**Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control**
**Journal homepage: http://kinetik.umm.ac.id**
**ISSN: 2503-2267**
**Vol. 10, No. 1, February, Pp. 63-74**


# Classification of sleep disorders using support vector machine

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## Article Info

**Keywords:**
Sleep Disorder, Insomnia, Sleep Disorder Classification, Sleep Apnea, Support Vector Machine

**Article history:**
Received: July 08, 2024
Accepted: November 04, 2024
Published: February 01, 2025

**Cite:**
N. Nuraeni and M. Faisal, "Classification of Sleep Disorders Using Support Vector Machine", *KINETIK*, vol. 10, no. 1, Feb. 2025.
https://doi.org/10.22219/kinetik.v10i1.2054

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## Abstract

Sleep disorders become a severe concern in our busy modern lifestyles, which are often overlooked and can cause significant negative impacts on an individual's health and quality of life. This research explores the implementation of machine learning, specifically Support Vector Machine, to facilitate quick and accurate sleep disorder diagnosis. Data shows that sleep deprivation or disturbed sleep is becoming common in society, with 62% of the adult population experiencing dissatisfaction with their sleep quality. This has a significant economic impact and affects the health and productivity sectors. This study uses Kaggle Sleep Health and Lifestyle dataset of 400 data samples, applying Support Vector Machine to classify sleep disorders using three testing scenarios. The results showed an accuracy rate of 92%, confirming that Support Vector Machine can potentially improve the diagnosis of sleep disorders, enabling early intervention and better treatment for patients. Thus, this research contributes to understanding and treating sleep disorders, improving people's overall quality of life.

## 1. Introduction

In our busy and demanding modern lifestyle, the need for sleep is often overlooked [1]. People tend to get stuck in a hectic cycle, where work, social activities, digital entertainment, and other obligations can cause sleep disturbances that interfere with the sleep they need [2]. As a result, sleep deprivation or poor-quality sleep is common. Sleep is when the human body and mind recuperate [3]. During sleep, the body undergoes various important processes such as muscle recovery, memory consolidation, and immune system regulation [4]. Sleep deprivation or disturbed sleep can significantly negatively impact a person's health and quality of life. In the short term, sleep deprivation can lead to decreased concentration and cognitive performance, mood disturbances, physical fatigue, and increased risk of accidents [5][6]. In the long term, sleep deprivation is linked to an increased risk of severe health disorders such as heart disease, diabetes, obesity and mental disorders such as depression and anxiety [7][8].

Data shows that 62% of the adult population worldwide is dissatisfied with their sleep quality. Insomnia affects approximately 38-40% of older adults, while Obstructive Sleep Apnea (OSA) affects 15-30% of men and 10-30% of Women [9]. Sleep deprivation has become an often-overlooked global health crisis with significant economic impact [10]. Sleep disorders not only affect individual health but also significantly burden society through their impact on the health sector and productivity. Thus, awareness of the importance of quality sleep and efforts to prevent and treat sleep disorders is crucial in maintaining society's overall well-being. In medicine, diagnosing sleep disorders involves a comprehensive approach that starts with a detailed sleep history and a focused physical examination, especially of the upper airway, as highlighted in research papers [11][12]. Diagnostic testing, ranging from portable monitoring to polysomnography in the laboratory, is essential to confirm suspicions of sleep-related breathing disorders (SRBDs), such as obstructive hypopnea sleep apnea syndrome (OSAHS) [13]. However, physical diagnosis takes a long time. This condition encourages many studies to find methods to speed up diagnosis with high accuracy.

Research conducted by Reyhand et al. used Naïve Bayes classifier to identify types of sleep disorders, resulting in 79% accuracy [14]. Similarly, a study using Naïve Bayes classifier on sleep disorder classification obtained an accuracy of 80% [15]. Another study discussing brain tumor classification using Support Vector Machine resulted in an accuracy of 98.3% [16]. From the results of previous studies, it can be seen that Naïve Bayes classifier has lower accuracy rate. This is due to the assumption of features independence used by the method. These features are often related, potentially reducing the model's accuracy. On the other hand, Support Vector Machine is proven to be more effective in classifying complex and non-linear data using kernel methods, which can significantly improve the model's accuracy.

Therefore, this study proposes to classify sleep disorders by using Support Vector Machine.

This study used the Kaggle Sleep Health and Lifestyle dataset of 400 data covering sleep-related variables and daily habits. In this study, the Support Vector Machine is applied to classify sleep disorder based on the variables in the dataset. The main objective of this research is to find a hyperplane that can separate two classes of data with a maximum margin. Thus, this research is expected to provide helpful information about the solutive actions that can be taken to overcome sleep disorders.

## 2. Research Method

Sleep disorders classification is the process of categorizing data into one label category. It aims to identify and classify different type of sleep disorders based on patterns and characteristics from the data. In this study, Support Vector Machine with different types of kernels were used for sleep disorder classification, as depicted in Figure 1.

