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Classification of Risk and Protective Factors for Students' Mental Health Using Data Mining Techniques

Rika Damayanti*, Fiqih Satria
Universitas Islam Negeri Raden Intan Lampung, Indonesia
rikadamayanti@radenintan.ac.id*

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Abstract

Mental health issues affecting university students, particularly first-year students, are increasingly concerning, with many experiencing anxiety, depression, and substance abuse. Globally, approximately one in three first-year students faces these challenges. In the U.S., 22% of students receive psychiatric treatment, while in Indonesia, 10% of youth aged 15-24 report psychological problems, with suicide rates on the rise. These disorders negatively impact academic performance, emotional well-being, and social interactions, with contributing factors such as lifestyle, genetics, and gender. Unhealthy habits heighten the risk, while regular physical activity and engagement in hobbies act as protective factors. This research aims to analyze the risk factors and mental health protection of students using a data mining approach. With classification techniques, this research is expected to provide a holistic understanding of the risk factors causing mental health disorders among students and to identify the protective factors. Based on responses from 1,039 students across 15 districts in Lampung Province, the analysis identifies key risk factors including academic pressure, poor time management, heavy workloads, and lack of social support. Protective factors identified include spending time in nature, ensuring sufficient sleep, and balanced participation in student organizations. Findings suggest that universities should implement targeted mental health interventions, provide counseling services, offer workshops and peer support groups, and create a supportive, green campus environment to enhance student well-being and mitigate stress.

INTRODUCTION

Mental health among students has emerged as a critical issue within higher education today. The dynamic development of the brain and the psychological conditions experienced by students, particularly during their initial years at university, render them susceptible to psychological disorders (Prasetio & Triwahyuni, 2022; Satriyo, 2022). Research indicates that one in three first-year students across 19 universities in eight countries are suspected to suffer from common disorders, including anxiety, mood disorders, and substance abuse (Auerbach et al., 2018). Research in America indicates that around 22% of students are undergoing psychological or psychiatric treatment due to excessive anxiety, 17.3% are experiencing depression, and 11% are experiencing panic attacks (American College Health Association [ACHA], 2018). In Indonesia, the Basic Health Research reports that 10% of those aged 15-24 experience psychological disorders, 6.2% experience depression, and there is a 10.6% suicide rate among those aged 10-20 (Kemenkes, 2018). Recent data from the National Criminal

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Information Center of the Indonesian National Police recorded 971 suicide cases in Indonesia, surpassing the previously reported figure of 900 cases. This increase highlights the growing concern over mental health issues and the need for enhanced suicide prevention efforts in society. It is important to note that these numbers may not fully reflect the actual number of cases, as underreporting could occur due to social stigma and limitations in data collection systems (Pusiknas Polri, 2023).

Impact of psychological disorders on students encompasses academic performance, emotional management, and social relationships. For instance, students experiencing depression may endure persistent sadness, feelings of unappreciation, and a sense of emotional uselessness. Cognitively, repetitive negative thinking can impede academic achievement and hinder effective information processing (Emery, 2019; Misbah et al., 2022). Challenges in achieving satisfactory academic performance often led to increased dropout rates among students (Hjorth et al., 2016), while individuals suffering from depression typically withdraw from social environments (American Psychiatric Association [APA], 2013).

Several risk factors for psychological disorders in students involve lifestyle, genetic factors, gender, cohort, and history of using psychological services (Beiter, 2015; Dachew et al., 2015; Velten et al., 2018). Unhealthy lifestyles, such as smoking, and irregular physical and mental activities can increase the risk of psychological (Velten et al., 2018). Conversely, regular physical activities and hobbies can reduce the level of psychological disorders and enhance well-being (Moore, 2018; Netz et al., 2005).

This research aims to analyze the risk factors and mental health protection of students using a data mining approach. With classification techniques, this research is expected to provide a holistic understanding of the risk factors causing mental health disorders among students and to identify the protective factors.

Results of this research are expected to assist universities and policymakers in developing more targeted and effective prevention strategies. This study not only focuses on risk factors but also provides insights into protective factors that can support students in managing mental health and enhancing the overall higher education experience, along with the mental health services offered by universities.

Literature Review

Research on mental health issues among students has produced a variety of findings that highlight the complexity of this topic. Specific psychological risks and protective factors that undergraduate students face, which significantly influence their mental well-being (Prasetio & Triwahyuni, 2022). In contrast, the WHO World Mental Health Surveys International College Student Project, led (Auerbach et al., 2018), reported a broader prevalence and distribution of mental disorders among college students, emphasizing the global nature of these challenges. Oppenheimer, (2022) examined suicide and self-injury from a developmental psychopathology perspective, indicating the need for integrative approaches in future studies.

