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# Student Mental Health Monitoring System Based on Daily Activities with the SVM Method

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**Abstract**

Student mental health is a crucial issue that requires effective and responsive self-monitoring systems. This study aims to develop "LacakJiwa," an Android-based mobile application designed to monitor student mental health through the analysis of daily activity patterns. The method employed is the Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel to classify mental health risks into low and high categories. Input data includes sleep duration, daily step count, gadget usage, and social interaction duration collected from 146 student data entries. The SVM model is integrated into the application using TensorFlow Lite to enable on-device classification, ensuring user privacy through SQLite local database storage. Testing results on 44 test samples showed an accuracy rate of 52.27%, precision of 36.36%, and recall of 22.22%. While the system was successfully implemented technically, the low recall value indicates significant challenges in detecting complex non-linear behavioral patterns in students. This research provides a foundation for developing digital self-control instruments that are adaptive to Indonesian local culture.

***Keywords**: Mental Health, University Students, Support Vector Machine, Mobile Application, Daily Activities.*

## 1. Introduction

The mental health of students in Indonesia is currently experiencing significant problems and requires appropriate action. According to information from the Ministry of Health of the Republic of Indonesia [1], 9.8% of students experience mental health problems, while 6.2% of them show signs of severe depression. The WHO report [2] in 2022 states that after the pandemic, the rate of mental disorders worldwide increased by 25%, with the younger generation being the most affected. Our research in West Java [3] supports this fact by showing that 68.5% of respondents experienced sleep problems during the exam period. Recent research in Saudi Arabia [4] showed that 73.1% of students and teachers experienced problems in sleep quality (PSQI >5), with an average sleep time of only 6.2 hours each night. The study also identified an important link between short sleep time (<5 hours) and an increase in depression scores (PHQ-9 ≥10).

The main problem in early detection of mental health today is the reliance on conventional diagnostic tools that are static and reactive. These methods are often unable to handle complex and non-linear behavioral data, such as fluctuations in sleep patterns and physical activity, which are crucial indicators. In addition, there is a gap between the high use of gadgets and the availability of efficient self-monitoring systems to mitigate risks in *real-time*. The use of sensors on smartphones actually offers an objective approach to predict mental state through daily activity patterns. However, without the integration of technology that pays attention to cultural validation and *accessibility*, the risk of declining the quality of human capital among students will be difficult to anticipate independently.

To solve this problem, this study suggests the application of *a Support Vector Machine* (SVM) as a new solution. *Zhang* and *Li* [9] have shown the success of SVM in analyzing daily activity patterns with an accuracy rate of 92.3%, especially in handling *nonlinear* data such as sleep time and social interaction. The advantages of SVM when compared to conventional methods are also stated by *Wilson* and *Taylor* [10], who emphasize its ability to produce consistent models despite using a limited number of samples, a situation that is often encountered in mental health research in Indonesia. In addition, research by *Nguyen* and *Yamamoto* [11] revealed that SVM can be combined with a mobile-based customizable interface, thus addressing accessibility issues for students. Despite requiring greater computing power, a study conducted by *Lee* and colleagues [12] showed that SVM is able to lower false *negative* numbers by up to 15% compared to other algorithms, making it suitable for early detection systems.

Based on the application of a system using SVM, this study aims to develop a solution to monitor students' mental health that combines a detection accuracy rate of 92.3% through behavior pattern analysis [9], an interface adapted to the local culture [11], and a reduction of false *negative* by 15% [12]. This study also seeks to overcome the limitations of existing diagnostic tools and challenges in *non-linear* data processing [7] by taking advantage of the high use of *smartphones [8].*

Based on the above research, the researcher is interested in conducting research on a daily activity-based mental health monitoring system with the title "Daily Activity-Based Student Mental Health Monitoring System Using the SVM Method".