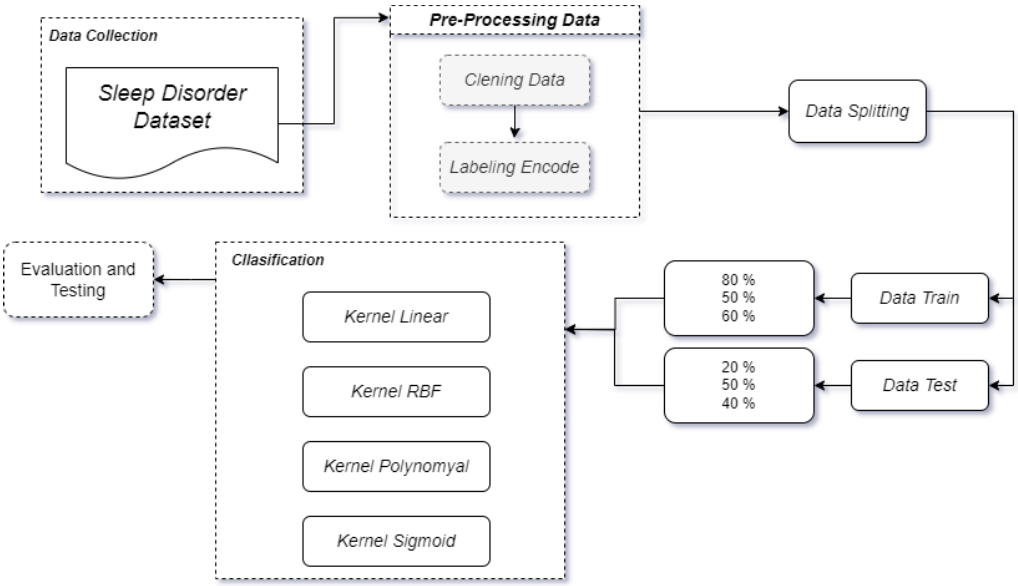



*Figure 1. Research Process*

### 2.1 Data Collection

This study used Kaggle's Sleep Health and Lifestyle dataset, comprising 400 data samples. The data was then split randomly to ensure both subsets were representative and free from bias. Three hundred twenty samples were used as training data to train the machine learning model. The model was optimized to recognize patterns better and improve sleep disorder classification performance.

*Table 1. Table Dataset*

| Person ID | Gender | Age | Occupation | Sleep Duration | Quality of Sleep | Physical Active Level | Stress Level | BMI Category | Blood Pressure | Heart Rate | Daily Steps | Sleep Disorder |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Male | 27 | Software Engineer | 6.1 | 6 | 42 | 6 | Overweight | 126/83 | 77 | 4200 | None |
| 2 | Male | 28 | Doctor | 6.2 | 6 | 60 | 8 | Normal | 125/80 | 75 | 10000 | None |
| 3 | Male | 28 | Doctor | 6.2 | 6 | 60 | 8 | Normal | 125/80 | 75 | 10000 | None |
| 4 | Male | 28 | Sales Representative | 5.9 | 4 | 30 | 8 | Obese | 140/90 | 85 | 3000 | Sleep Apnea |

Table 1 displays the Sleep Health and Lifestyle dataset, including data on various individuals regarding sleep duration, sleep quality, physical activity levels, stress levels, and other health factors such as BMI, blood pressure, and heart rate. Many of them experienced sleep disorders such as Sleep Apnea. Features such as sleep duration, sleep quality, physical activity, stress, BMI, blood pressure, and heart rate were significant in predicting sleep disorders.

Important features affecting the sleep quality in this dataset are sleep duration, sleep quality, physical activity level, and stress level, as they directly related to a person's rest quality. Additional features such as age, gender, occupation, BMI, blood pressure, heart rate, and daily steps also provide in-depth information on health conditions and lifestyle that affect sleep quality.

## 2.2 Preprocessing Data

During data preprocessing, any unnecessary labels were removed, while features and target variables were separated. Furthermore, the values in the target variable were separated into two columns and converted into numeric data types. Preprocessing was performed on categorical and numerical features using a pipeline consisting of steps such as imputing missing values and transforming categorical features into numerical representations. This pipeline automatically enables systematic and efficient data processing, thus ensuring the cleanliness and integrity of the data before further analysis. The preprocessing results can be seen in Figure 2.

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | Sleep Disorder |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | -1.753096 | -1.298887 | -1.098280 | -0.825418 | 0.347021 | -0.330002 | -0.268102 | 1.654719 | -1.619584 | 2 |
| 1 | 0.0 | 1.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | -1.637643 | -1.173036 | -1.098280 | 0.039844 | 1.475592 | -0.459239 | -0.755640 | 1.170474 | 1.970077 | 2 |
| 2 | 0.0 | 1.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | -1.637643 | -1.173036 | -1.098280 | 0.039844 | 1.475592 | -0.459239 | -0.755640 | 1.170474 | 1.970077 | 2 |
| 3 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | -1.637643 | -1.550588 | -2.771424 | -1.402260 | 1.475592 | 1.479309 | 0.869486 | 3.591698 | -2.362273 | 1 |
| 4 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | -1.637643 | -1.550588 | -2.771424 | -1.402260 | 1.475592 | 1.479309 | 0.869486 | 3.591698 | -2.362273 | 1 |

*Figure 2. Preprocessing Data*

Figure 2 represents the data that has gone through the preprocessing stage, including removing irrelevant fields, filling in missing values, adjusting the feature scale, and converting category fields to numerical form. The Sleep Disorder column has been converted to a numeric value, and category columns such as gender, occupation, BMI category, and blood pressure were represented by values of 0 or 1. Numeric features such as age, height, and weight have been standardized, ensuring that the data is ready for further analysis using machine learning models and that quality and consistency are maintained.

