homogenous sample within a specific age range. To maintain uniformity, the research focused exclusively on students aged 18–25, ensuring that the findings represent this critical developmental stage. Undergraduate students often face academic pressure, social transition, and financial burdens that significantly affect their psychological well-being [22]. The college period coincides with the “emerging adulthood” stage of development, making this group particularly vulnerable to academic mental health issues. Factors such as mental toughness, social support, and resilience play a crucial role in determining their well-being [23]. Compared to the much broader and more heterogeneous millennial generation, undergraduate students offer a more consistent sample group in terms of age and circumstances, making them more suitable for specific studies and interventions. Meanwhile, the millennial generation—which spans ages 25 to 40—faces different challenges, such as work pressure, emotional exhaustion, and economic instability [24]-[25] Although they are also affected by factors such as social media use and cultural changes, focusing on students provides a more targeted research direction and enables the development of concrete campus policies relevant to their needs [26].

A purposive sampling technique was employed to recruit participants [27], allowing the selection of individuals who voluntarily agreed to participate in the study after providing informed consent. This study involved 396 undergraduate students enrolled at Universities in Palembang City, Indonesia. The participants were selected through stratified sampling to ensure representation across different academic programs and year levels [28]. The age of the participants ranged from 18 to 25 years. In terms of gender distribution, the sample consisted of 266 women (67.2%) and 130 men (32.8%). While gender balance was considered during the recruitment process, a higher participation rate was observed among female students, a pattern commonly reported in studies related to psychological well-being and mental health. 396 students were surveyed, representing various academic disciplines, semesters, and demographic profiles. This approach ensured that the data reflected diverse perspectives across the student body. By integrating these methodological considerations, the study ensured a comprehensive and equitable representation of the target population, providing a solid foundation for robust and generalizable findings.

2.2. Data Collection

Data was collected using a structured, anonymous, self-administered questionnaire distributed physically [29] and online over two months. To accommodate the linguistic diversity of the student population, the survey was made available in Indonesian language. To ensure broad participation, the data collection process was carried out five times across three locations within the university, including common areas such as the library, student center, and designated classrooms. This inclusive approach ensured that the study represented diverse perspectives across the student body, as shown in Figure 1.

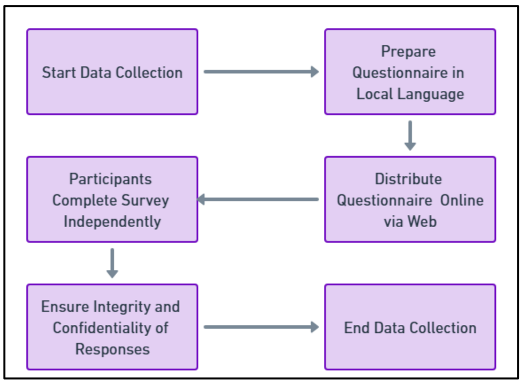

Figure 1. Data Collection Process

Participants completed the survey independently, with sessions organized during class breaks or specified times to minimize disruption to their academic routines. In addition, counsel (counselees) were actively involved in the process, completing the questionnaire independently to preserve the integrity and confidentiality of their responses. For the online mode, weekly reminder emails and notifications were sent to encourage participation and boost response rates. This multi-faceted approach ensured a comprehensive and efficient data collection process, accommodating in-person and remote participants while maintaining the study's inclusivity and reliability.

2.3. Instruments

The instrument used to measure levels of depression, anxiety, and stress among participants was The Depression Anxiety Stress Scale-42 (DASS-42), which consists of 42 self-report items divided into three subscales: depression, anxiety, and stress [30]. The scale uses a 4-point Likert format, with options from 0 ("Does not apply to me at all") to 3 ("Applies to me most of the time") [31], allowing participants to reflect on the frequency and intensity of their experiences during the previous week. The DASS-42 has been validated and widely used in research related to emotional disorders. Reliability testing results with Cronbach's Alpha showed a high value of 0.92, indicating excellent reliability and consistency in measuring emotional states. Although validity could not be tested directly in this study, based on the high reliability, it can be considered that the instrument is conceptually valid for measuring depression, anxiety, and stress. The DASS-42 is valid in many previous studies and has become a standard instrument in measuring these three emotional states. Compared to single-domain tools like the PHQ-9 (which focuses solely on depression) or GAD-7 (focused on generalized anxiety), the DASS-42 provides a more integrative picture of an individual's emotional functioning [23],[26],[32]. Unlike the DASS-42, the BDI does not assess anxiety or stress, both of which can significantly impact students' daily functioning. In contrast, the DASS-42's multidimensional nature makes it well-suited for capturing the nuanced mental health experiences common in the student population.