Additionally, Labuhn (2022) focused on the trends and causes of adolescent suicide in the United States, providing important insights into the vulnerabilities of young people. Azasu & Joe (2023) investigated suicide correlates among middle and high school students in Ghana, revealing region-specific factors that affect mental health outcomes. In Indonesia, Ayuningtyas et al. (2018) conducted a comprehensive analysis of the mental health landscape, suggesting strategies to address the increasing prevalence of mental health disorders. Collectively, these studies illustrate the multifaceted nature of mental health issues across different contexts and indicate the need for tailored interventions and strategies that meet the needs of diverse populations. Kurniawan et al. (2024) showed that depression and low self-esteem are strong predictors of suicidal behaviour among adolescents, which is also relevant in the college context. Fine et al. (2022) explains that unhealthy social interactions, including friendships with substance users, increase the risk of behavioural disorders in Indonesia, especially in bandar lampung. Junilia et al. (2023) examined the levels of depression, anxiety, and stress of new Malahayati University students.

Despite the substantial body of knowledge produced by these studies, significant gaps remain. Most research on student mental health primarily identifies risk and protective factors through traditional methods, often overlooking advanced data analytics techniques, such as classification methods, which could enhance the modeling and prediction of mental health outcomes (Armstrong et al., 2019; Haliwa, 2022; Hazzard, 2023). As a result, there is a considerable gap in understanding how these sophisticated analytical techniques can provide deeper insights into student mental health.

Much of the research conducted on this topic tends to focus on global trends or specific countries, such as the prevalence of anxiety, depression, and suicidal ideation among university students, or country-specific analyses, especially in regions that are often under the spotlight. particularly the United States and Ghana (Arhin-Larbi & Owu-Annan, 2023; Auerbach et al., 2018; Azasu, E., & Joe, 2023; Zhang, 2023). However, there is a noticeable lack of studies that specifically examine the mental health risk factors and protective mechanisms relevant to university students in Lampung Province, Indonesia. This absence of localized research limits the applicability of findings to the unique context and needs of students in this region, underscoring a critical area for future investigation.

Current studies typically emphasize either risk factors or protective factors, but they often fail to offer a comprehensive model that integrates both elements (Patel, 2023; Haliwa, 2022; Iovoli et al., 2024; Priestley & Spanner, 2021). Furthermore, the relationship between mental health services provided by universities and their effectiveness in reducing psychological disorders has not been thoroughly explored. This gap indicates a need for further research to optimize these services for better support of student well-being.

Moreover, studies addressing mental health across various age groups or educational levels, such as middle and high school, tend to overlook the specific psychological challenges faced by university students (Baojing li, 2023; Campbell et al., 2022; Hjorth et al., 2016; Zuriguel-Pérez et al., 2019). These demographic experiences unique transitions, particularly when moving into higher education, which requires targeted research to understand and address their distinct mental health needs.

In conclusion, while considerable progress has been made in understanding mental health issues among students, significant gaps in research still exist. Addressing these gaps through localized studies and the application of advanced analytical methods will be essential in developing effective interventions tailored to the unique needs of diverse student populations.

Mental health among university students has emerged as a critical concern in higher education globally (Zulkarnain et al., 2024). Transitions to university life, combined with emotional changes during young adulthood, render students particularly susceptible to psychological disorders (Cage et al., 2021). First-year students often experience substantial academic pressures, lifestyle adjustments, and social transitions, leading to anxiety, depression, and, in severe cases, suicidal tendencies (Beiter, 2015). Research indicates that these psychological conditions adversely impact well-being, academic performance, and social interactions.

Despite these concerning trends, research employing modern analytical techniques to study mental health among university students in Indonesia remains scarce. Most studies focus on broader populations or rely on traditional methods that may lack depth necessary for effective prevention and intervention strategies (Baojing li, 2023; Musyimi et al., 2018). While risk factors such as academic stress, social isolation, and unhealthy lifestyles have been identified, research exploring protective factors like mental health services and social support that could mitigate these risks is insufficient (Barbayannis et al., 2022; Salazar-granizo & Hueso-montoro, 2024; Schneiderman et al., 2008).

Recognizing the importance of mental health for academic success and personal well-being, this study aims to fill existing gaps by employing a data mining approach to classify and analyze both risk and protective factors influencing students' mental health. Advanced classification techniques will identify patterns within mental health data, providing a comprehensive understanding of factors contributing to psychological disorders. Furthermore, this study will explore the effectiveness of university mental health services in promoting psychological well-being, offering valuable insights for targeted interventions.

Focusing specifically on university students in Lampung Province, this research will address unique cultural, social, and educational challenges affecting mental health. Findings will enrich academic literature on mental health in higher education while providing practical recommendations for universities and policymakers to enhance mental health services. Ultimately, this research aims to improve students' mental health, academic performance, and overall university experience, fostering a healthier and more supportive educational environment.

