Journal of Artificial Intelligence and Engineering Applications

Website: https://ioinformatic.org/

15th June 2024. Vol. 3. No. 3; e-ISSN: 2808-4519

Somnambulism Classification Model Using Decision Tree Algorithm

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Abstract

Somnambulism, commonly known as sleepwalking, is a sleep disorder classified under parasomnias and poses potential dangers to both the individual affected and those nearby. This condition often goes unnoticed by the person experiencing it, making early detection and intervention challenging. This study aims to develop a classification model for somnambulism using the C4.5 decision tree algorithm, focusing on identifying key risk factors and supporting early diagnosis and treatment strategies. The research adopts the CRISP-DM (Cross Industry Standard Process for Data Mining) methodology, which comprises six stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. A dataset of 400 records was used, containing attributes such as age, sleep quality, stress level, and BMI category. Analysis results revealed that the "Age" attribute serves as the root node due to its highest information gain value, indicating its significant role in classification. The constructed model achieved an accuracy rate of 71.25% and a classification error rate of 28.75%. While the overall performance of the model is fairly satisfactory, it shows limitations in accurately identifying minority classes like Insomnia and Sleep Apnea. In conclusion, the model offers potential as a decision-support tool for analyzing sleep disorders, although further enhancement is necessary to improve its accuracy and generalizability, particularly for more diverse and imbalanced datasets.

Keywords: *Data Mining; Somnambulism; Sleep Disorders; C4.5 Algorithm; Classification*

1. Introduction

Somnambulism, more commonly referred to as sleepwalking, is a complex sleep disorder categorized under parasomnias[1][2]. It manifests as episodes where an individual engages in physical activities—such as walking, sitting up, or even performing routine tasks—while still in a sleep state and without conscious awareness[3]. These behaviors typically occur during the deep stages of non-rapid eye movement (non-REM) sleep [4][5], a phase when the body experiences its most restorative rest but certain motor regions of the brain may remain active. This partial arousal results in the sleeper being able to move, yet remain disconnected from conscious perception and memory.

Sleepwalking has long intrigued both the medical community and the general public due to its seemingly paradoxical nature: individuals appear awake, with their eyes open and limbs active, yet are cognitively disengaged[4]. Upon waking, they rarely retain any memory of their actions. This disconnect between motor function and awareness makes somnambulism not only mysterious but also potentially dangerous. Sufferers may unknowingly harm themselves or others—falling down stairs, exiting the home, or interacting with sharp objects—without any recollection of the event afterward.

Epidemiologically, somnambulism is more prevalent among children, especially those between the ages of 4 and 12[1][6]. In most pediatric cases, the condition is benign and resolves spontaneously with age. However, in adolescents and adults, the persistence of sleepwalking may signal deeper underlying issues, such as chronic sleep deprivation, neurological disorders, or psychological stress. Adult-onset or chronic somnambulism warrants further clinical evaluation[7][8], as it tends to involve more complex and prolonged behaviors compared to childhood episodes.

Several factors are known to contribute to the emergence of sleepwalking. Genetic predisposition plays a significant role; individuals with a family history of parasomnias are at a notably higher risk. Physiological factors such as fatigue, irregular sleep schedules, and co-occurring sleep disorders (e.g., sleep apnea or restless legs syndrome) can act as triggers. Environmental stimuli—such as noise, light, or an uncomfortable sleeping environment—may disrupt the sleep cycle and lead to episodes. Additionally, the consumption of certain substances, including alcohol, sedatives, or medications affecting the central nervous system, has been linked to increased somnambulistic activity[9].

The diagnosis of somnambulism requires a careful clinical approach. Physicians typically begin by gathering a detailed sleep history[7], including reports from bed partners or family members, and may recommend keeping a sleep diary. In more complex cases, polysomnography—an overnight sleep study—can be employed to monitor brain waves, breathing patterns, heart rate, and muscle activity