When completed as a self-administered online questionnaire, the responses are automatically processed to generate scores for the Depression, Anxiety, and Stress subscales of the DASS-42. Each participant's responses are quantified into raw scores and then categorized into severity levels such as normal, mild, moderate, severe, or severe. This immediate scoring capability streamlines the assessment process and facilitates the rapid identification of individuals who may require further psychological support or intervention. The automated scoring system enhances accuracy and minimizes human error, making it a practical and efficient tool for research and clinical applications.

The scoring of the DASS-42 follows established cut-off points to classify the severity of symptoms for each subscale. Based on standardized thresholds, respondents' scores are categorized into the following severity levels, as shown in Figure 2:

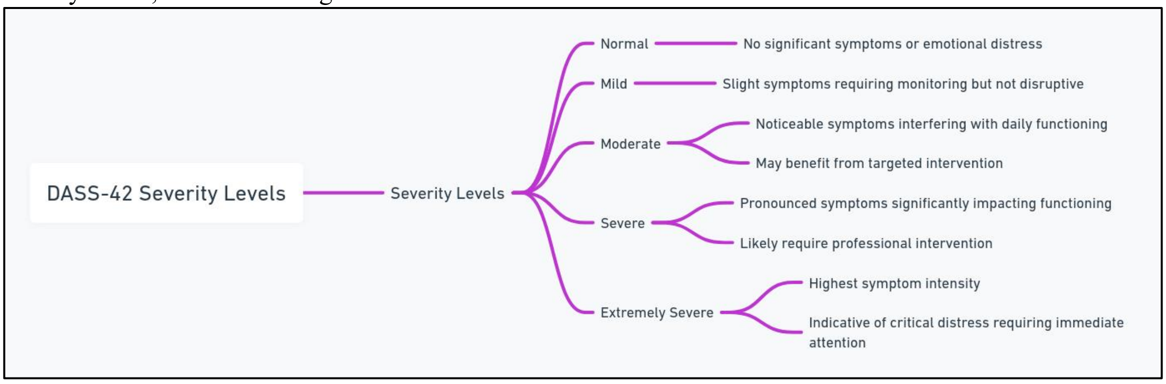

Figure 2. DASS-42 Scale

- **Normal:** Indicates no significant symptoms or emotional distress.
- **Mild:** Reflects the presence of slight symptoms that may require monitoring but are not significantly disruptive.
- **Moderate:** Suggests noticeable symptoms that could interfere with daily functioning and may benefit from targeted intervention.
- **Severe:** Denotes pronounced symptoms that significantly impact functioning and likely require professional intervention.
- **Extremely Severe:** Represents the highest symptom intensity, indicative of critical distress requiring immediate attention and support.

Table 1. DASS-42 Report

Level	Depression	Anxiety	Stress
Normal	0–9	0–7	0–14
Mild	10–13	8–9	15–18
Moderate	14–20	10–14	19–25
Severe	21–27	15–19	26–33
Extremely Severe	28+	20+	34+

Each of the three subscales is scored separately, as shown in Table 1, by summing responses for the relevant items, yielding a total score determining the severity classification. This system allows for nuanced evaluation, facilitating individual and group-level analysis. The DASS-42 has been extensively validated across diverse cultural contexts, ensuring its reliability and applicability for use with students from varied linguistic and demographic backgrounds. In this study, participants completed the scale independently as part of the data collection process, further promoting anonymity and the accuracy of self-reported data. This robust instrument thus serves as a vital tool for identifying the prevalence and severity of depression, anxiety, and stress within the target population. Based on commonly accepted mental health assessments, individuals classified as Normal or Mild generally display emotional and psychological conditions that remain relatively stable. While those in the Mild category may exhibit some early or subtle symptoms, these are typically not severe enough to significantly disrupt everyday functioning [33]. Consequently, both Normal and Mild statuses can be considered indicative of *"good"* implying that substantial clinical intervention is not immediately required.

In contrast, individuals in the Moderate, Severe, or Extremely Severe categories experience more pronounced or critical symptoms that have the potential to interfere substantially with daily activities and overall quality of life [33]. Consequently, these higher-intensity classifications necessitate *"counseling"* or professional support to prevent further deterioration and to facilitate effective management or recovery.

