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# Application of Support Vector Machine Algorithm For Classification of Sleep Disorders

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**Abstract**

*Sleep disorders* such as insomnia and sleep apnea are health problems that can have a serious impact on a person's quality of life. Early detection of these disorders is important to prevent the risk of more severe complications. This study aims to build a *sleep disorder* classification model using the *Support Vector Machine (SVM)* algorithm by evaluating the influence of four types of *kernels*, namely Linear, Polynomial, Radial Basis Function (RBF), and Sigmoid. The dataset used comes from the Sleep Health and Lifestyle Dataset which contains information about individual characteristics related to sleep and lifestyle. The research process follows the CRISP-DM stages from data understanding, data preparation, modeling, to model evaluation using accuracy, precision, recall, and F1-score metrics. The evaluation results show that the Polynomial *kernel* produces the best performance with 91.6% accuracy, followed by Linear, RBF, and Sigmoid. This finding shows that the selection of the right *kernel* in *SVM* has a significant effect on classification quality. This research contributes to the utilization of *machine learning* to detect *sleep disorders* and opens up opportunities for the development of more accurate and efficient diagnostic systems.

***Keywords***: *Sleep Disorders, Support Vector Machine, Kernel, Classification, Machine Learning*

## 1. Introduction

Sleep is a natural condition of the mind and body that occurs repeatedly and is characterized by decreased awareness, inhibited sensory activity, and decreased interaction with the surrounding environment, which plays an important role in maintaining human physical and mental health [1] Along with age, elderly individuals experience changes in sleep patterns such as a decrease in sleep duration and an increase in the frequency of nighttime wakefulness which is part of the aging process [2]Sleep disorders include various conditions such as insomnia, hypersomnia, circadian rhythm disorders, and sleep disorders caused by poor sleeping habits or environmental conditions [3]Sleep disorders are known to have a significant impact on reducing concentration and daily activities, which then contribute to a decrease in quality of life [4]In the elderly, sleep disturbances can even trigger hypertension because it is associated with activation of the sympathetic nervous system and an increase in stress hormones [5]. The causes of sleep disturbances in the elderly are complex, including chronic diseases, medication consumption, psychological problems, and physiological changes such as disrupted circadian rhythms [6]Although sleep disorders have a significant impact on health and quality of life, their diagnosis in the field is often delayed due to limited access to medical examinations and lack of awareness of the importance of sleep quality. One potential approach in assisting the sleep disorder detection process is the utilization of artificial intelligence-based systems, specifically through automatic classification using health and lifestyle data. However, not many studies have specifically addressed how kernel variations in the Support Vector Machine (SVM) algorithm can affect classification performance in the context of sleep disorders, especially when the data used is non-linear and complex. In fact, proper kernel selection is one of the key aspects in optimizing SVM performance.

Several previous studies have applied the Support Vector Machine (SVM) algorithm in the classification of sleep disorders and showed promising results. [7]compared the performance of Random Forest and SVM algorithms in detecting sleep apnea using physiological and lifestyle parameter-based datasets. SVM showed an accuracy of 91.5%, slightly below Random Forest which reached 92.7%, but still competitive in the context of medical classification. However, this study did not discuss in depth the type of kernel used in SVM, making it difficult to assess whether the performance achieved is optimal or can still be improved by selecting a more appropriate kernel. Another study by Khansa & Fatah (2024) also used SVM along with two other algorithms (Naïve Bayes and Neural Network) for sleep disorder classification using the Sleep Health and Lifestyle Dataset. In this study, SVM showed an accuracy of 90.92%, which was below the Neural Network that reached 93.08%. However, a significant shortcoming in this study is that it does not explain the selection and influence of SVM kernel type on model performance, even though kernel type has a major impact in determining the ability of SVM to optimally separate non-linear data. These two studies show that SVM is a powerful classification method for detecting sleep disorders, but have not specifically explored the effect of kernel variation, thus opening up opportunities for further research that focuses more on this aspect.

Based on this background, this study aims to classify sleep disorders using the Support Vector Machine (SVM) algorithm by exploring the effect of different kernel types on model accuracy. Through this approach, it is expected to find the most optimal kernel configuration to improve the accuracy of predictions in the classification of sleep disorders, as well as contribute to the development of a more accurate and efficient machine learning-based sleep disorder detection system.