during sleep, helping to rule out other coexisting disorders. Identifying the precise cause is essential to formulating an effective treatment plan.
Treatment strategies vary depending on the severity and frequency of the episodes. For mild cases, improving sleep hygiene—ensuring consistent sleep schedules, reducing screen time before bed, and maintaining a comfortable sleeping environment—can significantly reduce episodes[5]. Stress reduction through methods such as mindfulness, yoga, or therapy is also beneficial, especially when emotional distress is a contributing factor[10]. In more severe or high-risk cases, pharmacological intervention may be necessary. Medications such as benzodiazepines or certain antidepressants can help regulate sleep architecture, although these must be used under medical supervision due to potential side effects and the risk of dependency[11].
Cognitive Behavioral Therapy (CBT) has emerged as an effective non-pharmacological approach, particularly in patients whose episodes are triggered by anxiety or unresolved psychological stress[12][13]. Safety measures are also crucial: removing sharp objects, locking doors and windows, and installing motion detectors can help protect individuals during episodes[14].
Understanding somnambulism is crucial not only for clinical management but also for advancing sleep research. Despite its seemingly harmless appearance, sleepwalking can significantly affect quality of life, disrupt relationships, and lead to dangerous situations. Therefore, early identification, informed intervention, and continuous monitoring are essential to reduce risks and improve patient outcomes[15][16][17].
Recent advancements in wearable technology and sleep monitoring devices offer promising avenues for enhancing the understanding and management of somnambulism. Tools such as actigraphy watches and smart sleep trackers can unobtrusively collect real-time physiological and behavioral data during sleep, enabling continuous assessment beyond the confines of clinical settings. This technological integration not only facilitates early detection of abnormal sleep patterns but also supports personalized treatment strategies. As data-driven insights become increasingly accessible, they hold the potential to revolutionize both diagnostic precision and the efficacy of interventions in managing sleepwalking behavior.

2. Research Methods

2.1 Research Stages

The research steps for developing a track record model in optimizing employee performance can be seen in Figure 1 below.

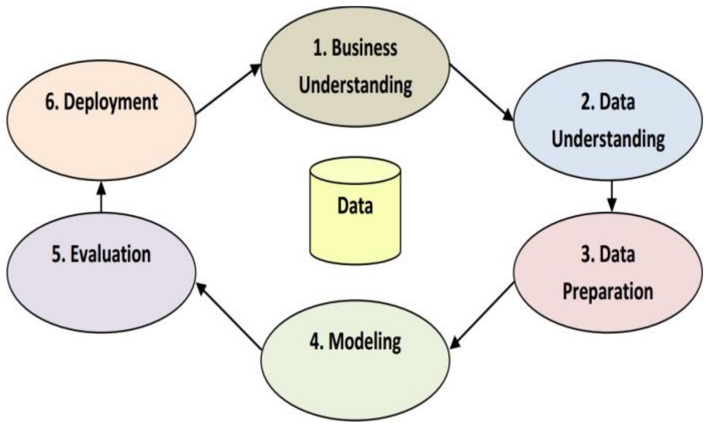

Figure 1: Research Stages

The figure illustrates the stages in the **CRISP-DM (Cross-Industry Standard Process for Data Mining)** methodology, which consists of six interconnected steps. The process begins with **Business Understanding**, the phase where the project's main objectives are identified based on the user's needs and problem context. This is followed by **Data Understanding**, where initial data exploration is conducted to assess the structure, quality, and characteristics of the available data.
The third stage, **Data Preparation**, involves processing and cleaning the data to make it suitable for modeling. This includes selecting relevant features, handling missing values, and transforming the data to fit the requirements of the chosen algorithm. The process continues with **Modeling**, where data mining techniques—such as the decision tree algorithm—are applied to build predictive models based on the prepared data.
Once a model has been developed, the **Evaluation** phase is used to assess its performance, typically by measuring accuracy and error rates. If the results are acceptable, the process advances to the **Deployment** stage, where the model is implemented in a real-world environment to support decision-making or automation. The entire process is centered on data, which serves as the core that connects all stages within the CRISP-DM framework.

2.2 Business Understanding

This stage aims to understand the business objectives and translate them into data mining problems. At this point, the goals are clearly defined, and strategies or plans are developed to guide the entire data mining process.
In the context of this research, the business understanding stage is focused on medical problems related to somnambulism (sleepwalking). This disease requires a more efficient diagnostic approach because it is often not detected in the early stages. Therefore, the classification model developed aims to provide a data-based solution to detect risk factors that trigger somnambulism. The application of data mining methods in the health sector is expected to provide practical value to support clinical decisions and prevention efforts.