This research aims to achieve several key objectives. First, data mining and classification techniques will develop a robust understanding of both risk and protective factors, providing data-driven insights into the mental health landscape of university students. Second, the study will concentrate on students in Lampung Province, offering localized insights into mental health challenges and tailored recommendations for services. Additionally, this research seeks to integrate risk and protective factors into a comprehensive model, equipping universities and policymakers with actionable strategies for mental health prevention and promotion. By identifying patterns linked to students' psychological well-being, this study will contribute insights that enhance the effectiveness of university mental health programs and policies.

METHODS

Population and the Methods of Sampling

This research focuses on students from various universities spread across 15 districts / cities in Lampung Province with 15 universities as samples in this study. The sampling method used is cluster random sampling (Bryman, 2016; Cochran, 1977; Rudianto et al., 2022). The online questionnaire link was randomly distributed to the students without considering certain factors (Aziz et al., 2022; Netriwati et al., 2023). This is done to ensure that the obtained sample represents the overall student population in Lampung Province. A total of 1,039 students participated in this study by filling out the questionnaire. The sufficiently large number of respondents allows researchers to obtain more representative and accurate research results.

Instrumentation

In total, 1,039 active students from 15 regencies and cities in Lampung Province participated in the online questionnaire distributed through social media. This questionnaire aims to measure levels of depression, anxiety, and stress, as well as risk factors and protective factors for mental health among students. Instruments used include the depression Anxiety Stress Scale-21 (DASS-21) and an instrument for assessing mental health risk and protective factors for students.

Depression Anxiety Stress Scale-21. The mental health of students is categorized, and the severity level is determined based on respondent data obtained from the DASS-21 (Lovibond, 1995). The respondents' answers to the DASS-21 questionnaire are transformed into scores presented in Table 2. After the mental health of students is categorized into Depression, Anxiety, or Stress categories. The next step is to determine the levels of Depression, Anxiety, and Stress into three levels (mild, moderate, severe) by summing the scores from each respondent's answers using the formula presented in Table 3 (Lovibond, 1995).

Table. 1 DASS-21 Questionaries.

Questions	Category	Code
I find it difficult to calm down.	Anxiety	A1
I feel like my mouth is dry.	Stress	S1
I can't feel any positive emotions at all.	Depression	D1
I have difficulty breathing (for example, breathing too fast, panting without physical activity).	Stress	S2
I find it hard to start things.	Anxiety	A2
I tend to overreact to situations.	Anxiety	A3
I experience trembling (for example, in my hands).	Stress	S3
I feel anxious.	Anxiety	A4
I feel completely hopeless.	Depression	D2
I feel very irritable.	Anxiety	A5
I find it hard to relax.	Depression	D3
I feel sad and depressed.	Depression	D4
I feel intolerant of disruptions to my activities.	Anxiety	A6
I feel very nervous.	Anxiety	A7
I feel like nothing can make me happy.	Depression	D5
I feel worthless.	Depression	D6
I feel irritable.	Stress	S4
I feel changes in heart rate (for example, faster heartbeat).	Stress	S5
I feel scared for no apparent reason.	Anxiety	A8
I feel life is meaningless.	Depression	D7
I find it very difficult to stay calm.	Depression	D8

Table 2. Scoring DASS-21 Questionaries.

Answer	Score
Very Often	4
Often	3
Sometimes	2
Never	1

Table 3. Mental Health Assessment Formula.

Component	Formula	Mental Health Level
Depression	(D1+D2+D3+D4+D5+D6+D7+D8)	8 – 12 : Mild Depression 13 – 18 : Moderate Depression 19 – 32 : Severe Depression
Anxiety	(A1+A2+A3+A4+A5+A6+A7+A8)	8 – 12 : Mild Anxiety 13 – 18 : Moderate Anxiety 19 – 32 : Severe Anxiety
Stress	(S1+S2+S3+S4+S5)	5 – 8 : Mild Stress 9 – 13 : Moderate Stress 14 – 20 : Severe Stress

Instrument for Risk Factors and Mental Health Protection for Students. In addition to filling out the DASS-21 questionaires to measure levels of depression, anxiety, and stress, the students also completed a mental health survey consisting of 10 questions with 4-likert scale from 'Very often' to 'Never'. This survey aims to delve deeper into the risk factors and protective factors for their mental health (See Table 4).

Procedures

The steps to be undertaken in this research process include data collection, data selection to determine relevant data, data cleaning by addressing null attributes, data integration to combine related information from various attributes, The steps undertaken in this research process include data collection, data selection to determine relevant data, data cleaning by addressing null attributes, data integration to combine related information from various attributes, data transformation into a format that can be processed by Orange Data Mining software, application of the ID3 algorithm, model evaluation, and interpretation of decision tree analysis results (Kaufmann & Kamber, 2011). In the data preprocessing stage, additional steps were taken to improve data quality before inputting it into the software. Missing values were addressed by removing incomplete entries or imputing values where necessary to ensure dataset completeness. Data attributes were normalized to scale values within a consistent range, ensuring uniformity across features and preventing skewed analyses. Outliers that could significantly distort the results were identified and either removed or adjusted based on statistical thresholds to maintain data reliability and accuracy (Kaufmann. & Kamber, 2011). To clarify the research process, Figure 1 shows the research flow from data collection to interpretation of analysis results.