2.4. Ethical Considerations

The study received ethical approval from Universitas Sriwijaya's ethics review board, ensuring adherence to established guidelines for research involving human participants. Before data collection, participants were thoroughly briefed on the study's objectives, procedures, and rights as respondents. This briefing emphasized that participation was entirely voluntary, that individuals could withdraw from the study without consequence, and that their responses would remain strictly anonymous and confidential. Informed consent was obtained electronically, requiring participants to read and acknowledge a detailed consent form before proceeding with the survey. The consent form outlined the study's purpose, data protection measures, and voluntary participation, ensuring participants were fully aware of their involvement and its implications.

Recognizing the sensitivity of the topics addressed in the survey—namely, depression, anxiety, and stress—special provisions were made to safeguard participants' well-being. Students who experienced emotional distress during or after completing the questionnaire were provided with contact information for the university counseling center, where professional support and resources were readily available. This precautionary measure was explicitly communicated to participants both in the consent form and after the survey, demonstrating a commitment to their mental health and safety. By ensuring informed consent, providing clear information about participants' rights, and offering access to emotional support, the study maintained the highest ethical standards throughout its implementation. These measures not only protected participants but also reinforced the credibility and moral integrity of the research process.

2.5. Machine Learning

The process of predicting academic depression, anxiety, and stress begins with defining clear research objectives. The primary aim is to identify patterns and factors that contribute to these mental health issues within academic settings. Data is then collected using the DASS-42 questionnaire and educational records, ensuring a comprehensive dataset capturing relevant information. Once the data is collected, it is preprocessed to ensure quality and consistency. This involves cleaning the data to remove errors, encoding categorical variables for machine learning compatibility, and standardizing values to create a uniform dataset. After preprocessing, the data is split into two subsets: 80% for training the machine learning model and 20% [34][35] for testing its accuracy and reliability.

A Support Vector Machine (SVM) process, as illustrated in Figure 3, was selected as the machine learning model due to its proven effectiveness in classification tasks [36][37]. The model was optimized using cross-validation techniques to enhance its performance and generalizability [38]. Following optimization, the model's effectiveness was evaluated using key performance metrics such as accuracy, precision, recall, and F1 score [39]. Once validated, the next step involved interpreting the key predictive factors identified by the model, highlighting the most significant contributors to academic depression, anxiety, and stress [40]. The findings were documented, and practical recommendations were developed to support early detection and intervention strategies. This structured approach ensures that the research outcomes are reliable, actionable, and beneficial in addressing mental health challenges within academic environments.

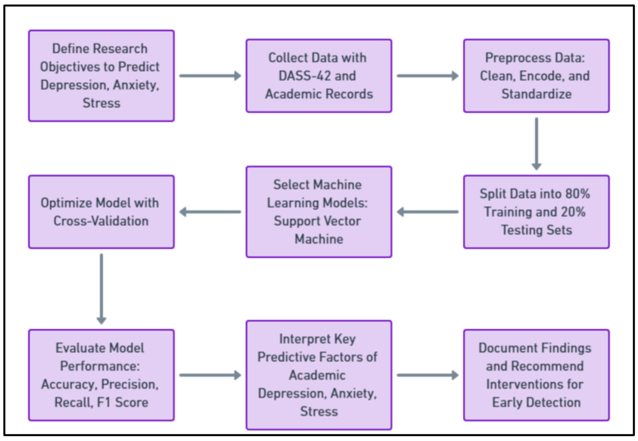

Figure 3. Machine Learning Process

2.6. Proposed Model Development and Contribution

Most previous studies using Support Vector Machine (SVM) for mental health prediction applied classification without addressing the class imbalance problem and limited feature representations, resulting in biased models toward the dominant classes. To address the issue of class imbalance, particularly the underrepresentation of 'counseling' mental health categories, this study employed SMOTE. Additionally, categorical features such as gender, study program, semester, sleeping patterns, and eating habits were encoded using one-hot encoding to improve feature granularity. These input features were preprocessed through encoding of categorical variables and normalization of numerical values. The output labels were classified into two categories: Good and Counseling.

SMOTE is an oversampling technique that generates synthetic examples for the minority class by interpolating between existing minority instances and their nearest neighbors in the feature space [28]. By artificially balancing the dataset, SMOTE helps improve the classifier's ability to learn meaningful patterns from all classes, thereby enhancing both recall and precision for underrepresented groups. The decision to employ SVM was based on its proven effectiveness in managing nonlinear, high-dimensional, and small-to-medium-sized datasets, characteristics often associated with mental health data. SVM is particularly advantageous in contexts where class boundaries are not linearly separable and overfitting must be minimized. Its robust mathematical foundation and generalization ability make it well-suited for multi-class classification problems in limited-feature environments [19][20].