2.3 Data Understanding

After identifying the problem, the next step involves collecting the relevant data. This data is then explored to understand its content, detect anomalies, and assess its relevance to the problem at hand.
Once the problem is identified, a deeper understanding of the data becomes crucial. The data used consists of various physiological and lifestyle attributes such as sleep duration, stress levels, and physical activity. By understanding the distribution of the data and correlations between attributes, researchers can identify early patterns that are potentially relevant to the risk of somnambulism. Descriptive statistical analysis and data visualization are used to uncover outliers, missing values, and general trends in the data that may affect the quality of the model later.

2.4 Data Preparation

At this stage, raw data is refined and transformed into a format suitable for modeling. Activities include selecting appropriate data tables, filtering records, choosing relevant attributes, and handling data quality issues like missing or inconsistent values.
This stage involves processing the raw data into a form that is ready to be used in modeling. In this study, the preparation process included handling missing data on attributes such as blood pressure and heart rate, as well as normalizing numeric data to equalize the scale between features. Data categories such as "Occupation Type" and "BMI Category" were converted into a numeric format that could be read by the algorithm. This process is critical to ensuring that the data fed into the model is free from structural bias or systematic errors.

2.5 Modeling

With clean and structured data, the modeling phase begins. Here, algorithms such as **C4.5 decision tree** are applied using tools like RapidMiner to create classification models that can identify patterns or rules.
With the data that has been prepared, the modeling stage is carried out using the C4.5 decision tree algorithm. This algorithm was chosen because of its ability to handle categorical and numeric attributes, and to produce a model that is easy to interpret in the form of a decision tree. This model will identify which attributes have the most influence on the classification of somnambulism risk. Testing is carried out using cross-validation methods and accuracy measurements to ensure that the model is able to classify effectively.

2.6 Evaluation

This phase evaluates the performance of the classification model, particularly its **accuracy** and **error rate**. The goal is to determine whether the model effectively solves the problem as intended. Results are interpreted to identify any potential improvements or issues before deployment.
In the evaluation phase, the built model is tested using test data to measure its actual performance. Model accuracy, precision, recall, and confusion matrix are analyzed to see how the model classifies sleepwalking cases compared to other sleep disorders such as insomnia and sleep apnea. The evaluation results show that the model has quite good accuracy, but also indicates an imbalance in classifying minority classes. This finding is an important basis for further improvements.

2.7 Deployment

Finally, the insights and outputs from the modeling process are compiled into a report or system that can be used by stakeholders. This deployment ensures that the results of the data mining project provide actionable value in the real-world application.
Once the model has been evaluated and approved, the final step is deployment, which is the application of the model results into a real environment. In this context, deployment can be the integration of the model into a decision support system in a sleep clinic or a mobile application for monitoring sleep disorder risk. Information from the model can be used by doctors or patients to understand risk profiles and design more personalized treatment strategies. Documentation of the results and visualization of the decision tree are also prepared to be easily understood by non-technical users.

3. Results and Discussion

In the research results, the author will describe the results of each stage in the CRISP-DM process, starting from:

3.1 Business Understanding

At the business understanding stage, this study focuses on understanding the problems related to somnambulism or sleepwalking, which is a sleep disorder that can endanger sufferers and those around them. Diagnosing somnambulism is often challenging due to the lack of effective analysis methods to identify relevant patterns. This causes limitations in providing early intervention and prevention of the risk of somnambulism.

Therefore, this study aims to build a somnambulism classification model using a decision tree algorithm. This model is designed to identify important factors that influence the risk of somnambulism, classify individuals based on risk levels with high accuracy, and provide insights that support decision making in the early diagnosis and treatment of somnambulism. Understanding these needs and objectives is a strategic foundation for designing a research process that includes collecting relevant data, selecting features, and applying the right classification algorithm.

In addition to identifying risk factors and improving diagnostic accuracy, this research also addresses the gap in data-driven approaches to sleep disorder management. Traditional diagnostic methods for somnambulism often rely heavily on subjective observation or anecdotal reports from family members, which can be inconsistent and insufficient for clinical assessment. By utilizing a machine learning model, particularly a decision tree algorithm, this study seeks to introduce an objective and systematic approach that can support healthcare professionals in making informed decisions.