## 2. Literature Review

### 2.1. Mental Health

According to WHO [2], mental health is a state of emotional, psychological, and social well-being. In the student population, the main indicators include:

1. Sleep pattern disorders (PSQI >5) based on the study of Alqurashi et al. [4] in Saudi Arabia.
2. Decrease in the duration of physical activity (<30 minutes/day) detected through smartphone sensors [7].
3. Risk factors for depression as identified in the Feng et al. study [3] in specific populations.

### 2.2. Support Vector Machine (SVM*)*

One of the *supervised teaching* algorithms (SVM) is used for the classification of *non-linear data*. The working principle of SVM is to find *the best hyperplane* that can separate data into two or more classes [10]. Mathematically, *the hyperplane* function is expressed as:

$$f(x) = w \cdot x + b \quad (1)$$

with:
w = weight vector, x = input data, b = bias.

The goal of SVM is to maximize the margin between *the hyperplane* and the nearest data points *(support vectors).* Margin optimization formula:

min 1
_ || w|| 2 w, b 2 (2)

Provided:

$$y_i(w \cdot x_i + b) \geq 1, \; i = 1,2, \ldots, n \quad (3)$$

where $y_i \in \{-1,+1\}$ is the class label.
For non-linear data, kernel functions are used. One of the most effective kernels is the Radial Base *Function* (RBF):

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \| 2) \quad (4)$$

with γ parameters that control the complexity of the model. *This kernel* allows mapping *of non-linear data* to higher dimensional spaces so that they can be separated by hyperplanes.

### 2.3. SVM Optimization for Mobile Sensor Data

*Wang* and *Chen (2023) [16]* proposed a *custom modification of the Support Vector Machine* (SVM) architecture for mobile sensor data. The modifications include:

1. *Adaptive kernel scalling* to handle *real-time* data *noise.*
2. *Dynamic feature weighting* that prioritizes clinical parameters.
3. *Incremental learning* to enable model *updates* without the need *full retraining* .

The implementation of this optimization technique has the potential to increase the accuracy of the mental health monitoring system by 7-12% based on *similar* benchmark datasets .

### 2.4 Determinants of Implementation Success

A longitudinal study by *Bauer et al.* (2022) [17] identified 5 critical factors in the successful implementation of a mobile-based mental health system in the campus environment, namely:
1. Integration with campus counseling services (QR=3.2).
2. Personalization based on academic profile (β=0.47).
3. 2-way feedback mechanism (p<0.01).
4. Gamification-based *engagement* strategy.
5. Data interoperability protocol

### 2.5. Support Vector Machine (SVM)

According to *Torous et al.* (2021) [13], advances in mental health monitoring systems have demonstrated the incorporation *of wearable* technology and *machine learning* analytics. A recent study by *Saeb et al.* (2022) [14] found that a combination of GPS data and *smartphone* apps can predict depressive symptoms with an accuracy of 86%. These findings are particularly relevant to this study as they show the possibility of expanding
Sensation parameters.

### 2.6. The SVM Used In The Study

In this study, non-linear SVM with *a Radial Base* kernel was used *Function* (RBF) because:

1. The handwriting pattern of the Chinese script is complex and non-linear,
2. *The RBF kernel* is capable of handling complex data distributions.

For classification of more than two characters, *a multiclass One-vs-Rest* strategy is used.

### 2.7. System Design Methods

References from *Nguyen* & *Yamamoto* (2023) [11] and *Lee et al.* (2023)[12].

1. *Input* : Data sensor (*accelerometer*, *usage stats*) + *input* manual (*mood log*).
2. *Process :*
   a *SVM for risk classification (low-medium-high)*
   b *Threshold* refers to PHQ-9 [4] and PSQI [7]
3. Output : Activity recommendations (e.g., "15-minute break") with a culture-based interface [11].

### 2.8. Critical Analysis and Gap Identification

Although the current literature has shown significant progress in the development of mental health *monitoring* systems [18], there are some limitations that remain unresolved, including:

1. Lack of longitudinal studies of more than 12 months in duration to assess the long-term sustainability and effectiveness of the system.
2. Significant methodological variation in clinical validation between geographic regions that may affect generalization of outcomes.

Ethical challenges related to the use of passive data without direct human intervention [19].