## 2.3 Support Vector Machine

Support vector machine analyzes and classifies sleep disorders in this case study. The data wass labeled using encoding techniques, including dataset collection and cleaning. The labeled data was divided into training and testing data with various proportions. Classification used several Support Vector Machine kernels, such as linear, RBF, sigmoid, and polynomial. Subsequently, the model was evaluated to assess its performance in detecting sleep disorders.

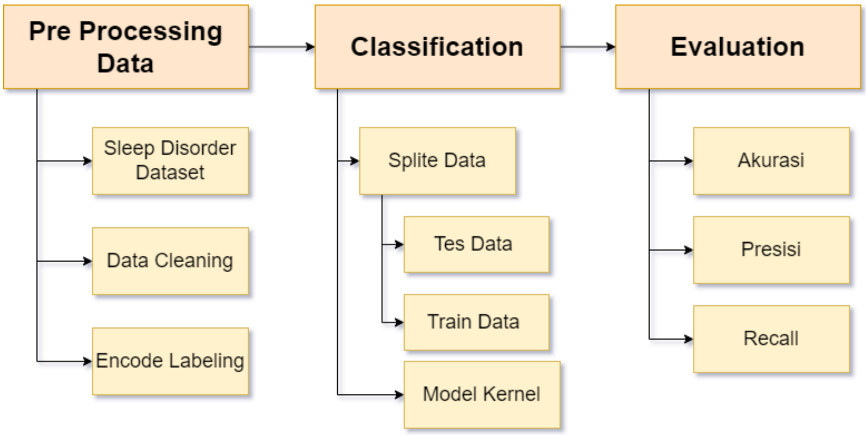



*Figure 3. Support Vector Machine Block Diagram*

Figure 3 illustrates the process of classifying sleep disorder data using Support Vector Machine with four types of kernels, including linear, RBF, sigmoid, and polynomial. The process started with cleaning the sleep disorder dataset and labeling and encoding the data. After that, the data was divided into two subsets: training data and testing data. The training data was used to train the Support Vector Machine model with each kernel, while the testing data was used to evaluate the model's performance. This model evaluation determines the performance of each kernel in classifying sleep disorder data to find the most effective kernel to improve the classification accuracy [17]. Support Vector Machine is an algorithm that has proven effective in classification and regression in machine learning [18]. In this case, Support Vector Machine was used to classify sleep disorders in the hope of providing solutions that can help in the diagnosis and treatment of sleep disorders. Classification can be grouped into two categories based on the type of the kernel used: Linear Support Vector Machine and Non-Linear Support Vector Machine [19] [20].

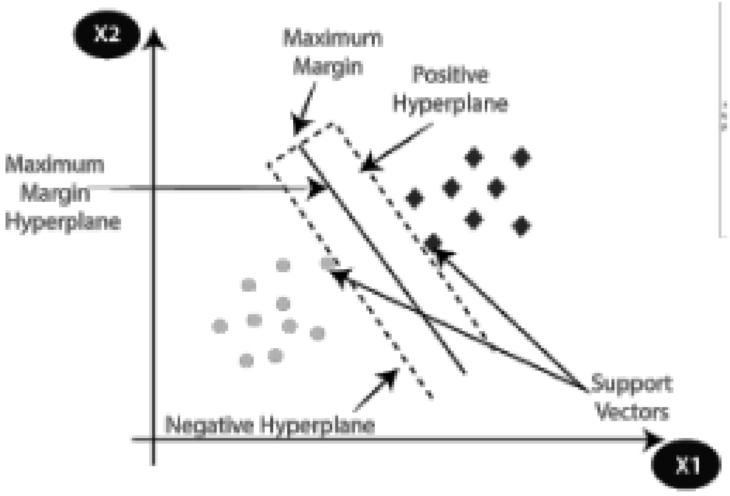
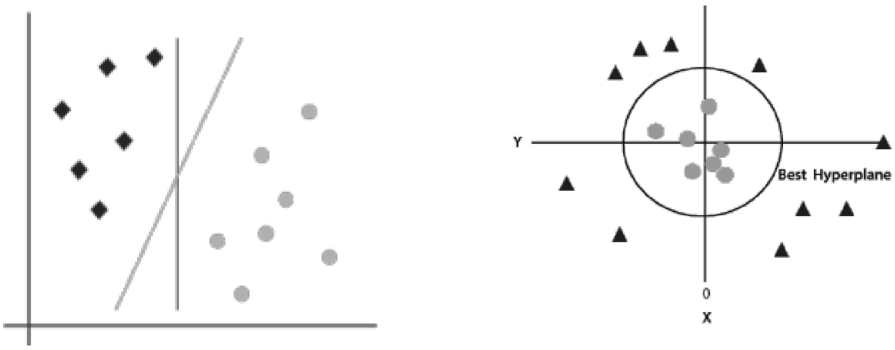



*Figure 4. Architecture Support Vector Machine*

Figure 4 illustrates how the hyperplane separates the two classes with an optimal margin and highlights the role of support vectors, i.e., nearby data points that determine the position and orientation of the hyperplane. There are four kernels in Support Vector Machine. The linear kernel in Support Vector Machine measures the similarity between two data points by calculating the dot product between two feature vectors [21]. When classifying data using Support Vector Machine and linear kernels, the data is strictly separated using a hyperplane that enlarges the distance (margin) between data from different classes [20]. The linear kernel function is expressed as $K(x, xi) = x. xi$ helps determine the proximity of two data points in the feature space. The main goal of Support Vector Machine is to find the best hyperplane that separates two classes with the most significant margin, which means that the new data is more likely to be classified correctly. Non-linear Support Vector Machine is a classification method that uses various kernel functions to handle data that cannot be linearly separated [19], as seen in Figure 5.