Furthermore, the classification model developed in this study is expected to serve as a predictive tool that not only assesses current conditions but also anticipates potential future risks. This aligns with the broader goal of preventive healthcare, where early detection can lead to timely interventions and minimize the likelihood of harm. Establishing a reliable and interpretable model will also contribute to raising awareness and understanding of somnambulism in both medical and public domains, ultimately improving patient outcomes and quality of life.

3.2 Data Understanding

In the data understanding stage, this study focuses on the exploration and initial analysis of the dataset used to build a somnambulism classification model using the decision tree algorithm. The dataset used consists of 400 data, which contain various relevant attributes, such as:

1. Person ID: Unique identifier for each individual.
2. Gender: Individual gender (Male/Female).
3. Age: Individual age in years.
4. Occupation: Individual profession/employment status (eg, office worker, manual worker, student).
5. Sleep Duration (hours): Total hours of sleep per day.
6. Quality of Sleep (scale: 1-10): Subjective rating of sleep quality, ranging from 1 (poor) to 10 (very good).
7. Physical Activity Level (minutes/day): Time spent on physical activity each day in minutes.
8. Stress Level (scale: 1-10) : Subjective rating of stress level, ranging from 1 (low) to 10 (high).
9. BMI Category : Classification of individual BMI (Underweight, Normal, Overweight, Obese).
10. Blood Pressure (systolic/diastolic) : Measurement of blood pressure, displayed as systolic divided by diastolic.
11. Heart Rate (bpm) : Heart rate at rest in beats per minute.
12. Daily Steps : Number of steps taken by an individual per day.
13. Sleep Disorder : Presence of sleep disorders (None, Insomnia, Sleep Apnea).

The data distribution is analyzed to understand the proportions in each attribute category. For example, the analysis is conducted to determine the distribution of individual gender in the dataset, the proportion of age in a particular category, the number of individuals in each BMI category, and the distribution of stress levels or sleep quality. In addition, the distribution of sleep disorders such as insomnia or sleep apnea is also analyzed to provide initial insights into patterns in the data. With this analysis, the proportion of data in each category can be determined, for example the percentage of individuals with low versus high sleep duration, the relationship between stress levels and sleep quality, or the distribution of sleep disorders by profession and age. Understanding these distributions provides a strong foundation for model development, helps identify attributes that are significant in predicting sleepwalking, and ensures that the dataset has a balanced and appropriate representation for further analysis.

To ensure the reliability of the dataset, data preprocessing is also carried out during this stage. This includes identifying and handling missing values, checking for data inconsistencies, and transforming categorical variables into numerical formats suitable for algorithmic processing. For example, categorical attributes such as gender, occupation, BMI category, and sleep disorder types are encoded using appropriate techniques like label encoding or one-hot encoding. Normalization or standardization may also be applied to numerical attributes to ensure all features contribute proportionally to the model's learning process.

Furthermore, exploratory data analysis (EDA) is employed using visual tools such as histograms, box plots, and correlation matrices to identify potential relationships or outliers in the data. Through EDA, patterns such as a negative correlation between stress levels and sleep quality or a higher frequency of somnambulism among individuals with sleep apnea may be observed. These findings guide the feature selection process and help refine the modeling strategy by highlighting which variables are most influential in the classification of somnambulism risk.

3.3 Data Preparation

Data Cleaning

In the data cleaning stage, the Person ID attribute was identified as an attribute that only serves as a unique identifier for individuals in the dataset. This attribute has no direct relevance or significant contribution to the analysis aimed at predicting somnambulism. Therefore, this attribute was removed from the dataset as part of the feature selection step. This step was taken to avoid potential noise or interference that could arise due to irrelevant data, which could ultimately affect the analysis process or reduce the accuracy of the classification model.

In addition, the removal of this attribute also aims to simplify the data structure, thereby simplifying the analysis process, data processing, and model development. This decision is supported by the principle that attributes that do not provide added value to the model or analysis are better removed to improve process efficiency and final results.