## 2. Research Methods

The methods used in this research are as follows:


Source: Research results (2025)
**Fig . 1:** CRISP-DM Method Stages

In the implementation of this research, the work process applied refers to the CRISP-DM (Cross Industry Standard Process for Data Mining) framework, which is then modified to suit the needs and scope of the study. CRISP-DM is a method that has been widely used in various data mining projects due to its systematic and flexible stage structure. The model generally consists of six main phases: project understanding, data understanding, data preparation, modeling, evaluation, and deployment. However, in the context of this research, the deployment stage is not included because the main goal is not to implement the system into a real environment, but to design, build, and test the performance of the classification model based on the Support Vector Machine (SVM) algorithm.This adjustment was made to keep the focus of the analysis on evaluating the performance of the model in classifying sleep disorders, rather than on technical implementation into operational systems or software. Although it does not fully follow the CRISP-DM structure, the approach used still maintains its basic principle, which is a systematic flow of thinking in data processing. This adjustment also reflects the importance of methodological flexibility in data-driven research, especially when the approach has to be aligned with the experimental and evaluative objectives of the study.

### 2.1 Project Understanding

Project understanding or commonly known as business understanding is an early and crucial stage in CRISP-DM that focuses on defining the problem, data mining objectives, and planning strategies to achieve research objectives through a deep understanding of the context and desired development direction [8]

### 2.2 Data Understanding

Data understanding is the initial stage in collecting and studying data to understand the structure and determine how to handle it appropriately [9]The data used in this study was obtained from the Kaggle site with the title Sleep Health and Lifestyle Dataset, which consists of 374 entries and 13 attributes. This dataset includes various information, such as Person ID, Gender, Age, Occupation, Sleep Duration, Quality of Sleep, Physical Activity Level, Stress Level, BMI Category, Blood Pressure, Heart Rate, and Daily Steps. The target label is the Sleep Disorder attribute which is classified into three classes, namely Normal, Insomnia, and Sleep Apnea, with the majority of respondents in the Normal category. The relatively balanced class distribution makes this dataset suitable for application to Support Vector Machine-based classification methods, especially in comparing the performance of different kernel types.

### 2.3 Data Preparation

The data preparation stage includes various important activities to determine the right dataset for use in modeling, and requires careful thought to identify and fix various problems with the data so that the resulting data is of good quality and in accordance with the needs of the analysis [10]The data preparation stage in this research includes three main processes, namely feature selection, target selection, and data sharing. The process is carried out in stages as follows:

***1. Feature Selection***
Feature selection is the process of selecting the most relevant and informative subset of features from the overall features available in the data, which aims to reduce data dimensionality, improve predictive model performance, avoid information redundancy, and improve efficiency in analysis and modeling [11]At this stage, feature selection is carried out to filter out attributes that are considered relevant in supporting the classification process. Attributes such as Person ID are removed because they are unique identifiers and do not contribute information to predictions. Next, features are selected that are used as input variables. This process is done manually before the data is entered into Orange Data Mining.

***2. Target Selection***
Target selection is an important process in the data preparation stage, which identifies specific variables or attributes that are the main focus of the analysis, either to be predicted, classified, or explained by the model to be built. This process aims to determine the target variables or labels that act as a reference in model training, so that the model can learn to recognize patterns from input data to produce accurate predictions or classifications. The selection of the right target greatly affects the success and accuracy of the model in achieving the predetermined analysis objectives.
In this case, the Sleep Disorder attribute was chosen as the target variable because it reflects the respondent's sleep disorder condition. The value of this attribute consists of three classes, namely Normal, Insomnia, and Sleep Apnea, each of which represents the respondent's sleep condition.

***3. Data Sharing***
Data sharing is a crucial step in classification modeling that aims to separate data into several sub-sets for training, testing, and evaluating model performance to measure the generalization ability of the model to data that has never been seen before [12]

In data division, the dataset is divided into two parts using the 10-fold cross-validation scheme in Orange Data Mining. The division ratio used is 90% for training data and 10% for test data. The randomized cross-validation scheme is used so that the model is tested in various combinations of data, which aims to minimize bias due to fixed data division, and ensure more stable evaluation results.