This study introduces a novel approach to early mental health detection by evaluating an optimized Support Vector Machine (SVM) model against a widely used machine learning algorithm—Random Forest—using a real-world academic dataset integrated with a validated psychological instrument (DASS-42). Unlike many existing studies that rely on rich data sources such as clinical indicators, wearable sensors, or comprehensive psychological profiles, this research adopts a lightweight and practical design. It utilizes basic academic and demographic features—gender, age, program of study, semester, and self-reported sleep duration—making it particularly suitable for deployment in resource-constrained educational environments. The enhanced SVM model demonstrates significantly improved recall and precision for minority classes, notably in identifying students requiring 'Counseling' support. This targeted performance improves fairness and actionability, addressing a critical gap in the literature: the need for accessible, efficient, and equitable early detection systems where detailed mental health data may not be available.

3. RESULTS AND DISCUSSION

This section presents the results of the analysis conducted to explore mental health patterns among university students based on self-reported data. The findings are organized according to the research questions and hypotheses outlined in the introduction. Descriptive statistics were first applied to summarize the sample's demographic characteristics, followed by inferential analyses to assess the relationships between critical mental health variables. The results are presented in tables and figures to illustrate the distribution, trends, and significant associations observed in the data. The analysis provides insight into the mental health status of university students, highlighting potential patterns, variations across demographic groups, and correlations between mental health indicators.

3.1. Data Analysis

The dataset used in this study contains self-reported mental health data from university students, with a specific focus on depression, anxiety, and stress levels. The primary objective of the analysis was to identify patterns and correlations between mental health indicators and various demographic and academic variables, including age, gender, academic performance, and social factors. Given the rising concerns about mental health in educational settings, this study seeks to uncover potential trends and relationships that may help inform student interventions and support systems [42][43].

The analysis began with examining the sample's demographic characteristics and assessing students' self-reported mental health status. Descriptive statistics were used to summarize the distribution of depression, anxiety, and stress scores, as well as the demographic data. Inferential statistical methods, such as correlation analysis and regression models, were then employed to explore the relationships between mental health and the demographic and academic variables. Particular attention was given to understanding how these factors may contribute to variations in mental health outcomes and identifying any significant associations that could guide further research and practical interventions.

3.2. Data Preparation

The dataset includes 396 entries, each containing demographic information such as sex, age, field, semester and other related variables along with self-reported mental health scores for depression, anxiety, and stress. The analysis examined the relationships between these mental health variables and demographic factors, ensuring all data points were complete across all categories. The dataset was carefully reviewed and prepared for analysis, with all entries containing valid and complete information for the mental health scores. This thorough data-cleaning process ensured the subsequent statistical analyses' accuracy and integrity, as shown in Figure 4.

```
RangeIndex: 396 entries, 0 to 395
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   sex         396 non-null    object
 1   age         396 non-null    int64
 2   field       396 non-null    object
 3   entering    396 non-null    int64
 4   semester    396 non-null    int64
 5   sleeping    396 non-null    object
 6   eating      396 non-null    object
 7   depression  396 non-null    object
 8   anxiety     396 non-null    object
 9   stress      396 non-null    object
dtypes: int64(3), object(7)
```

Figure 4. Dataset Self-Reported Data

To maintain the integrity and reliability of the analysis, rows with incomplete mental health information were excluded from the dataset like sequence number, student id and name. This process ensured that the subsequent analyses were based on a complete data set, minimizing potential biases introduced by missing values. The decision to exclude incomplete data was based on the understanding that missing values could distort the findings and affect the accuracy of any conclusions drawn from the analysis. Following this step, the remaining data were thoroughly examined and prepared for statistical analysis to identify patterns and relationships between demographic variables and mental health indicators. The following section outlines the results derived from this cleaned dataset.

3.3. SMOTE Analysis

The analysis of mental health scores revealed notable trends in the levels of depression, anxiety, and stress reported by university students, as shown in Figure 5. The analysis, which categorizes student mental health into “Good” and “Counseling,” reveals two principal findings. First, the majority of students are classified as “Good,” suggesting a generally stable level of mental health across the university population. Second, a smaller but significant subset of students is identified as “Counseling,” indicating that these individuals experience psychological concerns or stressors serious enough to merit professional intervention. These results highlight the dual focus required for effective campus mental health strategies. On one hand, maintaining and reinforcing the positive mental health of most students is vital; on the other, there is a clear need to offer targeted support services for those who are at risk or already experiencing more pronounced difficulties. Recommendations include providing consistent access to counseling, organizing preventive programs (such as workshops and peer networks), and ensuring early detection of mental health challenges through screenings. Overall, while many students exhibit resilience and well-being, the presence of a subgroup needing counseling underscores the importance of comprehensive mental health provisions. By addressing these varying needs, universities can better promote overall student wellness and academic success.