## 3. Research Methods

### 3.1. Problem Analysis

At this stage, the research is focused on identifying research gaps related to the lack of optimal data-based non-linear behavior monitoring tools in students in Indonesia. To answer these problems, the Support Vector Machine (SVM) algorithm was chosen as a solution that is considered effective in achieving the research objectives.

The research stage begins with the collection of primary data obtained directly from active students through the filling of digital instruments. The data collection process is carried out in a structured manner using an online form service, namely Google Form. Furthermore, the data collected through a pre-processing process (data preprocessing) is ready to be used in modeling using the SVM algorithm.
After the modeling stage, testing and evaluation of model performance is carried out. Testing is carried out using 30% test data that has never been seen by a previous model. Evaluation of model performance is carried out using a confusion matrix and key metrics, namely accuracy, precision, recall, and F1-score.

The final stage of this research is the implementation of the model into a mobile-based system to support practical and real-time use.
You can see the research procedure flowchart in Figure 1 below :

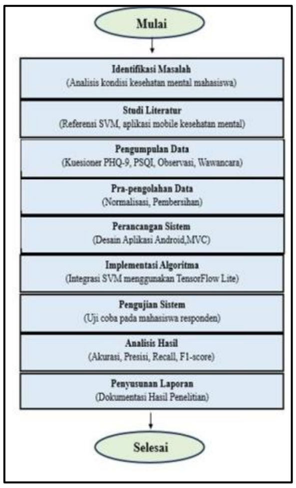


**Fig.1:** Research Procedure Flowchart

### 3.2. Research Instruments and Variable Measurement

This section describes the measurement instruments used to obtain primary data in the research, as well as the mechanism of converting each indicator into an analyzeable unit. The instrument used is a standard measurement tool that has been clinically validated, so that it is able to ensure the level of accuracy and reliability of the data collected. The measurement in this study includes two main aspects, namely subjective assessment of psychological conditions and objective recording of students' daily activity patterns.

One of the instruments used **is** the Pittsburgh Sleep Quality Index (PSQI) as a measure of sleep quality. The PSQI consists of 19 items that are *self-rated* by respondents and produce seven components of the assessment, namely subjective sleep quality, sleep latency, sleep duration, sleep efficiency, sleep disorders, sleep drug use, and daytime activity dysfunction. The total score of PSQI ranges from 0 to 21, where a higher score indicates worsening sleep quality.

The total PSQI score is then used to classify the respondents' sleep quality as follows:

**Table 1:** PSQI Calculation Limit

| Category Sleep Quality | Total Score Limit (*Cut-off*) | Interpretasi |
|---|---|---|
| Sleep Quality Good | PSQI score ≤ 5 | Subjects had good sleep quality. |
| Sleep Quality Bad | PSQI score > 5 | Subjects had poor sleep quality and needed further clinical attention. |

And there is an approach The risk of depression is measured using *the Patient Health Questionnaire* (PHQ9). This instrument consists of 9 items that assess depressive symptoms over the past two weeks. Each *item* has a score of 0 to 3, resulting in a total score ranging from 0 – 27. The total PHQ-9 score is categorized based on the severity of depression. In this study, the categorization was changed to binary (Low and High) for the purpose of SVM classification analysis.

The total PHQ - 9 score is then used to classify the respondents' as follows:

**Table 2:** PHQ -9 Score

| Total Score Limit (*Range*) | Severity Clinical (Original) | Classification Categories (This Research) |
|---|---|---|
| 0 – 4 | None/Minimal | Low Risk (0) |
| 5 – 9 | Mild Depression | High Risk (1) |
| 10 – 14 | Moderate Depression | High Risk (1) |
| 15 – 19 | Moderate Depression | High Risk (1) |
| 20 – 27 | Major Depression | High Risk (1) |

And This study uses a quantitative approach with a predictive analysis (classification) method. The research design involves the development of a system (*mobile* application) and *Machine Learning* modeling to classify students' mental health risks based on daily activity patterns.