### 2.4 Modeling

Modeling is the process of building a system that is able to recognize patterns in data and generate predictions based on these patterns [13]This stage is very important in data analysis because the model built will be used to test hypotheses, solve problems, and provide insights that are useful for decision making. The selection of the right algorithm and adjustment of model parameters are also an important part of this stage to ensure accurate and reliable prediction results. This stage aims to build a classification model using a Support Vector Machine (SVM) model that is evaluated using four types of kernels, namely: linear, polynomial, RBF, and sigmoid. Each kernel was tested independently to compare its performance in classifying the three types of sleep disorders. The models were configured through the SVM widget in Orange Data Mining, with no advanced parameter settings such as C-value or gamma, so all kernels were used in the default configuration offered by the platform.

### 2.5 Evaluation

Evaluation is the process of measuring the performance of a machine learning model to determine how well it performs its tasks, such as prediction or classification, especially when faced with new data that has never been seen before, so as to assess the generalization ability and reliability of the model in real situations [14]

Once the model is trained, its performance is tested using various evaluation metrics, which include classification accuracy, confusion matrix, and Receiver Operating Characteristic (ROC) curve analysis. The entire process was conducted visually through the Orange Data Mining interface, which facilitates the workflow from the data input stage to the visualization of model evaluation results in an interactive and systematic manner. The evaluation was conducted to measure the effectiveness and reliability of each model in classifying the three target classes. The model with the best performance based on this evaluation will be used as the main reference in the results analysis and discussion.

## 3. Results and discussion

In this section, the results of applying the Support Vector Machine (SVM) classification algorithm to sleep disorder data are thoroughly analyzed. The main focus lies on evaluating the performance of the model in distinguishing between three categories of sleep states: Insomnia, Sleep Apnea, and None. The discussion includes understanding the project objectives and the characteristics of the data used, followed by data processing such as feature selection, target categorization, and data partitioning. Then modeling is done using the SVM algorithm with several types of kernels. Classification results were analyzed using accuracy metrics, confusion matrix, and ROC curves to assess the quality of model predictions for each class. This evaluation provides insight into the effectiveness of the model as well as the reliability of machine learning approaches in the context of sleep disorder detection based on daily habit data.

### 3.1 Project Understanding

This research aims to develop a classification model that can identify a person's sleep condition, whether it includes Insomnia, Sleep Apnea, or None, based on daily activity data and health factors. The background of this project stems from the importance of early detection of sleep disorders in an effort to prevent long-term health problems. Conventional methods often rely on clinical observation or expensive medical devices, while data-driven approaches allow for faster and more efficient identification. By utilizing the Support Vector Machine (SVM) algorithm, this research seeks to uncover patterns in the data that are significantly correlated with types of sleep disorders, thereby supporting the diagnosis and decision-making process in the healthcare field.

### 3.2 Data Understanding

The dataset used in this study contains 374 rows with 13 columns that describe individual characteristics related to sleep conditions. Each column includes attributes such as Person ID, Gender, Age, Occupation, Sleep Duration, Quality of Sleep, Physical Activity Level, Stress Level, BMI Category, Blood Pressure, Heart Rate, Daily Steps, and Sleep Disorder. The data understanding process is done through initial exploration using Microsoft Excel, to ensure there are no empty values and recognize the data distribution of each attribute. This dataset consists of a combination of numerical and categorical features, and all of them are used in the modeling stage because each has a potential influence on a person's sleep condition.

The discussion of the research and test results obtained is presented in the form of a theoretical description, both qualitatively and quantitatively. Experimental results should be displayed in the form of graphs or tables. Graphs may follow the format for diagrams and figures.

**Table 1:** Sleep Disorder Dataset

| Person ID | Gender | Age | Occupation | Sleep Duration | Quality of Sleep | Physical Activity Level |
|---|---|---|---|---|---|---|
| 1 | Male | 27 | Software Engineer | 6.1 | 6 | 42 |
| 2 | Male | 28 | Doctor | 6.2 | 6 | 60 |
| 3 | Male | 28 | Doctor | 6.2 | 6 | 60 |
| 4 | Male | 28 | Sales Representative | 5.9 | 4 | 30 |
| 5 | Male | 28 | Sales Representative | 5.9 | 4 | 30 |

**Table 2:** Sleep Disorder Dataset

| Stress Level | BMI Category | Blood Pressure | Heart Rate | Daily Steps | Sleep Disorder |
|---|---|---|---|---|---|
| 6 | Overweight | 126/83 | 77 | 4200 | None |
| 8 | Normal | 125/80 | 75 | 10000 | None |
| 8 | Normal | 125/80 | 75 | 10000 | None |
| 8 | Obese | 140/90 | 85 | 3000 | Sleep Apnea |

| | | | | | |
|---|---|---|---|---|---|
| 8 | Obese | 140/90 | 85 | 3000 | Sleep Apnea |

## 3.3 Data Preparation

The data preparation stage in this research involves several important processes to prepare the data before entering the modeling stage which aims to prepare the data to be eligible for optimal analysis and modeling. This stage includes the process of feature selection, target selection, and data division. Each step is systematically organized to improve the quality of the data as well as the performance of the classification algorithm to be used. This stage involves several important processes to prepare the data before entering the modeling stage.