(a) (b)

*Figure 5. (a) is Support Vector Machine on a Linear Kernel, and Figure (b) is a Non-linear Support Vector Machine Kernel.*

Kernel functions, also known as kernel methods, are utilized to convert the data from a low dimension to a higher dimension, thus facilitating more effective data separation [20]. Several non-linear kernel functions often used in classification including the Polynomial Kernel, which converts the input data to a higher dimension to find the most efficient separation hyperplane, as presented in Figure 6. Gaussian RBF kernel classifies non-linear data with an infinite-dimensional feature space to produce a unique linear solution, while Sigmoid kernel, derived from artificial neural networks, often has difficulty in finding parameters with positive values, which can be seen in Figure 5.

Support Vector Machine (SVM) is one of the methods frequently used in data classification, both linearly and non-linearly separable data. In its application, SVM uses several types of kernels to help separate data in a higher dimensional space for easier classification. Figure 6 provides an overview of how different kernels classify the data points.

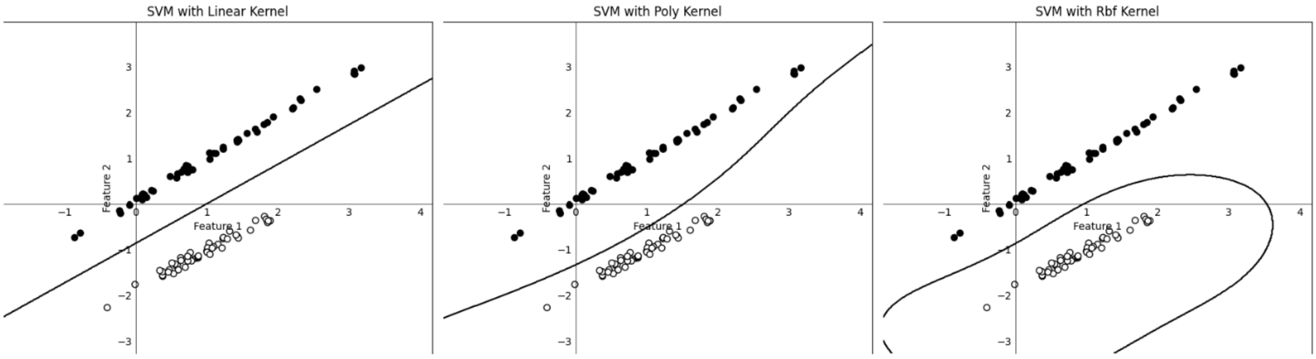



*Figure 6. Plot the data in the kernel*

Figure 6 illustrates how different kernels in Support Vector Machine (SVM) classify data points. Specifically, Figure 6 shows three types of kernels: Linear, Polynomial, and Radial Basis Function (RBF). Each kernel shows a different approach to finding the optimal hyperplane to separate the data.

The first plot (SVM with Linear Kernel) shows a linear hyperplane that aims to maximize the margin between two classes of data points, represented as black and white circles. The linear kernel worked well for linearly separable datasets, meaning that a straight line can effectively classify the data into two groups. In the second plot (SVM with Polynomial Kernel), the data points were separated by a curved decision boundary. Polynomial kernels are particularly useful when the data cannot be separated by a straight line, and they map the original input space to a higher-dimensional space, allowing for more complex relationships between features. The third plot (SVM with RBF Kernel) shows a more flexible decision boundary that can effectively adapt to the shape of the data. The RBF kernel is commonly used for data that cannot be linearly separated, as it can create complex and curved boundaries by mapping the data into a higher-dimensional space. It is effective in capturing complex patterns that may not be easily separable in the original feature space.

These different kernel functions illustrate how SVMs can be adapted to various data distributions, allowing greater flexibility in the classification task depending on the complexity and nature of the dataset.

### 2.4 Test Scenario

In the model testing process, the available data was divided into training and testing data. This division objectively evaluates the model's performance [22]. In this scenario, three test scenarios were carried out with different data division ratios, as seen in Table 2.

*Table 2. Testing Scenarios*

| No | Ratio | Number of Train Data | Number of Test Data |
|---|---|---|---|
| 1. | 80: 20 | 256 | 64 |
| 2. | 50: 50 | 160 | 160 |
| 3. | 60: 40 | 192 | 128 |

From Table 2, in this scenario, there is a larger proportion of training data than testing data, but it is smaller than in the first scenario. This balanced the data used for training and testing, by adding more data for training.