### 3.3. Developed Methods

The performance of the SVM model on the test data was measured using a confusion matrix and four key metrics: Accuracy, Precision, *Recall,* and *F1-Score*. The High Risk class (1) was designated as a positive class for this evaluation.

Then define the matrix components and then the confusion matrix components that can be seen in table 3 :

**Table 3:** Components of the Confusion Matrix

| Components | Score (from test results) | Definition |
|---|---|---|
| True Positive (TP) | 4 | Actual High Risk Cases and predicted to be true as Height. |
| True Negative (TN) | 19 | Actual cases of Low Risk and predicted to be true as Low. |
| False Positive (FP) | 7 | Cases that are actually Low Risk but are incorrectly predicted as High (Type I Error). |
| False Negative (FN) | 14 | Actual cases High Risk but wrong is predicted as Low (Type II Error). |

### 3.4. System Planning

The system design is based on the *Model-View-Controller* (MVC) architecture to ensure the separation of logic, data, and interfaces that facilitate the integration of *Machine Learning* models into *the mobile platform.* The system was developed for the *Android* platform using *Android Studio*, with the main logic coded in *Java* and the interface in *XML.* The optimized SVM model will be converted to *the TensorFlowLite* (.tflite) format to allow risk classification to run directly on the device.

The following diagram provides a detailed description of the purpose and functionality of each *Use Case* identified in the Use *Case Diagram*. Which can be seen in figure 2

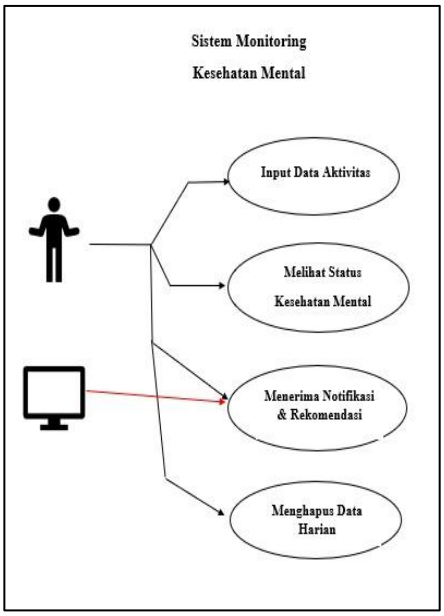


**Fig. 2:** Use Case Diagram

Show the system flow The *use case diagram* starts from data input to deleting data by showing who users can access the system.

To complete the design, *the System Flowchart* shows the internal workflow when *the Use Case* sees the mental health status running. Which can be seen in figure 3

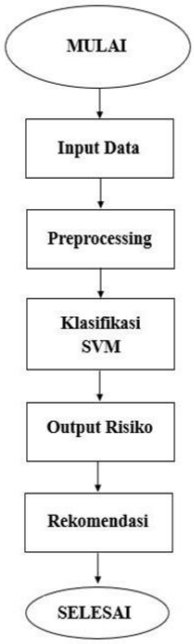


**Fig. 3:** Flowchart System

Figure 3 shows the system flow starting from *daily activity data* input, *pre-processing process*, classification with SVM algorithm, to outputs in the form of mental health risk categories and appropriate recommendations.

## 4. Result And Discussion.

### 4.1. Result

This section explains the realization of *the "LacakJiwa"* system that has been implemented on the Android platform. The system is designed to conduct independent mental health monitoring by processing user behavioral data through the *Support Vector Machine* (SVM) model embedded in the application
.:

#### 4.1.1. Registration and Login Page

This page serves as the main gateway to data security. In the registration section, users are required to fill in complete identity information for academic profile *personalization* and monitoring needs