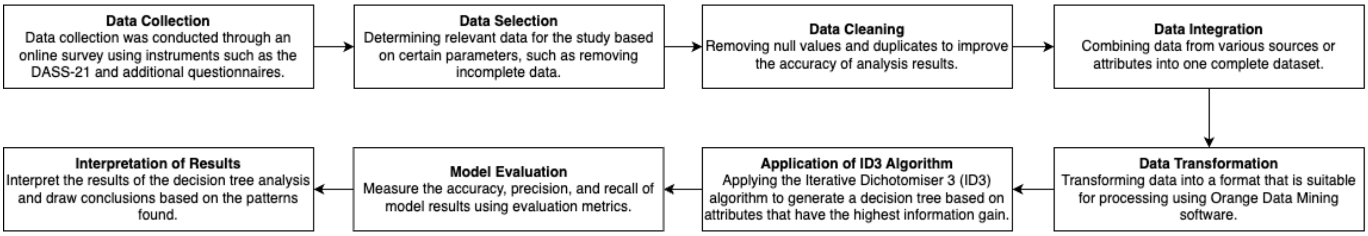

Figure 1. Research flowchart.

Table 4. Questionnaires Risk Factors and Mental Health Protection for Students.

Questions
Do you feel overwhelmed by the amount of college assignments?
Do you feel anxious and worried about not being able to meet the desired grade target?
Do you find it difficult to manage your time between studying and other activities?
Do you feel lonely and don't have close friends on campus?
Are you involved in student organization activities?
Are you able to adapt to changes and difficult situations?
Are you involved in extracurricular activities on campus?
Do you have a consistent sleep routine (7-8 hours) every night?
Do you feel your condition improves when you are in green open spaces?
Do you believe and are you convinced that worshiping and praying to God gives you strength and support in facing difficulties?

Data Analysis

The analysis of risk factors and mental health protection was conducted using data mining techniques with the ID3 decision tree algorithm to recognize patterns formed from the generated decision tree. The ID3 algorithm was chosen due to its simplicity and efficiency in handling categorical data, which aligns well with the types of variables used in this study, such as academic pressure, sleep habits, and social interactions. Unlike more complex algorithms such as C4.5 or Random Forest, ID3 constructs decision trees by selecting attributes with the highest information gain, making it computationally less intensive and easier to interpret. Additionally, the ID3 algorithm provides a clear hierarchical structure that facilitates the identification of key decision-making factors related to students' mental health. The performance of the ID3 model was evaluated using metrics such as Area Under the Curve (AUC), Classification Accuracy (CA), F1 Score, Precision, Recall, and Matthews Correlation Coefficient (MCC) (Quinlan, 2007). This approach ensures that the selected algorithm not only classifies data accurately but also provides meaningful insights into the most influential factors contributing to mental health outcomes (Quinlan, 2007).

RESULTS AND DISCUSSION

Findings presented in the pie chart underscore the pressing mental health challenges faced by the population studied, necessitating a thorough examination of the underlying factors contributing to these stress and anxiety levels.