### 2.5 Prediction

After training, the Support Vector Machine model was used to predict the previously withheld testing data class. This prediction used the trained model to classify unseen data during training, hoping to provide accurate results and good generalization [23]. In Support Vector Machine, the decision function used to make predictions on testing data was based on the weight vector (w) and bias value (b) written in Equation 1.

$$f(x) = \ wx + b \tag{1}$$

In Equation 1, the decision function value for testing data $x$ is denoted as $f(x)$. The weight vector learned during model training, denoted by $w$, influences this decision function. This weight vector interacts with the feature vector of the testing data, denoted by $x$, to help determine the data class. In addition, a bias value $b$ is also added to shift the decision function. Using this approach, Support Vector Machine can classify different types of sleep disorders based on patterns and characteristics in the data.

### 2.6 Evaluation

The model performance was evaluated using various metrics, such as accuracy, confusion matrix, and classification report. Accuracy measures the degree of agreement between predicted and actual values, while the confusion matrix provides information on the model's ability to distinguish between different classes. In addition, the classification report provides details of the model's performance for each class, allowing for a more in-depth analysis of the model's performance.

**2.6.1 Accuracy:** describes the extent to which a model or system successfully makes correct predictions compared to the total number of predictions made [24], which can be calculated using Equation 2.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Number\ of\ all\ data} \tag{2}$$

**2.6.2 Precision:** describes an evaluation measure that quantifies the extent to which the positive results provided by the classification model are relevant. In the context of classification, precision measures the proportion of positive results pertinent to the total positive results predicted by the model [25]. In other words, precision measures the accuracy of the optimistic predictions given by the model. Precision is calculated by using Equation 3.

$$Precision = \frac{Number\ of\ true\ positive\ predictions}{Number\ of\ true\ positive\ predictions + Number\ of\ negative - positive\ predictions} \tag{3}$$

.

**2.6.3 Recall:** describes an evaluation measure that quantifies the extent to which a classification model can identify or detect all relevant instances of a class that are positive [25]. In the context of classification, recall measures the proportion of actually positive instances successfully identified or detected by the model. Recall is calculated by using Equation 4.

$$Recall = \frac{Number\ of\ correct\ positive\ predictions}{Number\ of\ optimistic\ and\ pessimistic\ predictions} \tag{4}$$

## 3. Results and Discussion

In the results and discussion stage, the implementation of the model using Support Vector Machine (SVM) with four different types of kernels in the classification process is explained. This stage includes data collection, data cleaning and encoding labeling, data division into training and testing sets, SVM model implementation with each kernel, and model performance evaluation for each kernel used.

In the modeling stage, classification was performed with four different types of kernels from Support Vector Machine (SVM). The linear kernel separated the data linearly, the polynomial kernel transformed the data to a higher dimension, and the RBF kernel was used to classify non-linear data in an infinite feature space. The model's evaluation results are depicted in Figure 7.

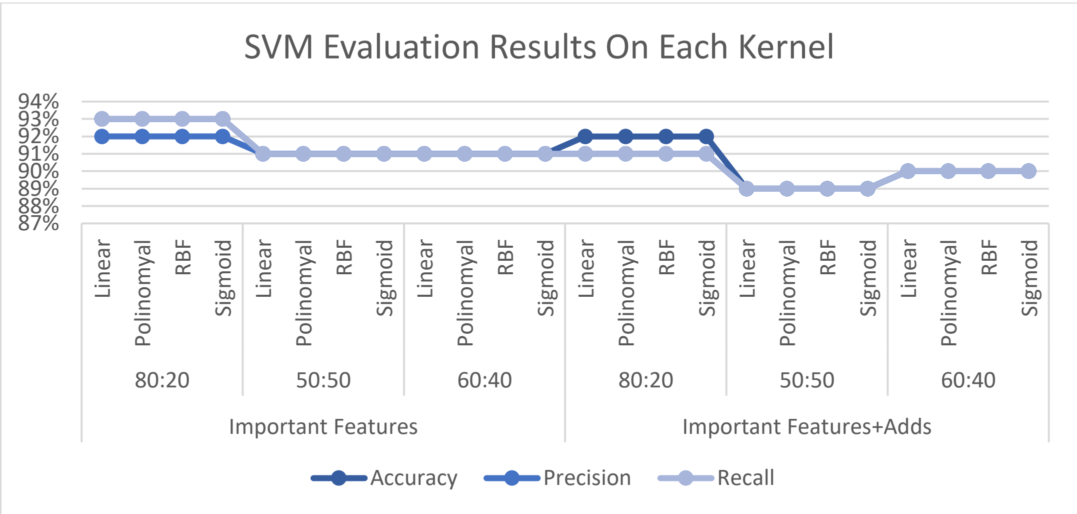



*Figure 7. Model Evaluation Results*

In general, in testing the SVM models for predicting sleep quality, two sets of features were tested: Important Features and Important Features combined with Additional Features. The evaluation results show that the models using important features that were directly related to sleep quality provided better performance compared to those using all available features. Additional features did not to provide significant improvement and might even cause a slight decrease in the model performance. The following is a more detailed analysis based on the three test scenarios seen in Table 3 and Table 4.