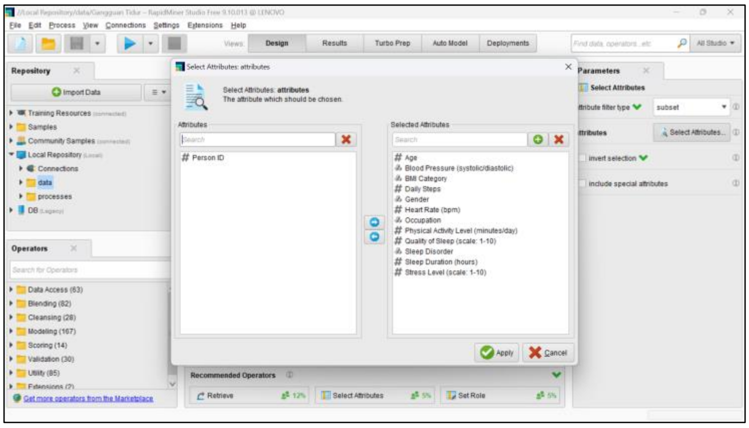

Figure 2: Attribute Selection

Since the amount of data available is quite large, the author performs a data split process with a proportion of 80:20, where 80% of the data is used as training data to build the model, while the remaining 20% is used as testing data to evaluate model performance. This division is done to ensure that the resulting model can learn from the majority of available data while still allowing for testing of model performance on new data that was not seen during training. This step is important to avoid overfitting and ensure model generalization to data that has never been encountered before.

Here is the link to the dataset I used: https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset

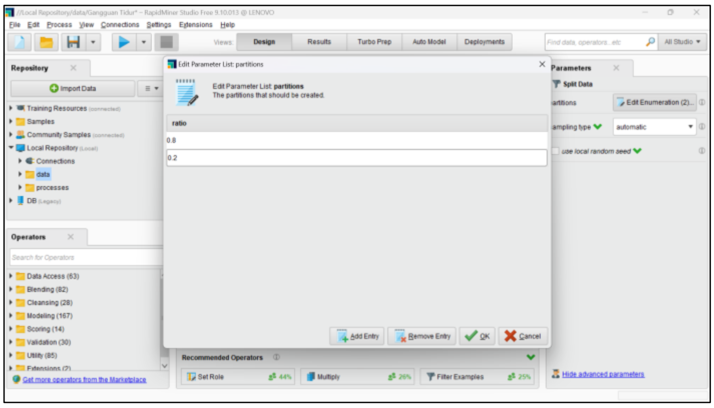

Figure 3: Split Data

3.4 Modeling

After all the data has been processed, the next step is to apply the appropriate modeling technique. This study uses the Decision Tree model, specifically the C4.5 type. The stages of implementing the C4.5 algorithm in this study include:

1. Determining the variables or attributes to be used in modeling.
2. Selecting the root node by calculating the entropy value, then continuing by calculating the information gain value.
3. In the C4.5 algorithm, the selection of root nodes and branches for each node is done based on the highest information gain value. Calculations in this method can be done manually or with the help of software such as Microsoft Excel.
4. Total entropy is calculated by considering the amount of data in the target class, namely the categories "None", "Insomnia" and "Sleep Apnea".

$$Entropy(Total) = \left(-\frac{58}{80} * log_2\left(\frac{58}{80}\right)\right) + \left(-\frac{16}{80} * log_2\left(\frac{16}{80}\right)\right) + \left(-\frac{6}{80} * log_2\left(\frac{6}{80}\right)\right)$$
$$= \mathbf{1{,}081}$$

Here I do an example calculation by using one of the existing attributes, namely I choose the Gender attribute.

Calculating Gender Entropy:

$$Entropy(Female) = \left(-\frac{23}{33} * log_2\left(\frac{23}{33}\right)\right) + \left(-\frac{6}{33} * log_2\left(\frac{6}{23}\right)\right) + \left(-\frac{4}{23} * log_2\left(\frac{4}{23}\right)\right)$$
$$= \mathbf{1{,}179}$$

$$Entropy(Male) = \left(-\frac{35}{47} * log_2\left(\frac{35}{47}\right)\right) + \left(-\frac{10}{47} * log_2\left(\frac{10}{47}\right)\right) + \left(-\frac{10}{47} * log_2\left(\frac{10}{47}\right)\right)$$

$$= \mathbf{0,986}$$

Calculating Information Gain:

$$Gain(Total, Gender) = 1{,}081 - \left(\left(\frac{33}{80} * 1{,}179\right) + \left(\frac{47}{80} * 0.986\right)\right)$$

$$= \mathbf{0,016}$$

Calculation of *Entropy*, *Information Gain*, *Gain Ratio* using *Microsoft Excel software* can be seen in one of the table examples below.