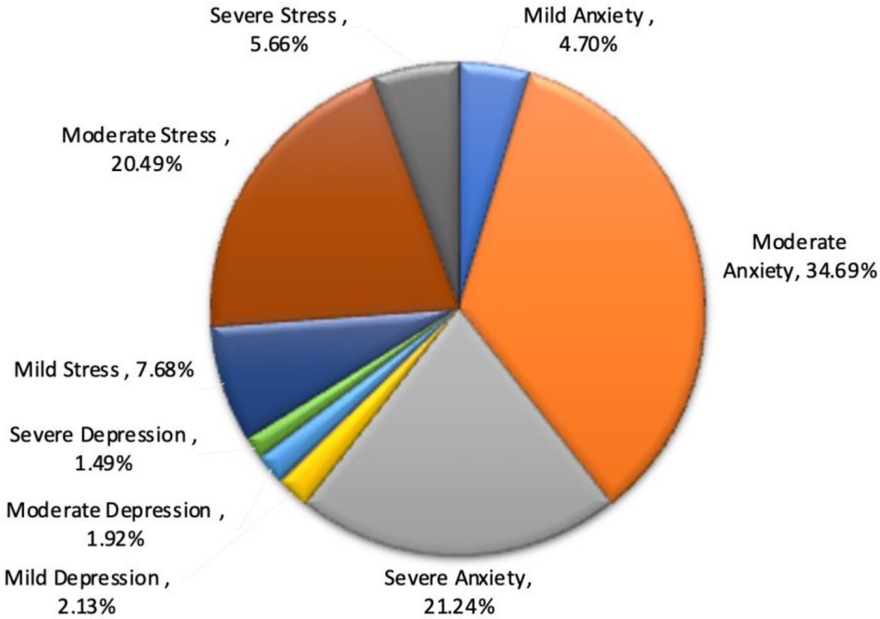

Figure 2. Mental Health of Students in Lampung Province in 2024

Based on the assessment results of mental health categories and levels, students in Lampung Province experience various mental disorders, namely Anxiety (60.63%), Stress (33.83%), and Depression (5.54%). This indicates that the mental health of students in Lampung Province needs serious attention. Anxiety disorders are the most common type of mental disorder experienced by students in Lampung Province, with a percentage reaching 60.63%. This consists of mild anxiety (4.70%), moderate anxiety (34.69%), and severe anxiety (21.24%). Stress disorders are also one of the mental disorders quite commonly experienced by students in Lampung Province, with a percentage reaching 13.83%. This consists of mild stress (7.68%), moderate stress (20.49%), and severe stress (5.66%).

Although the percentage is not as high as anxiety and stress disorders, depression disorders are also an important concern, with 5.54% of students experiencing them. This consists of mild depression (2.13%), moderate depression (1.92%), and severe depression (1.49%). From the initial 1,039 data points, several data cleaning steps were taken to improve the quality of the analysis. Duplicate data was found in several variables, such as (Anxiety, Depression), (Stress, Anxiety), and (Stress, Anxiety, Depression). This duplicate data has been deleted to ensure the accuracy of the analysis. Removal of mild mental health disorder data: Data from students with mild mental health disorders were removed from the analysis. This is done to focus on student data with moderate to severe levels of disruption that require more intensive intervention.

Table 5. Selection of Dependent Variables for the Data Mining process

Mental Health	Cases
Moderate Stress	192
Severe Stress	53
Stress	245
Moderate Anxiety	325
Severe Anxiety	199
Anxiety	524
Moderate Depression	18
Severe Depression	14
Depression	32
Total	801

After the data cleaning process, 937 data entries remain. Out of these 937 data points, 801 have moderate to severe mental health levels. This data will be used for analysis using the ID3 data mining algorithm.

Data Mining Processing

The data mining analysis in this study uses Orange Data Mining Software Version 3.36.2. The aim is to study patterns and trends in students' mental health data (Kaufmann & Kamber, 2011). See Figure No. 4 ID3 Decision Tree Results can be found at the following link: https://drive.google.com/file/d/12EBdVik-kLdDJHUo99oek7PjPeC5PWM/view?usp=sharing

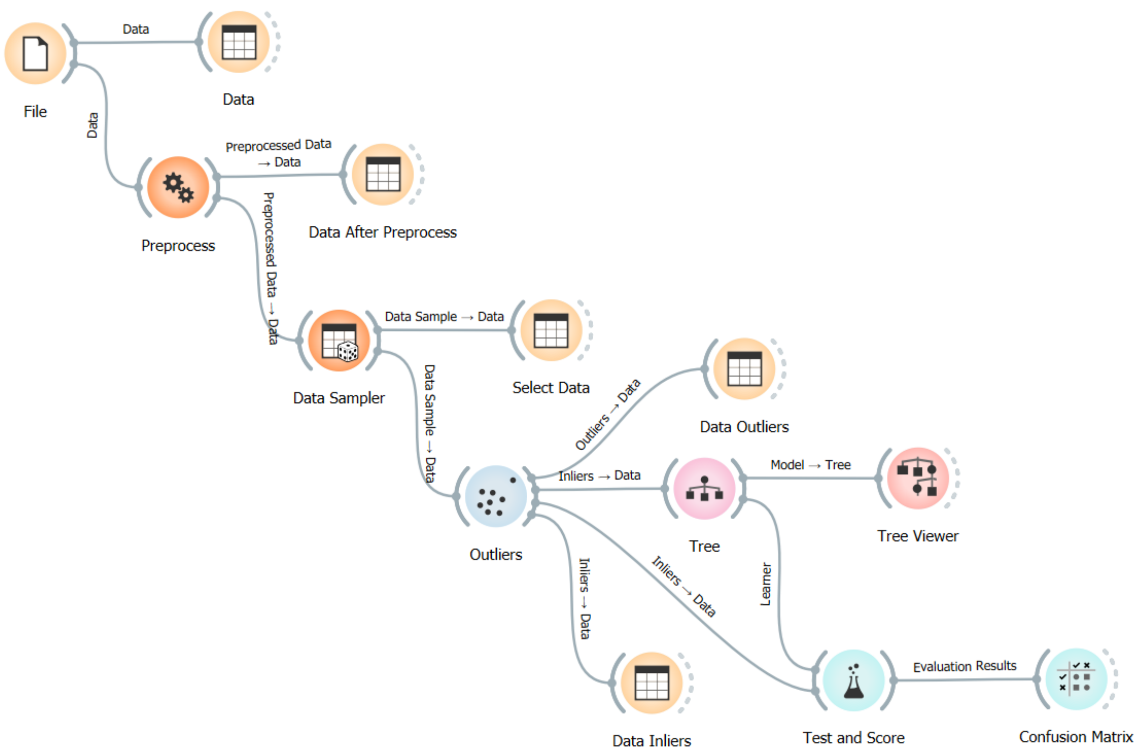

Figure 3. ID3 analysis using orange software.