*Table 3. Important Feature Model Evaluation Results*

| Features | Ratio | Kernel | Accuracy | Precision | Recall |
|---|---|---|---|---|---|
| Important Features | 80:20 | Linear | 93% | 92% | 93% |
| | | Polinomyal | 93% | 92% | 93% |
| | | RBF | 93% | 92% | 93% |
| | | Sigmoid | 93% | 92% | 93% |
| | 50:50 | Linear | 91% | 91% | 91% |
| | | Polinomyal | 91% | 91% | 91% |
| | | RBF | 91% | 91% | 91% |
| | | Sigmoid | 91% | 91% | 91% |
| | 60:40 | Linear | 91% | 91% | 91% |
| | | Polinomyal | 91% | 91% | 91% |
| | | RBF | 91% | 91% | 91% |
| | | Sigmoid | 91% | 91% | 91% |

In general, the results of testing the SVM models for predicting sleep quality show that the model using important features only provides higher accuracy results compared to the model using both important and additional features in almost all testing scenarios. The tests were conducted with three different data splits (80:20, 50:50, and 60:40) and used four types of kernels: linear, polynomial, RBF, and sigmoid.

Table 3 is the testing scenario using Important Features, the SVM model achieved the highest accuracy of 93% with a data split of 80:20 for all types of kernels. Meanwhile, at 50:50 and 60:40 data split, the accuracy of the model was 91%. Precision and recall also showed similar results, with relatively high and consistent values for all kernels.

*Table 4. Model Evaluation Results of Important Features and Additional Features*

| Features | Ratio | Kernel | Accuracy | Precision | Recall |
|---|---|---|---|---|---|
| Important Features+Adds | 80:20 | Linear | 92% | 91% | 91% |
| | | Polinomyal | 92% | 91% | 91% |
| | | RBF | 92% | 91% | 91% |
| | | Sigmoid | 92% | 91% | 91% |
| | 50:50 | Linear | 89% | 89% | 89% |
| | | Polinomyal | 89% | 89% | 89% |
| | | RBF | 89% | 89% | 89% |
| | | Sigmoid | 89% | 89% | 89% |
| | 60:40 | Linear | 90% | 90% | 90% |
| | | Polinomyal | 90% | 90% | 90% |
| | | RBF | 90% | 90% | 90% |
| | | Sigmoid | 90% | 90% | 90% |

Table 4 shows the evaluation results using Important Features and Additional Features, the accuracy of the model decreases slightly. In the 80:20 scenario, the accuracy achieved was 92%, while in the 50:50 and 60:40 scenarios, the accuracy decreased to 89% and 90%. Precision and recall also experienced similar decrease. This indicates that adding features do not always improve the model performance, and in some cases, it may cause a decrease in accuracy due to irrelevant information or redundancy in the additional features.

### 3.1 Scenario 1

Figure 8 shows the testing scenario using data with 80:20 split, the SVM model was tested on two sets of features: Important Features and a combination of Important and Additional Features. The evaluation results show that both sets of features provide fairly good accuracy results, but there are differences in the resulting performance.

For the 80:20 scenario using Important Features, the model obtained an accuracy of 93.18%, with 92.32% precision and 93.15% recall. These results show that the important features such as sleep duration, sleep quality, physical activity level, and stress level have a significant influence on sleep quality. The confusion matrix and classification report show that the model is quite good at classifying the three target classes, with fairly consistent F1-score in each class. The best parameters obtained for the RBF kernel were C=100 and gamma=1.

However, when additional features such as age, gender, occupation, BMI, blood pressure, heart rate, and daily steps were included (a combination of Important and Additional Features), the accuracy of the model slightly decreased to 92.42%. Precision and recall were also slightly lower than the scenario using important features alone. This suggests that the additional features did not significantly improve the performance of the model, and in some cases might cause a slight decrease in performance due to possible noise or redundancy in the additional features.