Table 1: Example of C4.5 algorithm calculation using Microsoft Excel

Total		Jlh Kasus (S)	None (S1)	Insomnia (S3)	Sleep Apnea (S3)	Entropy	Gain
		80	58	16	6	1,081	
Gender							0,016
	Male	47	35	10	2	0,986	
	Female	33	23	6	4	1,179	

After that, to find out the results on other attributes, do the same way. Here I get the highest Gain in the Age Attribute, so the Age attribute is the Root Node.

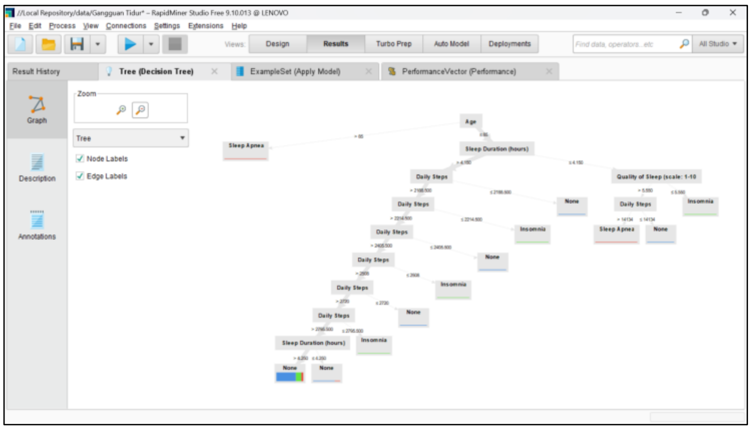

Figure 4: Decision Tree Visualization Results

3.5 Evaluation

The evaluation stage is carried out to assess the performance of the model that has been built using the performance method (classification). The results of the evaluation of model accuracy and performance are presented in the form of a confusion matrix generated using RapidMiner software. The confusion matrix of the C4.5 algorithm can be seen in Figure 5:

1. Confusion matrix accuracy algorithm C4.5

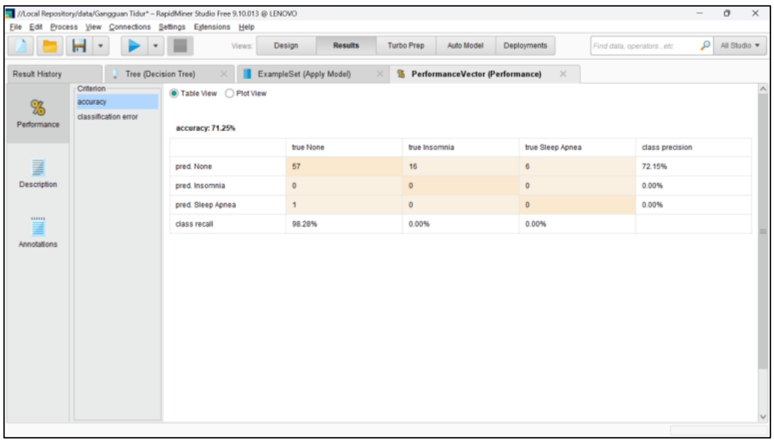

Figure 5: Confusion matrix accuracy table for the C4.5 algorithm on rapidminer

2. Confusion matrix classification_error algoritma C4.5

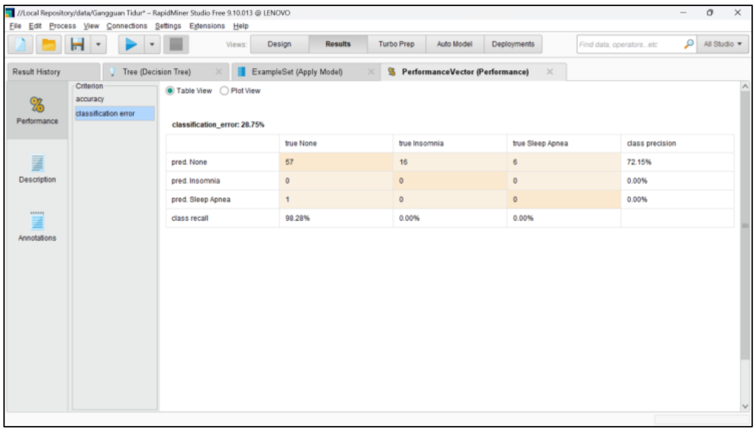

Figure 6: Table of confusion matrix classification_error algorithm C4.5 on rapidminer

3.6 Deployment

At the deployment stage, the model that has been evaluated and shows the best performance is applied to classify the types of sleep disorders, namely None, Insomnia, and Sleep Apnea. Based on the results displayed in the Performance Vector, the model has an accuracy rate of 71.25% with a classification error of 28.75%. The Confusion Matrix shows that the model successfully classifies 57 data in the None class correctly, while 16 data from the None class are misclassified as Insomnia, and 6 other data are misclassified as Sleep Apnea. However, the Insomnia class is not classified at all, and there is one data from the Sleep Apnea class that is misclassified as None. These results indicate that the model can be used to analyze sleep disorders, but it needs to be further improved to increase accuracy, especially in minority classes such as Insomnia and Sleep Apnea.

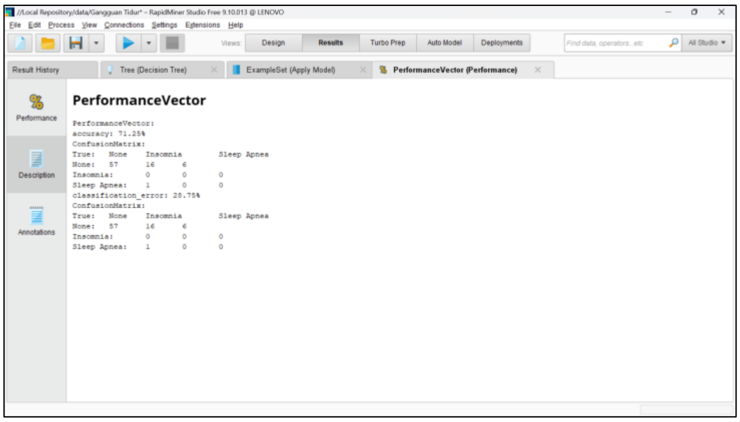

Figure 7: Results of Deployment Decision Tree on rapidminer

4. Conclusion

This study successfully identified risk factors for somnambulism using the C4.5 decision tree algorithm with an accuracy rate of 71.25%. The age attribute was found to be a significant factor in the classification of somnambulism. However, the model still faces limitations in the classification of minority classes such as Insomnia and Sleep Apnea. With these results, the model provides a strong foundation to support early diagnosis and treatment of sleep disorders. In the future, further development of the model is needed, such as improving data representation in minority classes and exploring alternative algorithms to improve performance and accuracy.
Moreover, integrating additional physiological and behavioral variables—such as sleep cycle data from wearable devices or psychological assessment scores—could further enhance the model's predictive capabilities. Future research may also benefit from applying ensemble methods or hybrid models that combine decision trees with other machine learning techniques to capture more complex patterns in the data. These improvements would not only increase classification precision but also contribute to the development of more personalized and effective interventions for individuals at risk of somnambulism.

Acknowledgement

I would like to express my sincere gratitude to all parties who have participated in the completion of this research. First of all, I would like to thank my colleagues and research assistants for their assistance in data collection and analysis, which have greatly contributed to the depth and quality of this work. Furthermore, I acknowledge the support of Universitas Muhammadiyah Asahan and STMIK Kaputama for the facilities and resources they have provided which were essential in carrying out this research. Lastly, I would like to thank LPPM

Universitas Muhammadiyah Asahan, which has funded this research, for its financial support. These acknowledgments only reflect a small portion of the support and encouragement I have received, and I greatly appreciate all who have contributed to this endeavor..