Predicted

Actual	Anxiety	Depression	Stress	Σ
Anxiety	397	4	64	465
Depression	9	8	5	22
Stress	118	2	123	243
Σ	524	14	192	730

Figure 5. Confussion Matrix

Table 6. ID3 Decision Tree Prediction Results

Mental Health	Incorrect Prediction	Correct Prediction	Data Count	Percentage of Correct Prediction
Anxiety	68	397	465	86,24%
Depression	14	8	22	36,36%
Stress	120	123	243	49,79%

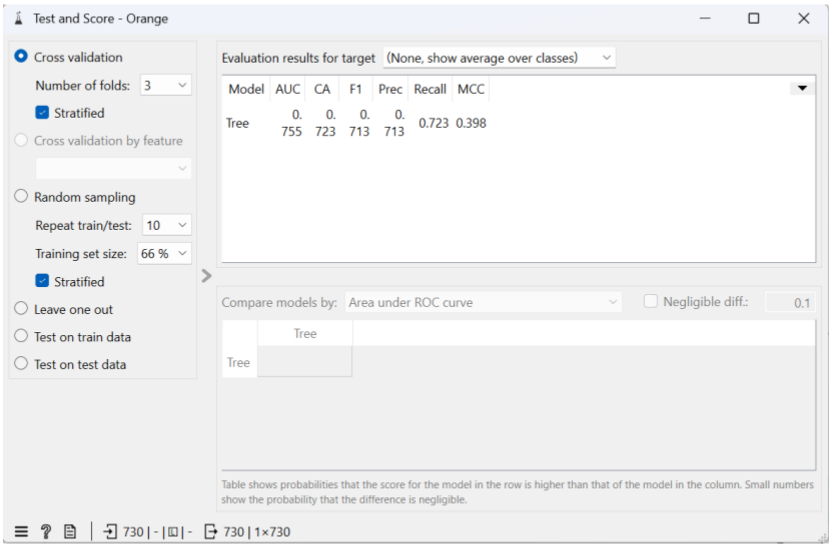

Figure 6. Results of the ID3 Model Test and Score

The analysis results show that the ID3 model/algorithm can be used to predict risk factors and mental health protection for students with fairly good accuracy. This model can help identify students at high risk of experiencing mental health problems and provide appropriate interventions.

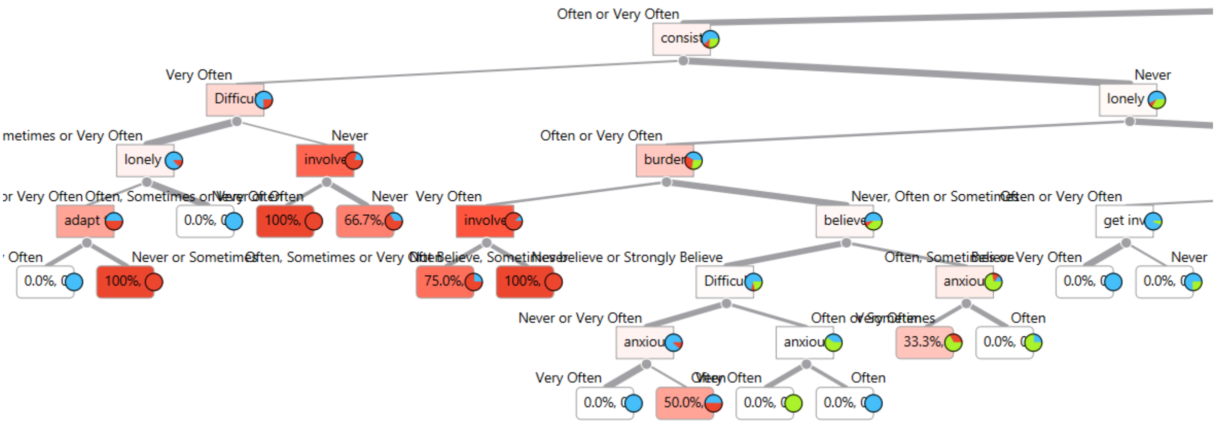

Figure 7. Analysis of Risk Factors and Mental Health Protection Factors for Students in Relation to the Depression Variable.

The decision tree analysis results from Figures 7, 8, and 9 provide insights into the primary risk factors and protective mechanisms associated with student mental health issues. In Figure 7, the first key split is determined by the consistency of sleep routines. This indicates that irregular sleep patterns significantly correlate with an increased risk of mental health issues, such as anxiety, depression, and stress. Students who maintained consistent sleep routines generally exhibited lower risks of mental health problems, supporting previous findings that highlight the importance of regular sleep for psychological well-being (Harvey, 2005).