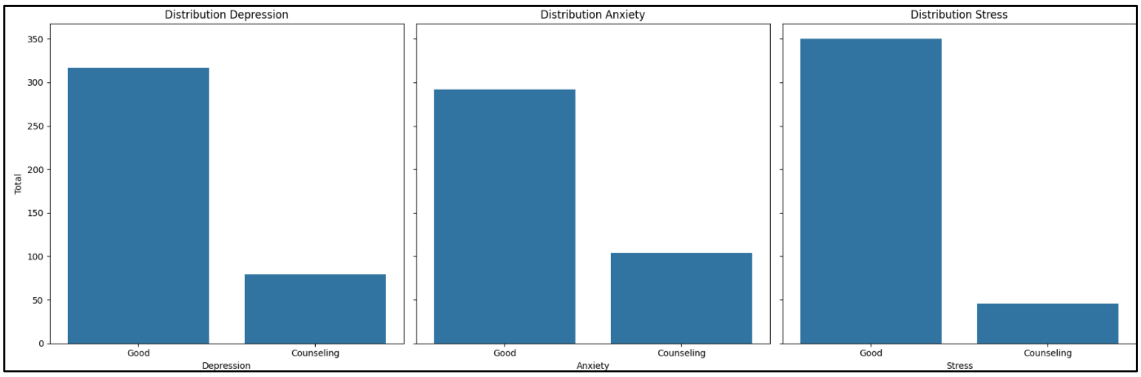

Figure 5. DASS-42 Distribution Result (Imbalance)

The proposed mental health prediction framework follows a structured pipeline, as illustrated in Figure 6. The modeling process begins with a dataset consisting of 396 student records collected through the DASS-42 instrument. Initially, a preprocessing stage is conducted in which categorical variables such as gender, field of study, academic semester, sleep quality, and eating habits are transformed using one-hot encoding. This step ensures that all input features are in a numerical format compatible with machine learning algorithms. Subsequently, the dataset is evaluated for three distinct mental health indicators: depression, anxiety, and stress. Each target is processed independently to allow for specific model tuning and performance assessment as shown in figure 6.

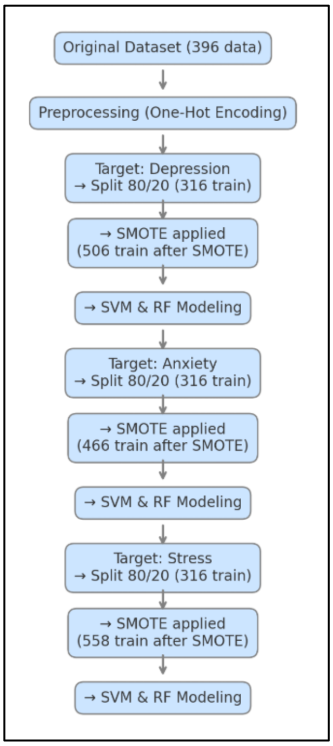

Figure 6. SMOTE Balancing Dataset

The data is split into training and testing sets with an 80:20 ratio, resulting in 316 training instances and 80 test instances. The SMOTE (Synthetic Minority Oversampling Technique) is then applied to the training set to address class imbalance, which is a common issue in mental health datasets where 'Good' cases dominate over 'Counseling' cases. As a result, the training data increases to:

- 506 samples for depression,
- 466 samples for anxiety, and
- 558 samples for stress, with equal class distribution.

The balanced training data is then used to train and evaluate two machine learning models: Support Vector Machine (SVM) and Random Forest (RF). These models are selected for their proven performance in classification tasks and their complementary strengths: SVM offers high sensitivity in imbalanced scenarios, while RF provides robustness and interpretability. This modeling pipeline enables a systematic and fair evaluation of each mental health dimension, providing insights not only into model performance but also into the structure and nature of the underlying data. The independent modeling of depression, anxiety, and stress allows for tailored performance tuning and highlights which aspects of mental health are most effectively predicted by each algorithm.

3.4. Descriptive Data Analysis

The analysis revealed notable gender differences in the mental health scores across depression, anxiety, and stress variables. Figure 7 shows the distribution of depression levels among male and female students, categorized into Good and Counseling groups. The chart reveals that the majority of students in both gender groups fall into the "Good" category, indicating that most students experience minimal depressive symptoms. However, a noticeable difference is observed in the Counseling category: male students show a slightly higher proportion of depression levels requiring counseling compared to female students. This suggests that, while depression rates remain relatively low across the sample, male students may experience a marginally higher burden of depressive symptoms. These findings reinforce next results seen in anxiety and stress patterns, further highlighting the importance of targeted mental health outreach, especially for male students who may be less likely to seek help despite needing support.