***1. Feature Selection***

Feature selection is done by removing five attributes that are considered less relevant to the classification process, namely Person ID, Gender, Blood Pressure, Heart Rate, and Daily Step. These attributes were removed because they did not contribute significantly to the prediction of sleep disorders based on initial observations and logical considerations. The retained attributes are Age, Occupation, Quality of Sleep, Physical Activity Level, Stress Level, and BMI Category, because they have a direct or indirect relationship to individual sleep conditions. This selection process was done manually before the data was imported into Orange Data Mining, to ensure that only informative features were used in the model training process.

| | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| 1 | Age | Occupation | Sleep Duration | Quality of Sleep | Physical Activity Level | Stress Level | BMI Category | Sleep Disorder |
| 2 | 27 | Software Engineer | 6,1 | 6 | 42 | 6 | Overweight | None |
| 3 | 28 | Doctor | 6,2 | 6 | 60 | 8 | Normal | None |
| 4 | 28 | Doctor | 6,2 | 6 | 60 | 8 | Normal | None |
| 5 | 28 | Sales Representative | 5,9 | 4 | 30 | 8 | Obese | Sleep Apnea |
| 6 | 28 | Sales Representative | 5,9 | 4 | 30 | 8 | Obese | Sleep Apnea |
| 7 | 28 | Software Engineer | 5,9 | 4 | 30 | 8 | Obese | Insomnia |
| 8 | 29 | Teacher | 6,3 | 6 | 40 | 7 | Obese | Insomnia |
| 9 | 29 | Doctor | 7,8 | 7 | 75 | 6 | Normal | None |
| 10 | 29 | Doctor | 7,8 | 7 | 75 | 6 | Normal | None |

**Fig. 2:** Feature Selection of Sleep Disorder Dataset

***2. Target Selection***

The Sleep Disorder attribute is set as the classification target because it is the variable to be predicted, which includes three categories: None, Insomnia, and Sleep Apnea. This target selection is done in Orange Data Mining by setting the column as Target in the File widget. Since the data is already in categorical form and does not require further transformation, this attribute is directly used by the classification model as the output label to be learned from the input features.

Columns (Double click to edit)

| | Name | Type | Role | Values |
|---|---|---|---|---|
| 1 | Age | numeric | feature | |
| 2 | Occupation | categorical | feature | Accountant, Doctor, Engineer, Lawyer, Manager, Nurse, Sales Representative, Salesperson, Scientist, Software Engineer, Teacher |
| 3 | Sleep Duration | numeric | feature | |
| 4 | Quality of Sleep | numeric | feature | |
| 5 | Physical Activity Level | numeric | feature | |
| 6 | Stress Level | numeric | feature | |
| 7 | BMI Category | categorical | feature | Normal, Obese, Overweight |
| 8 | Sleep Disorder | categorical | target | Insomnia, None, Sleep Apnea |

Source: Research Results (2025)

**Fig. 3:** Target Selection of Sleep Disorder Dataset

***3. Data Sharing***

Data sharing is done by dividing the dataset into 90% training data and 10% test data, using the Test and Score widget in Orange Data Mining. To improve the reliability of the evaluation results, this division was done 10 times with randomized cross-validation in each iteration. The 90:10 ratio was chosen because it provides a large enough proportion of training data for model learning while leaving enough test data to measure model performance. This approach allows for objective model testing and prevents overfitting of certain subsets of data.