Figure 8 shows that students who are actively involved in organizational activities are less likely to experience severe anxiety and stress. Active participation in student organizations fosters a sense of social connectedness and helps reduce feelings of isolation, aligning with Astin's (1999) research on the importance of social involvement. Conversely, students who rarely or never participate in such activities are found to be more vulnerable to mental health disorders, reinforcing the protective role of social support.

Figure 9 illustrates that students who struggle with time management are more prone to stress and anxiety, particularly if they also lack adequate social support. This finding supports Eisenberg's (2013) research, which identifies poor time management as a significant contributor to academic-related stress.

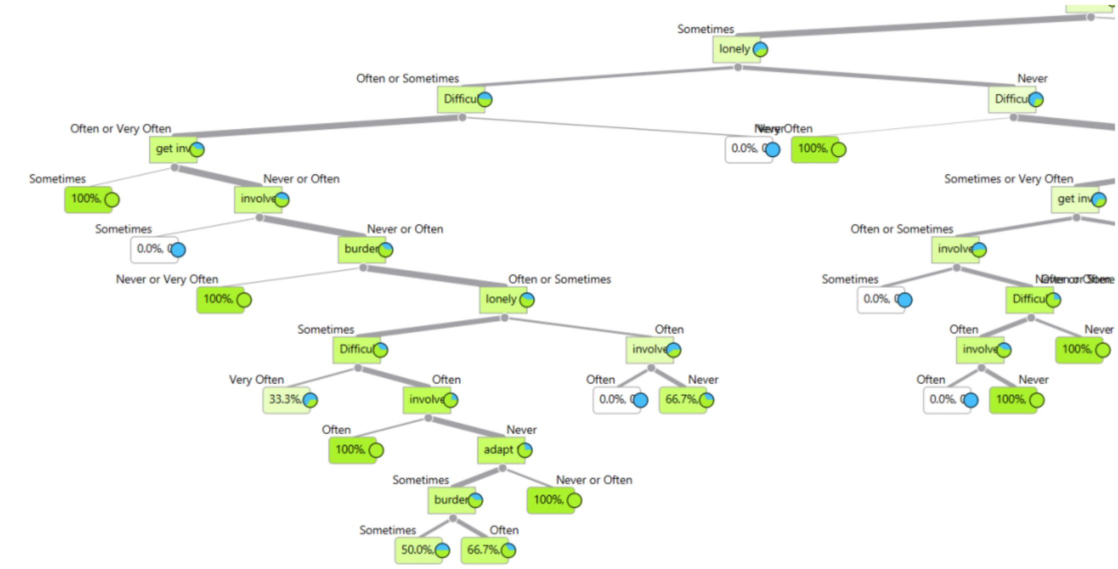

Figure 8. Analysis of Risk Factors and Mental Health Protection Factors for Students in Relation to the Stress Variable

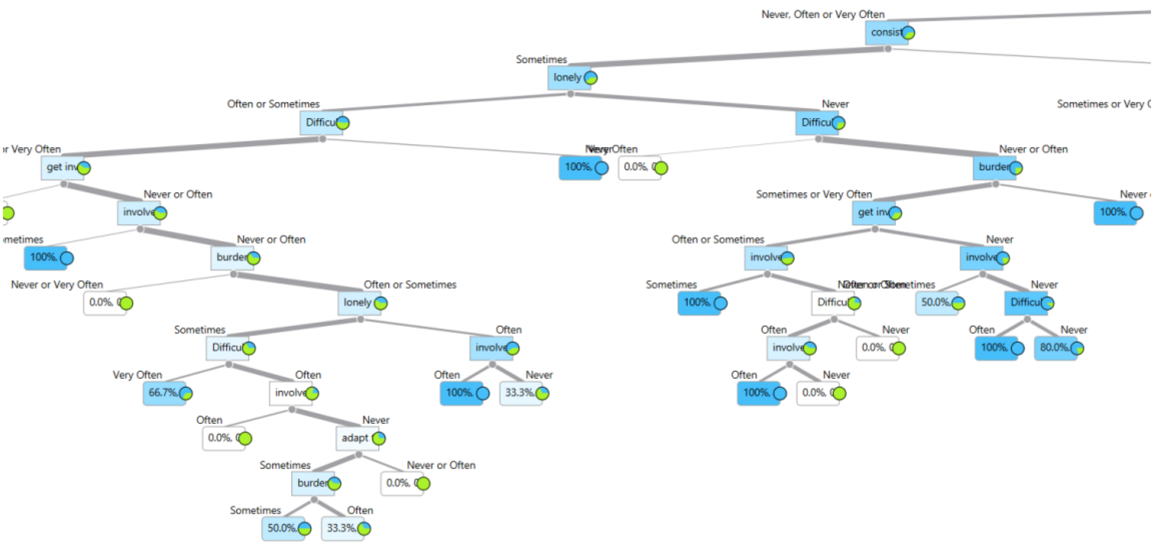

Figure 9. Analysis of Risk Factors and Mental Health Protection Factors for Students in Relation to the Anxiety Variable