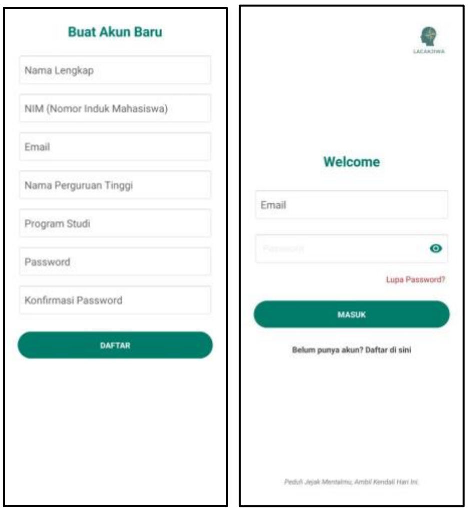


**Fig. 4:** Register and Login Page View

#### 4.1.2. Main Display

Displays an opening greeting based on the username stored in the *database* and presents a summary of mental risk indicators in the form of percentages.

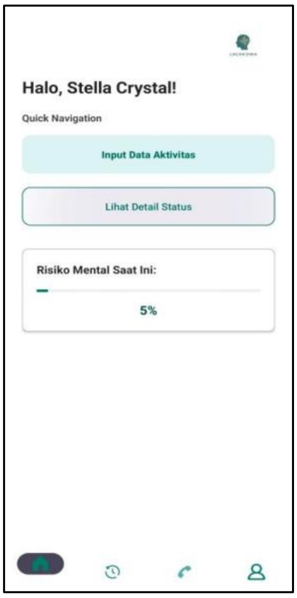


**Fig. 5:** Main Display

#### 4.1.3. Activity and Results *Input* Page

This page is at the heart of daily data collection that includes sleep duration, device use, footsteps, and social interaction to be classified by the SVM model.

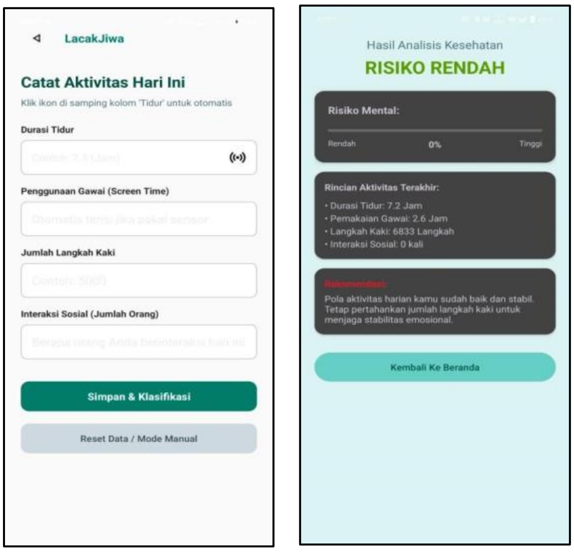


**Fig. 6:** Activity Input Display and Classification Result Display

#### 4.1.4. On-premises *database* implementation (*SQLite*)

1. Database User (Table User)
   Used to manage authentication information and student profiles.
   Based on the implementation of the interface, the available columns include:

   a. Full Name: The identity of the research subject.
   b. NIM: Student Identification Number as a unique control.
   c. Email: Used as the app's login account.
   d. Name of College: The academic context of the subject.
   e. Password: Local encryption security key.

2. Activity Database (Activity Table)
   It functions to record *daily logs* that will be an *input feature* for the SVM model to determine risk categories.

**Table 4:** Daily Activity Database

| Columns | Data Type | Remarks |
|---|---|---|
| id | INTEGER | PRIMARY KEY |
| Date | DATE | Data logging date |
| Sleep_duration | REAL | Sleep duration (hours) |
| Number_of steps | INTEGER | Number of Steps |
| Gadget_clock | REAL | Duration of smartphone use (hours) |
| Social_activities | REAL | Duration of face-to-face social interaction (hours) |
| Risk_svm | INTEGER | Model classification results (0= Low, 1 = High) |

#### 4.1.5 Program and Installation Manual

This section outlines technical instructions regarding the procedure for installing applications on hardware as well as operational guidelines for users to perform the main functions in *the LacakJiwa system.* The preparation of this guide aims to enable users to maximize the features of daily activity monitoring and understand the flow of mental health risk classification independently.