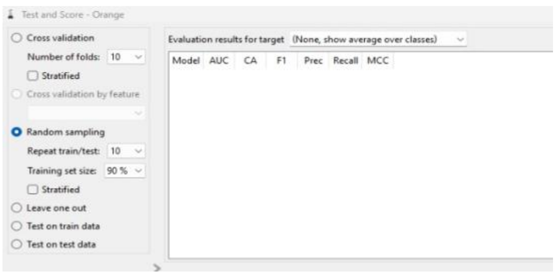
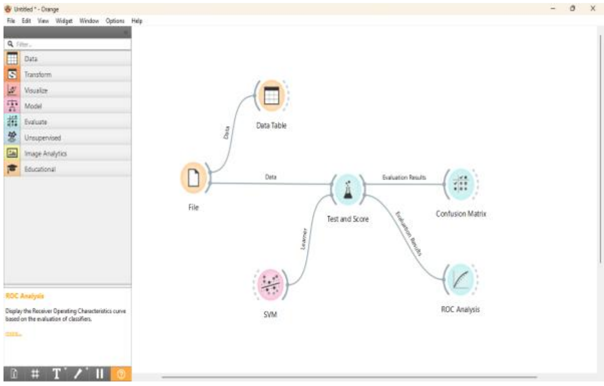



**Fig. 4:** Sleep Disorder dataset

## 3.4 Modeling

In the modeling stage, the Support Vector Machine (SVM) algorithm is used to build a classification model that is able to predict the type of sleep disorder based on existing attributes. To evaluate the effect of kernel function on model performance, four types of SVM kernels were tested separately, namely Linear, Polynomial, Radial Basis Function (RBF), and Sigmoid. Each kernel has a different approach in transforming data into a higher dimensional feature space to find the best separation boundary between target classes: None, Insomnia, and Sleep Apnea. The entire modeling process was performed using Orange Data Mining, from data processing to training and testing models with different kernel configurations. Each model was evaluated using performance metrics such as classification accuracy, precision, recall, and F1-score to determine which kernel is the most optimal in classifying sleep disorders.




Source: Research Results (2025)
**Fig. 5:** Sleep Disorder dataset modeling

## 3.5 Evaluation

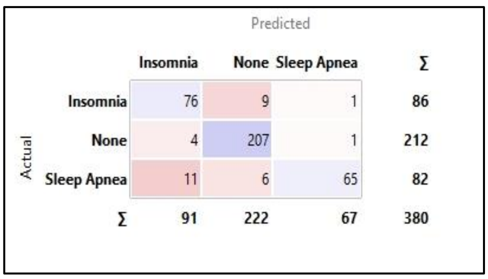
Evaluation is carried out to measure the performance of the SVM classification model in predicting the type of sleep disorder based on the data that has been prepared. The evaluation aims to assess how well the model recognizes patterns from input features and classifies data into three target classes, namely None, Insomnia, and Sleep Apnea. The evaluation process was conducted using the Orange Data Mining platform with a 10-fold cross-validation method, which ensures that the evaluation results are more stable and unbiased towards certain data divisions. The metrics used in the evaluation include Classification Accuracy (CA), Precision, Recall, and F1-Score, each of which provides an overview of the classification performance from a different perspective.

The evaluation results of the four SVM kernels are shown in Table 2. The Polynomial kernel shows the best performance with an accuracy of 0.916, followed by Linear at 0.897, RBF at 0.889, and the lowest is Sigmoid with an accuracy of 0.879. The F1-Score and Recall values also support this conclusion, where the Polynomial kernel excels in maintaining a balance between precision and sensitivity. This suggests that models with Polynomial kernels are able to capture non-linear patterns in the data better, resulting in more accurate classification than other kernels.

**Table 3:** Classification Accuracy Results of Sleep Disorder Dataset

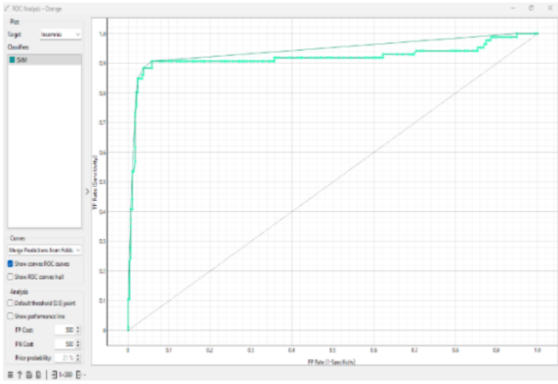
| Kernel | Classification Accuracy (CA) | F1-Score | Precision | Recall |
|---|---|---|---|---|
| Linear | 0.897 | 0.897 | 0.900 | 0.897 |
| Polynomial | 0.916 | 0.915 | 0.919 | 0.916 |
| RBF | 0.889 | 0.888 | 0.889 | 0.889 |
| Sigmoid | 0.879 | 0.878 | 0.886 | 0.879 |