Analysis of Risk Factors for Students' Mental Health

Main risk factors contributing to mental health issues among students include high academic pressure, difficulty managing time, a heavy college workload, and lack of social support. The pressure to achieve high grades often leads to significant stress, anxiety, and depression as students strive to meet expectations (Eisenberg, 2013). Additionally, challenges in managing time can exacerbate these feelings, leaving students feeling burdened and overwhelmed. A heavy college workload further compounds this stress, making it difficult for students to cope effectively, which can trigger anxiety and depressive symptoms. Moreover, a lack of social support intensifies these issues, as students may feel isolated and without a safe space to share their problems or seek assistance (Hefner & Eisenberg, 2009; Hidayah et al., 2022). Collectively, these factors create a challenging environment that can significantly impact students' mental well-being.

Analysis of Protective Factors for Students' Mental Health

Important protective factors that contribute to students' mental well-being include spending time in nature, ensuring sufficient and quality sleep, and moderate involvement in student organization activities (Bratman et al., 2015). Engaging with nature has been shown to reduce stress, anxiety, and depression by providing a calming effect and enhancing mood. In the context of university students in Lampung, this protective factor is particularly relevant due to the region's access to natural landscapes, such as beaches, parks, and mountainous areas. These environments provide students with accessible spaces for relaxation and physical activities, which can help alleviate academic-related stress and improve their mental health. Moreover, cultural values in Indonesia often emphasize a connection with nature, making outdoor activities not only a form of self-care but also a culturally embedded practice that reinforces community bonding and mindfulness.

Additionally, maintaining adequate and restorative sleep is crucial for both mental and physical health, as insufficient sleep can exacerbate feelings of stress, anxiety, and depression (Harvey, 2005). For university students in Lampung, balancing academic demands and personal responsibilities often disrupts their sleep routines. Addressing this issue through sleep hygiene education and campus initiatives promoting healthy sleep patterns could significantly enhance their psychological resilience. Furthermore, participating in student organization activities can foster a sense of community, facilitate social support, and allow students to develop new skills (Astin, 1999). However, it is essential to approach this involvement with moderation, as excessive participation can lead to increased time constraints and stress, ultimately negating its benefits. By nurturing these protective factors, students can better safeguard their mental health amidst the challenges they face.

This study contributes significantly to the body of knowledge by applying data mining techniques, specifically thee ID3 decision tree algorithm to analyze student mental health. In contrast to traditional studies, which often depend on linear regression or correlation analyses, this method utilizes decision tree analysis to uncover complex patterns in risk and protective factors (Quinlan, 2007). The incorporation of performance metrics such as AUC, Classification Accuracy, F1 Score, Precision, Recall, and Matthews Correlation Coefficient (MCC) highlights the methodological rigor and provides a comprehensive evaluation of the robustness of the mental health predictions. This innovative approach represents a significant advancement in both educational psychology and data mining, as it combines computational tools to deepen the understanding and prediction of student mental health outcomes (Powers, 2014) offering insights that traditional methods might not capture. By focusing on both risk and protective factors, this study provides a balanced perspective that could inform future mental health programs and policies tailored to the needs of students.

Despite the valuable insights derived from this study, several limitations need to be acknowledged. First, the study's reliance on self-reported data through online questionnaires may introduce biases such as social desirability bias or inaccurate reporting of mental health status. Second, while the random sampling method was used to gather a representative sample, the geographic concentration of students within Lampung Province may limit the generalizability of the findings to students in other regions or cultural contexts. Third, this study primarily focused on students' internal factors (academic pressure, time management, social support), while external factors such as economic status, family environment, and access to mental health services were not extensively explored. Lastly, the use of the ID3 decision tree algorithm, while useful for identifying patterns, might have limitations in capturing more complex relationships between variables, which could be addressed by using more advanced machine learning techniques such as random forests or neural networks.

CONCLUSIONS

Based on the results and discussion, it can be concluded that several key risk factors, such as high academic pressure, poor time management, heavy course loads, and lack of social support, significantly impact students' mental health, contributing to increased anxiety, stress, and depression. Conversely, protective factors, including spending time in green open spaces, ensuring adequate and quality sleep, and balanced participation in student organizations, play a crucial role in maintaining mental well-being. This study highlights the importance of comprehensive mental health programs in higher education institutions, which should include accessible counseling services, regular workshops on coping strategies and time management, and peer support groups to foster a sense of community. Additionally, universities should create supportive environments by providing green and healthy campus spaces and offering flexible academic policies during peak stress periods. Future research should consider external factors, such as socioeconomic background and family dynamics, while also leveraging advanced analytical methods like Random Forest or Neural Networks to enhance predictive accuracy and provide deeper insights into student mental health.

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