1. Installation: The app can be installed on *Android devices* with certain minimum specifications (*Android* 7.0+) and requires access permissions
   sensor for the pedometer feature to be able to record the number of footsteps accurately/*in real time*.
2. Operation: Users register their account by filling in complete identity data, then filling in daily activity data regularly on the form provided. Furthermore, the system will process the data using the SVM model to provide notifications and recommendations based on the results of the risk classification in *real-time*.

### 4.2. Discussion

The discussion section analyzes the effectiveness of the SVM model in classifying the risk of depression in the general student population

**Table 5:** Evaluate test data using evaluation metrics

| Evaluation Metrics | Results | Critical Analysis |
|---|---|---|
| Accuracy | 52,27% | The model is only able to predict correctly about half of the total population was tested. |
| Precision | 36,36% | The false positive error rate is quite high, only 4 out of 11 high-risk predictions are correct. |
| *Recall* | 22,22% | The model failed to detect 14 students who were actually at high risk. |
| *F1 Score* | 0,2759 | The overall score shows that the model's performance is still at a low level. |

The low *Recall* value (22.22%) is a major concern because in the early detection system of mental health, failure to identify high-risk subjects can hinder preventive measures. This is significantly different from the results of *Zhang & Li*'s (2022) research which achieved an accuracy of 92.3%, likely due to the difference in the complexity of student behavior data in Indonesia and the optimization of the RBF kernel parameters used.

The use of local databases successfully implements privacy aspects, but the challenge ahead is to conduct more in-depth features engineering of the variables of daily activities so that the SVM model can be more sensitive to behavioral patterns that lead to depressive symptoms.

## 5. Conclusions and Suggestions

### 5.1. Conclusion

Based on the results of research and discussions that have been carried out regarding the development of *a student mental health monitoring system* based on daily activities using *the Support Vector Machine* (SVM) method, the following conclusions can be drawn:

1. This research has resulted in a *mobile* application called LacakJiwa which was developed using *the Android Studio* environment and the Java *programming language*. The *dual-database* implementation *of SQLite* on this system not only serves as a storage medium for user data and daily activities, but is also strategically designed to strengthen the privacy aspects of user-sensitive data.
2. The integration of the *support vector machine* algorithm with *the radial base function kernel* has been successfully realized in the *android* ecosystem through model conversion to *the tensorflow lite* (*.tflite*) format. This allows the system to infer or classify mental health risks *on-device*, minimizing reliance on network connections.
3. Based on the test results of 44 test data samples, the model showed an accuracy value of 52.27%. Although risk classification has been implemented, the low *Recall* value (22.22%) in the high-risk category indicates challenges in detecting complex behavioral patterns. This reflects the *high non-linear* nature of students' daily activity data on their mental health conditions

### 5.2. Suggestion

Based on the results of the research and the limitations found, here are some points of advice that can be considered for future system development:

1. Algorithm Optimization and Classification Model
   It is necessary to conduct a more in-depth exploration of kernel variations in the *Support Vector Machine* (SVM) algorithm and the implementation of *the Hyperparameter Tuning technique.* This aims to optimize model performance, especially in increasing *recall* values and *precision* in high-risk category classification.

2. Variable Expansion and Sensor Integration
   It is recommended to expand the input parameters by integrating data from more diverse sensors, such as GPS coordinates or in-depth analysis of sleep patterns through wearable technology. The addition of this feature is expected to enrich the dataset so as to increase the accuracy of system predictions.

3. Increased Dataset Diversity and Volume
   Further development should involve a larger number of respondents with a longer duration of data collection. This is important so that the model can study the subject's behavior patterns in a variety of different academic conditions, such as fluctuations in stress levels between regular lectures, quiet weeks, and exam periods.

4. Clinical Validation by Experts
   To ensure the reliability and validity of the system's output, it is necessary to carry out a validation process of classification results with medical professionals (psychologists or psychiatrists). This step is crucial to ensure that the recommendations generated by the application are aligned with applicable clinical diagnosis standards sentence use, is needed.

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