References

[1] H. M. Stallman and M. Kohler, "Prevalence of sleepwalking: A systematic review and meta-analysis," *PLoS One*, vol. 11, no. 11, pp. 1–20, 2016, doi: 10.1371/journal.pone.0164769.
[2] A. Supriyatiningtyas, "Pengaruh Latihan Yoga Terhadap Pemenuhan Kebutuhan Tidur Pada Lansia di Panti Werdha Mojopahit Mojokerto," 2019.
[3] Q. adar BakhshBaloch, "No 主観的健康感を中心とした在宅高齢者における 健康関連指標に関する共分散構造分析Title," vol. 11, no. 1, pp. 92–105, 2017.
[4] E. D. Dariah and Okatiranti, "Hubungan Kecemasan Dengan Kualitas Tidur Lansia Di Posbindu Anyelir Kecamatan Cisarua Kabupaten Bandung Barat," *J. Ilmu Keperawatan*, vol. III, no. 2, pp. 87–104, 2015, [Online]. Available: https://ejournal.bsi.ac.id/ejurnal/index.php/jk/article/viewFile/156/149.
[5] D. P. Widodo and T. S. Soetomenggolo, "Perkembangan Normal Tidur pada Anak dan Kelainannya," *Sari Pediatr.*, vol. 2, no. 3, p. 139, 2016, doi: 10.14238/sp2.3.2000.139-45.
[6] Y. Chiba et al., "Childhood Sleepwalking and Sleep Terrors A Longitudinal Study of Prevalence and Familial Aggregation," *JAMA Pediatr.*, vol. 169, 2021.
[7] M. Clinic, "Mayo Clinic, 'Sleepwalking - Diagnosis and treatment,'" 2024.
[8] P. Bargiotas, I. Arnet, M. Frei, C. R. Baumann, K. Schindler, and C. L. Bassetti, "Demographic, Clinical and Polysomnographic Characteristics of Childhood- and Adult-Onset Sleepwalking in Adults," *Eur. Neurol.*, vol. 78, no. 5–6, pp. 307–311, 2017, doi: 10.1159/000481685.
[9] M. Reference, "Medscape, 'Sleepwalking Treatment & Management,'" 2024.
[10] I. M. Dwitayasa, "Hidup Sehat Bersama Yoga," *J. Yoga Dan Kesehat.*, vol. 1, no. 1, p. 83, 2020, doi: 10.25078/jyk.v1i1.1547.
[11] I. P. A. Wijayantha, I. G. Y. Putra, and I. G. A. A. Rasdini, "Gambaran Upaya Dalam Memenuhi Kebutuhan Tidur Lansia Di Panti Sosial Tresna Werdha Jara Mara Pati Singaraja," *J. Kesehat. Med. Udayana*, vol. 4, no. 2, pp. 63–72, 2018, doi: 10.47859/jmu.v4i2.144.
[12] J. M. Mundt *et al.*, "Behavioral and psychological treatments for NREM parasomnias: A systematic review," *Sleep Med.*, vol. 111, pp. 36–53, 2023, doi: 10.1016/j.sleep.2023.09.004.
[13] D. O'Regan *et al.*, "A Novel Group Cognitive Behavioral Therapy Approach to Adult Non-rapid Eye Movement Parasomnias," *Front. Psychiatry*, vol. 12, no. July, pp. 1–7, 2021, doi: 10.3389/fpsyt.2021.679272.
[14] D. P. Cardinali, "The Science of Sleep: Insights into Sleep Disorders and Sleepwalking Treatment," *J. Sleep Disord. Ther.*, vol. 12, p. 474, 2023.
[15] H. M. Stallman, "Assessment and Treatment of Sleepwalking Clinical," vol. 46, no. 8, pp. 590–593, 2017.
[16] Y. Dauvilliers, "Adult sleepwalking is serious condition that impacts health-related quality of life," *EurekAlert!*, 2013.
[17] R. Lopez, I. Jaussent, S. Scholz, S. Bayard, J. Montplaisir, and Y. Dauvilliers, "Functional impairment in adult sleepwalkers: A case-control study," *Sleep*, vol. 36, no. 3, pp. 345–351, 2013, doi: 10.5665/sleep.2446.