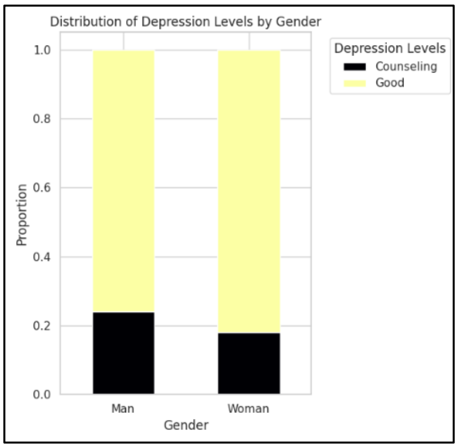

Figure 7. Depression by Gender

Figure 8 illustrates the distribution of anxiety levels among male and female university students, categorized into two groups: Good and Need Counseling. The data reveal that a higher proportion of students in both gender groups fall under the "Good" category, indicating relatively low levels of anxiety overall. However, a notable difference is observed in the proportion of students requiring counseling. Specifically, male students show a slightly higher proportion in the "Counseling" category compared to their female counterparts. This suggests that although anxiety levels are generally low across the sample, male students may be experiencing slightly greater psychological distress that reaches the threshold for counseling. These findings align with broader patterns in the depression data and further highlight the need for gender-sensitive mental health interventions, particularly focusing on male students who may underreport symptoms or delay seeking help despite elevated stress indicators.

Figure 9 presents the distribution of stress levels among male and female university students, divided into two categories: Good and Need Counseling. The visual data indicate that the vast majority of students in both gender groups fall into the "Good" category, suggesting that most students report manageable levels of stress. Only a small proportion of students—both male and female—fall into the "Counseling" category, indicating elevated stress levels that may require professional support. Notably, the proportion of students requiring counseling is nearly identical between men and women, suggesting no significant gender disparity in stress levels within this sample. This contrasts with the patterns observed in depression and anxiety, where gender differences were more pronounced. These findings imply that while stress is prevalent, it affects male and female students at similar rates, underscoring the importance of providing accessible stress management resources and preventative mental health programs for the broader student population.