Further evaluation is done by reviewing the confusion matrix of the classification results. In Figure 6, the confusion matrix results show the classification performance of the SVM model with Polynomial kernel for three classes of sleep disorders, namely Insomnia, None, and Sleep Apnea. In the Insomnia class, 76 out of 86 data were classified correctly, while 9 data were misclassified as None and 1 data as Sleep Apnea. For the None class, the model showed very high accuracy, with 207 out of 212 data successfully recognized correctly, and only 4 data misclassified as Insomnia and 1 data as Sleep Apnea. In the Sleep Apnea class, the model successfully identified 65 out of 82 data correctly, but there were 11 data that were misclassified as Insomnia and 6 data as None. Overall, the confusion matrix results reflect that the model has a very good classification ability, especially in recognizing the None and Insomnia classes, although there are still misclassifications in the Sleep Apnea class which may be caused by the similarity of symptoms between sleep disorders.

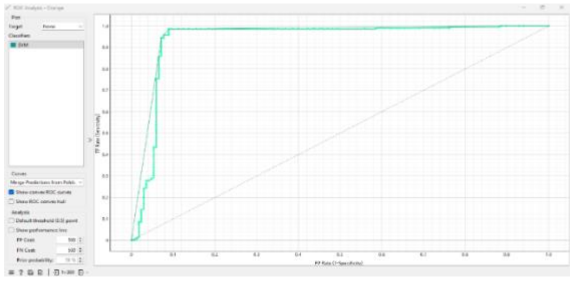



Source: Research Results (2025)
**Fig. 6:** Confusion Matrix Evaluation of SVM Algorithm.

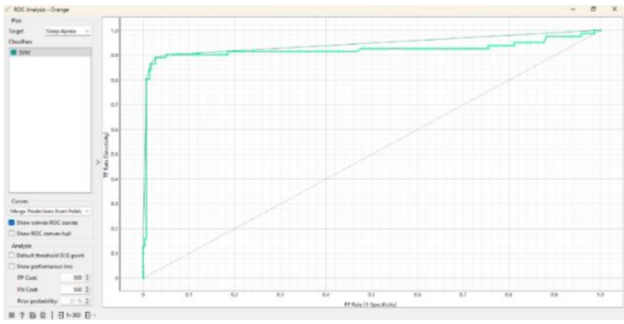
In addition to the confusion matrix, the model was also evaluated using the ROC curve for each target class. The ROC (Receiver Operating Characteristic) curve describes the relationship between True Positive Rate (TPR) and False Positive Rate (FPR), and shows the model's ability to distinguish between classes. The ROC results show that the None class has a curve closest to the upper left corner point, indicating excellent detection performance. The Insomnia class also showed a high curve, while Sleep Apnea was slightly lower, but still above the baseline. Overall, the area under the curve (AUC) for each class shows that the SVM model with Polynomial kernel has a strong discriminative ability against all three types of sleep disorders.



Source: Research Results (2025)
**Fig. 7:** ROC Curve for Sleep Disorder “Insomnia”



Source: Research Results (2025)
**Fig. 8:** ROC Curve for Sleep Disorder “None”



Source: Research Results (2025)
**Fig. 9:** ROC Curve for Sleep Disorder “Sleep Apnea”

## 4. Counclusion

This study shows that the Support Vector Machine (SVM) algorithm is effective in classifying sleep disorders based on health and lifestyle data. Of the four types of kernels tested, namely Linear, Polynomial, RBF, and Sigmoid, the Polynomial kernel provides the best results with an accuracy of 91.6 percent as well as high F1-Score, precision, and recall values. These results show that the Polynomial kernel is able to recognize non-linear patterns better than other kernels, resulting in more accurate predictions in distinguishing sleep conditions such as Insomnia, Sleep Apnea, and normal conditions. For future research, it is recommended to further explore the parameters of each kernel, such as C and gamma values, so that the performance of the model can be maximally improved. In addition, the use of larger and demographically diverse datasets needs to be considered so that the model can be tested under more representative conditions. The development of the model into a system or application is also important so that the research results can be utilized directly by the public and medical personnel in detecting sleep disorders quickly and efficiently.