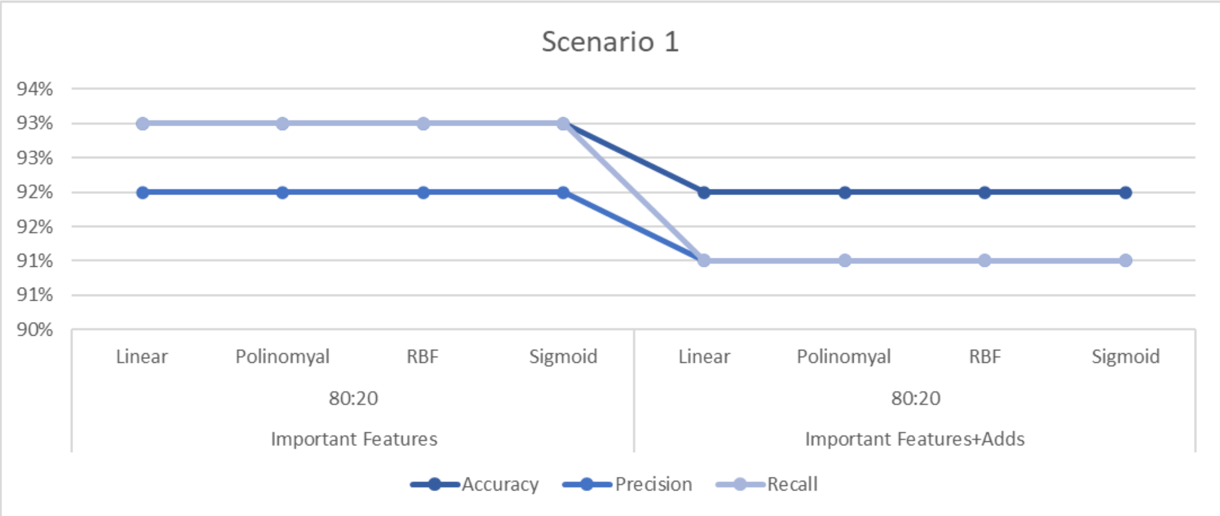



*Figure 8. Evaluation Results in Scenario 1*

### 3.2 Scenario 2

Figure 9 shows the test scenario with 50:50 data split, and the results show similar pattern. The accuracy of the model using Important Features is higher compared to Important Features combined with Additional Features. For example, in the 50:50 scenario, the accuracy for the model using Important Features reached 91.19%, while the model using the combination of Important and Additional Features only reached 90.88%. This result again shows that the important features are more effective in predicting sleep quality compared to using all available features.

The results of this evaluation show that the model remains more effective when focusing only on features that have a direct relationship with sleep quality. The addition of features does not provide better predictive value and even tends to overload the model with irrelevant information. This is evident from the performance degradation in almost all evaluation metrics, indicating that the model becomes less efficient at learning important patterns when there are too many features.

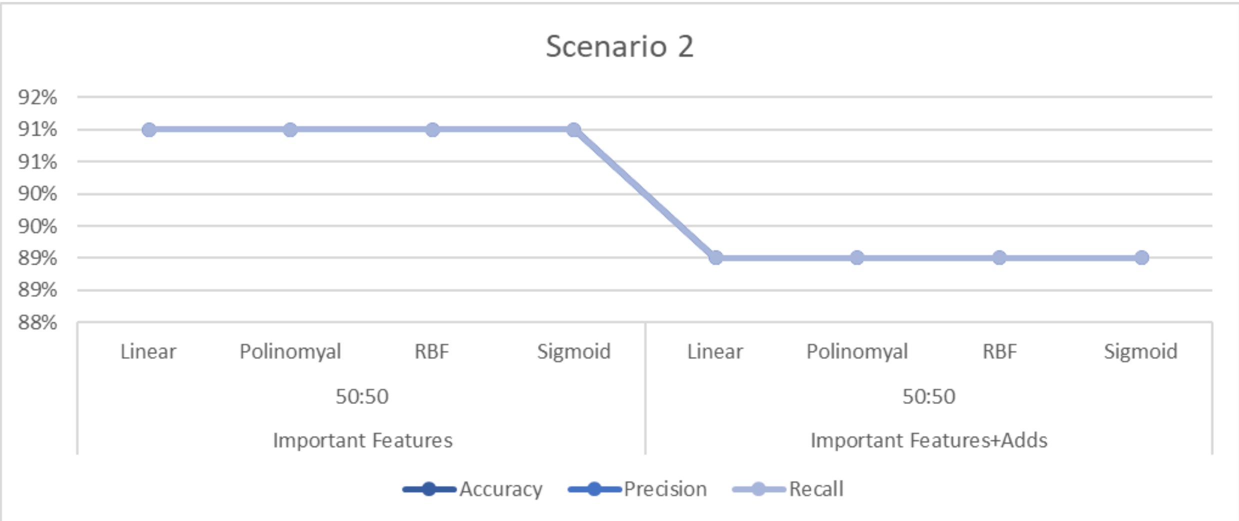



*Figure 9. Evaluation Results in Scenario 2*

### 3.3 Scenario 3

Figure 10 shows the testing scenario with 60:40 data split, the results also show similar pattern. The accuracy of the model using Important Features reached 91.25%, while the model using the combination of Important and Additional Features only reached an accuracy of 89.35%. This decrement was consistent with the two previous scenarios, where the addition of irrelevant features seems to interfere with the model's ability to predict accurately.

From this analysis, it can be seen that when the proportion of training and testing data is more balanced (60:40), the model still shows a decrease in accuracy even with additional features. This reinforces the argument that additional features add complexity to the model without significantly improving accuracy, precision, or recall. The use of irrelevant features in the model training process only increases the risk of overfitting, especially when the model has to learn patterns that are inconsistent or do not have a strong relationship with the prediction target.