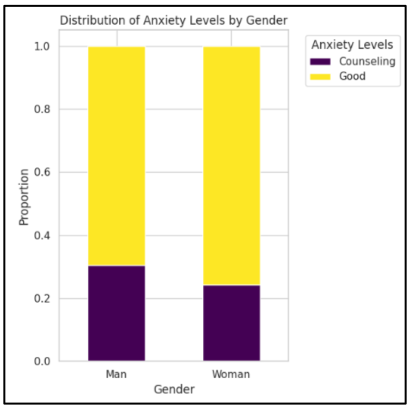

Figure 8. Anxiety by Gender

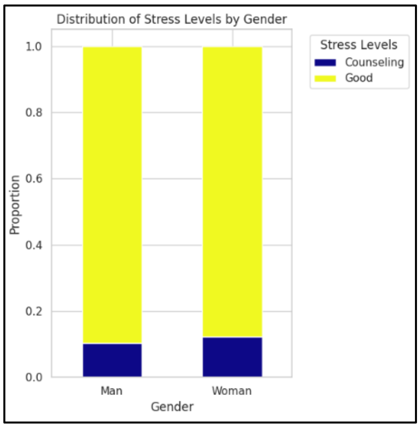

Figure 9. Stress by Gender

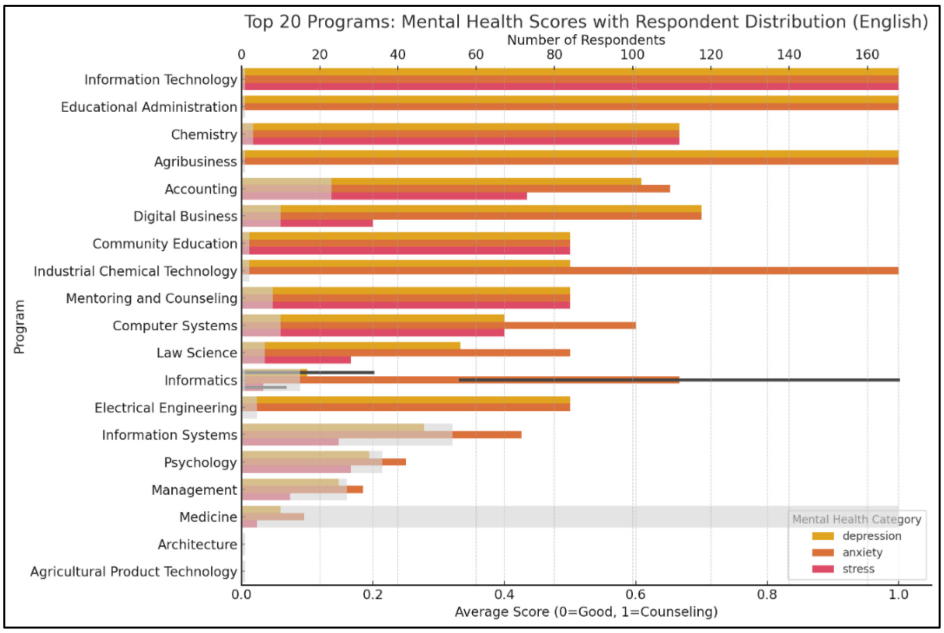

Figure 10. Program-Based Insights

Based on the DASS (Depression, Anxiety, and Stress Scale) results obtained from 396 records, 5 study programs show the most significant challenges in student mental health, specifically related to anxiety, depression, and stress. Educational Administration recorded the highest scores in all three categories, with anxiety approaching a score of 5, signaling immense emotional distress in students. In addition, high levels of depression and stress indicate the presence of significant academic and administrative burdens in this program, as shown in Figure 10.

The Information Technology study program exhibited elevated mental health scores, with anxiety levels approaching 1, indicating that a significant portion of students may fall into the "Counseling" category. Depression and stress scores were also relatively high, suggesting broader emotional challenges. These findings may be associated with the high academic pressure and the rapid pace of technological change, which require students to constantly adapt and stay current, potentially contributing to emotional strain and psychological fatigue. This suggests that, beyond academic pressures, students in this field face the added challenge of maintaining performance in a rapidly evolving domain [44]. Similarly, the Chemistry and Digital Business study programs displayed high anxiety levels, with Chemistry scoring above four and Digital Business close to 4, reflecting significant stress in both programs. In Chemistry, anxiety, and stress are likely triggered by academic pressures and complex laboratory tasks. In contrast, in Digital Business, anxiety is more closely tied to business performance expectations and technological innovation adaptation [45][46]. These findings illustrate that students in both programs encounter substantial challenges in managing academic and professional pressures. Overall, these programs reported the highest levels of anxiety, followed by significant depression and stress, indicating that students face considerable mental health challenges influenced by academic demands, practical workloads, and rapid professional changes [47].

Universities should provide targeted mental health support for students in high-stress programs like Information Technology, Chemistry, and Digital Business. Key strategies include improving access to counseling (both online and offline), integrating mental health education into the curriculum, offering flexible academic schedules, and implementing gender-specific interventions. Additionally, digital mental health tools have proven effective in reducing stress and can offer ongoing support to students facing emotional and academic challenges.

3.5. Machine Learning Technique

The study implemented a Support Vector Machine (SVM) model, enhanced with SMOTE to address class imbalance, for analyzing mental health patterns among university students. The primary goal was to predict levels of depression, anxiety, and stress using features such as gender, age, study program, and semester. These features were preprocessed through categorical encoding and numerical normalization to ensure consistent input for the model. The target labels were categorized into two classes: Good and Counseling.

The decision to use SVM was based on its well-documented effectiveness in handling high-dimensional, nonlinear, and imbalanced classification problems, which are common in mental health datasets. SVM's ability to find optimal decision boundaries with minimal generalization error makes it particularly suitable for small to medium-sized datasets where overfitting is a concern. Furthermore, its performance has been shown to be competitive if not superior in similar mental health prediction tasks. While alternative models such as Random Forest offer strong performance, SVM was selected in this study for its balance between accuracy, interpretability, and robustness in limited-feature environments.

Table 2. Depression Confusion Matrix Result

Model	Classification	Precision	Recall	F1-Score	Accuracy
Support Vector Machine(SVM)	Good	0.97	0.97	0.97	0.97
	Counseling	0.97	0.97	0.97	
Random Forest (RF)	Good	0.97	0.97	0.97	0.97
	Counseling	0.97	0.97	0.97	

Table 3. Anxiety Confusion Matrix Result

Model	Classification	Precision	Recall	F1-Score	Accuracy
Support Vector Machine(SVM)	Good	0.94	0.71	0.81	0.91
	Counseling	0.91	0.98	0.94	
Random Forest (RF)	Good	0.88	0.71	0.79	0.90
	Counseling	0.9	0.97	0.93	