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## References

[1] Balqis, I. P., Jusuf, M. I., Pateda, S. M., Antu, Y., & Karim, C. R. (2025). Hubungan Antara Kualitas Tidur dan Daya Konsentrasi pada Mahasiswa Kedokteran Universitas Negeri Gorontalo. Jambura Axon Journal, 2(1), 1–11.

[2] Berek, A. B., & Isa, S. M. (2025). Data Mining untuk Memprediksi Animo Masyarakat terhadap Proses Penerimaan Peserta Didik Baru. KESATRIA: Jurnal Penerapan Sistem Informasi (Komputer & Manajemen), 6(1), 219–226.

[3] Candrakasih, M. A. C., Krisbiantoro, D., & Waluyo, R. (2025). Perbandingan Random Forest Dan Support Vector Machine Untuk Klasifikasi Sleep Apnea. Technologia : Jurnal Ilmiah, 16(2), 337–344.

[4] Danil, S., Rahaningsih, N., Dana, R. D., & Mulyawan. (2025). Peningkatan Model Klasifikasi Pada Kab/Kota di Indonesia Menggunakan Metode Decision Tree. JITET (Jurnal Informatika Dan Teknik Elektro Terapan), 13(2), 829–835.

[5] Fransiska R, N. N., Anggraeni, D. S., & Enri, U. (2022). Pengelompokkan Data Kemiskinan Provinsi Jawa Barat Menggunakan Algoritma K-Means dengan Silhouette Coefficient. Tematik, 9(1), 29–35. https://doi.org/10.38204/tematik.v9i1.901

[6] Handayani, M., Fitri, A. U., Jayadilaga, Y., Makassar, N., & Negeri, U. (2023). Gambaran gangguan tidur yang dirasakan pada remaja dan dewasa muda di kota makassar. Jurnal Kesehatan, 11(1), 122–128.

[7] Hasibuan, R. K., & Hasna, J. A. (2021). Gambaran Kualitas Tidur pada Lansia dan Faktor-Faktor yang Mempengaruhinya di Kecamatan Kayangan, Kabupaten Lombok Utara, Nusa Tenggara Barat. Jurnal Kedokteran Dan Kesehatan, 17(2), 187–195. https://doi.org/10.24853/jkk.17.2.187-195

[8] Khansa, N., & Fatah, Z. (2024). Analisis Perbandingan Algoritma Machine Learning Dalam Klasifikasi Gangguan Tidur. Gudang Jurnal Multidisiplin Ilmu, 2(November), 76–81.

[9] Ningtyas, V. M. (2024). Hubungan kualitas tidur terhadap kejadian hipertensi pada lansia. Jurnal Sago Gizi Dan Kesehatan, 5(2), 288–295. http://dx.doi.org/10.30867/sago.v5i2.1422

[10] Pratama, A. K., Ashaury, H., & Umbara, F. R. (2024). Klasifikasi Data Gempa Bumi Di Pulau Jawa Menggunakan Algoritma Extreme Gradient Boosting. JATI (Jurnal Mahasiswa Teknik Informatika), 7(4), 2923–2929. https://doi.org/10.36040/jati.v7i4.7296

[11] Sidabutar, A. F., Habibi, R., & Rahayu, W. I. (2023). Perbandingan Metode Klasifikasi Untuk Pengelompokan Risiko Magang Mahasiswa. JATI (Jurnal Mahasiswa Teknik Informatika), 7(3), 2071–2076. https://doi.org/10.36040/jati.v7i3.7026

[12] Tantyoko, H., Sari, D. K., & Wijaya, A. R. (2023). Prediksi Potensial Gempa Bumi Indonesia Menggunakan Metode Random Forest Dan Feature Selection. IDEALIS : InDonEsiA JournaL Information System, 6(2), 83–89. https://doi.org/10.36080/idealis.v6i2.3036

[13] Utami, A. Y., Rosdiana, I., & Soffan, M. (2023). KORELASI KUALITAS TIDUR DENGAN FUNGSI KOGNITIF PADA LANJUT USIA : Studi Observasional Analitik di Panti Wredha Pucang Gading Semarang. Jurnal Ilmiah Sultan Agung, 1168–1177.

[14] Widiawati, N., Sari, B. N., & Padilah, T. N. (2022). Clustering Data Penduduk Miskin Dampak Covid-19 Menggunakan Algoritma K-Medoids. Journal of Applied Informatics and Computing, 6(1), 55–63. https://doi.org/10.30871/jaic.v6i1.3266