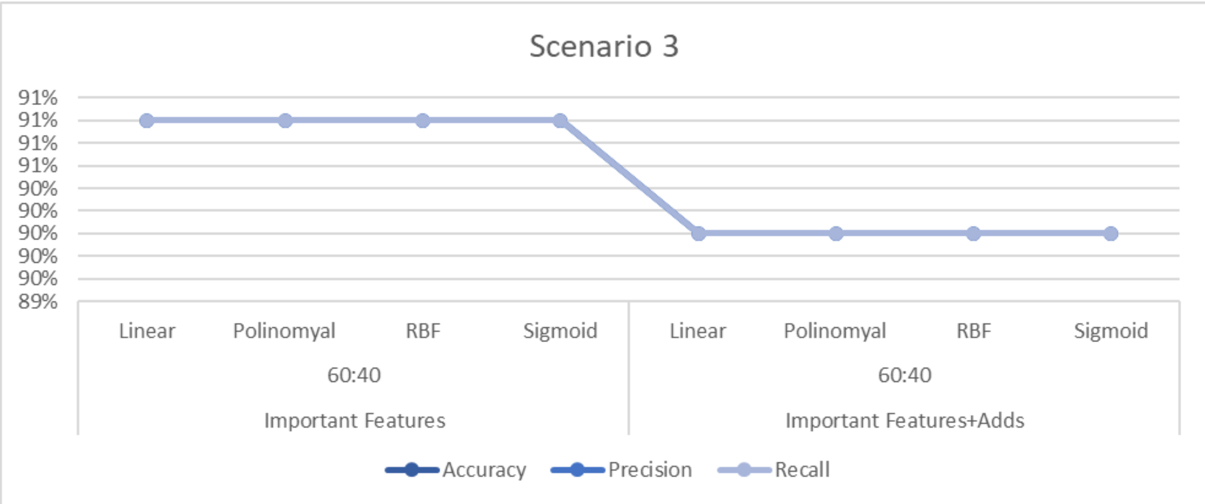



*Figure 10. Evaluation Results in Scenario 3*

### 3.4 Analysis Result

The testing results using four different types of kernels (linear, polynomial, RBF, and sigmoid) in three testing scenarios (80:20, 50:50, and 60:40) indicate that the important features directly related to sleep quality (such as sleep duration, sleep quality, physical activity, and stress level) are more effective in predicting sleep quality compared to using all available features. Additional features may contain less relevant information or may even lead to overfitting, resulting in decreased model performance. Therefore, careful feature selection is essential to improve the accuracy and efficiency of sleep quality prediction models. This shows that, despite the differences in characteristics between the types of kernels used, they provide similar performance on this dataset.

*Table 5. ANOVA Test Results*

| *Source of Variation* | *SS* | *df* | *MS* | *F* | *P-value* | *F crit* |
|---|---|---|---|---|---|---|
| Testing scenarios | 0,002816667 | 1 | 0,002816667 | 0,008260607 | 0,927788244 | 3,949321007 |
| Acurracy, precision, recall | 45,60138333 | 3 | 15,20046111 | 44,57930153 | 1,29266E-17 | 2,708186474 |
| Interaction | 0,000983333 | 3 | 0,000327778 | 0,000961293 | 0,999958498 | 2,708186474 |
| Within | 30,00587 | 88 | 0,340976 | | | |
| Total | 75,61105 | 95 | | | | |

Table 5 is used to show that there is no significant difference between kernels, which is proven through ANOVA statistical tests on the accuracy results of each kernel in all scenarios. The ANOVA test results show that the P-value >0.05 (error tolerance), which means that there is no significant difference in accuracy performance between kernels. This indicates that on datasets that tended to be linear and relatively simple, all Support Vector Machine kernels worked well and provided equally effective results.

Although there is no major difference between kernels, all kernels show a positive correlation to high accuracy. This shows the flexibility of Support Vector Machine in using different types of kernels that can adapt to the characteristics of the dataset. In this dataset, the linear kernel is effective because the data has a clear linear pattern.

However, if the dataset is more complex or has a non-linear pattern, the kernels, such as polynomial or RBF, will most likely provide a more significant increase in accuracy. Therefore, although the results of this study show insignificant difference between kernels, Support Vector Machine still offers important flexibility in handling different types of datasets in the future.

## 4. Conclusion

Sleep disorders are becoming a serious problem in our busy modern society, with significant negative impacts on individuals' health and quality of life. In the long term, sleep disorders are linked to the risk of serious diseases such as heart disease, diabetes, obesity, depression and anxiety. This research shows that Support Vector Machine performs well in sleep disorders classification, especially in scenarios with a training and testing data ratio of 80:20, which yields the highest accuracy. These results confirm that by using more training data, Support Vector Machine models can learn patterns more deeply and generalize well to smaller test data. However, although Support Vector Machine is effective in this context, the results obtained still leave room for improvement, especially in handling more complex or non-linear datasets. Therefore, further research needs to consider the use of other models that may be better suited to specific types of data and application needs.

The use of other models, such as Random Forest, Gradient Boosting, as well as deep learning-based approaches such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), can provide interesting alternatives to overcome the limitations of Support Vector Machine. Random Forest and Gradient Boosting have the ability to handle overfitting and perform better on datasets with many variables or features. On the other hand, CNN and RNN are superior in capturing more complex non-linear and temporal patterns. By comparing the performance of these models, future research can gain a deeper understanding of which models are best suited for sleep disorders classification on different datasets, resulting in more accurate and stable predictions.

The benefits generated from this research can have a significant impact in improving public health. By implementing machine learning in sleep disorders classification, the diagnosis process can become faster and more accurate, which in turn allows medical personnel to provide more timely interventions. Faster and more accurate diagnosis is crucial, as undetected or poorly treated sleep disorders can increase the risk of serious illnesses, such as heart disease, diabetes, and mental health problems such as depression and anxiety. In addition, in the future, the application of more advanced machine learning models, such as deep learning, can be integrated into digital-based health technologies. This will enable real-time monitoring of sleep patterns, provide personalized health recommendations based on data, and help reduce the burden on the health system through more proactive and efficient interventions.

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