Table 4. Stress Confusion Matrix Result

Model	Classification	Precision	Recall	F1-Score	Accuracy
Support Vector Machine(SVM)	Good	0.69	0.97	0.82	0.95
	Counseling	0.97	0.94	0.97	
Random Forest (RF)	Good	0.67	0.67	0.67	0.93
	Counseling	0.96	0.96	0.96	

An in-depth examination of Support Vector Machine (SVM) and Random Forest (RF) outcomes for detecting “Good” and “Counseling” mental health cases reveals consistently strong performance across three target conditions: depression, anxiety, and stress. In the realm of depression (Table 2), both models achieved an accuracy of 0.97, accompanied by near-perfect precision, recall, and F1-scores (all 0.97). When examining anxiety (Table 3) and stress (Table 4), performance differences between SVM and RF become more pronounced. For anxiety, SVM secures a slightly higher accuracy (0.91) than RF (0.90), attributable to its stronger precision (0.94) in identifying the “Good” class; however, both models exhibit only moderate recall for “Good,” suggesting possible overlapping feature distributions or imbalanced data that persist even after SMOTE is used to augment the minority class. In stress prediction, SVM outperforms RF (0.95 vs. 0.93 accuracy). Notably, RF’s near-perfect precision and recall (0.96 each) for “Counseling” are countered by its weaker performance (precision = 0.67, recall = 0.67) for “Good,” ultimately reducing its overall accuracy. By contrast, SVM maintains a more balanced classification of both categories. Despite SMOTE’s intention to address class imbalance, these residual misclassifications suggest that synthetic samples, while beneficial, cannot fully overcome feature overlap or inadequacies in feature representation. Without SMOTE, both models achieved high overall accuracy but demonstrated poor performance in identifying the minority “Counseling” class, as reflected in their low recall and F1-scores. After applying SMOTE, the recall and F1-scores for this class improved significantly—particularly in the stress classification task, where SVM’s recall increased from 0.75 to 0.94. However, this improvement came with minor trade-offs, such as reduced precision and the potential for increased feature overlap.

These findings suggest that the dataset and feature set for depression are sufficiently discriminative, allowing both SVM and RF to establish clear decision boundaries with minimal misclassification. Given that Synthetic Minority Over-Sampling Technique (SMOTE) was applied to mitigate potential class imbalance, these near-perfect metrics also indicate that either the data for depression were already balanced or that the discriminative features are robust enough for both models to perform at a similarly high level. SMOTE operates by generating synthetic data points for the minority class through interpolation between a data point and its nearest neighbors. Unlike random oversampling, it creates new instances that preserve the underlying distribution of the feature space, thereby reducing overfitting. This technique is particularly effective in improving model sensitivity toward underrepresented categories, such as “Counseling”. However, SMOTE does not inherently consider categorical context such as students' academic programs unless that information is explicitly included in the dataset and numerically encoded. Without such preprocessing, SMOTE focuses solely on the numerical feature space and may overlook group-specific distinctions. By combining SMOTE or alternative oversampling techniques with an expanded feature set, both SVM and RF may be refined to provide earlier and more accurate identification of individuals requiring counseling services, thus improving mental health support in university contexts.

4. CONCLUSION

In conclusion, the results highlight that SVM exhibits consistently higher accuracy across multiple indicators, especially for the minority “Counseling” group, rendering it particularly effective for early detection scenarios where overlooking at-risk students could have serious consequences. In contrast, RF demonstrates a generally balanced performance but occasionally falls short in identifying minority cases. Consequently, SVM stands out as the preferred primary model in contexts where prompt identification of students requiring psychological intervention is paramount. The incorporation of comprehensive data preprocessing, SMOTE-based class balancing, and structured feature encoding was instrumental in enhancing both models’ predictive power. SVM’s resilience to certain imbalances and its capacity to derive robust margins for classification, combined with SMOTE’s ability to broaden minority-class representation, make this integrated approach well-suited for early mental health detection. However, further augmentation of the feature set—for instance, adding longitudinal tracking, behavioral patterns, or physiological markers—has the potential to enhance separability between “Good” and need “Counseling” and to reduce misclassification arising from overlapping features.

SVM demonstrates marginally stronger performance for anxiety and stress, while both SVM and RF excel in detecting depression. Although SMOTE helps equalize the representation of “Counseling” cases, overlapping feature distributions and limited feature diversity still impede perfect separation of classes, particularly for “Good” in stress and anxiety. Future endeavors should therefore focus on enhancing feature variety—e.g., by incorporating behavioral or physiological indicators—to facilitate finer-grained distinctions between closely related classes.

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