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Optimization of Sleep Disorder Classification Using ANN with Multi-Method Feature Selection

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Abstract. Sleep disorders are health problems that can affect quality of life and have the potential to increase the risk of various chronic diseases. Therefore, a computational approach is needed to accurately and efficiently classify sleep disorders. The ANN model used has a two-layer hidden architecture with 128 and 64 neurons, respectively, and uses the ReLU activation function, equipped with a dropout layer to reduce overfitting. Three neurons with a softmax activation function make up the output layer, which produces probabilities for every class. To improve model performance, three feature selection methods were compared, namely Chi-Square, Information Gain, and Pearson Correlation. The test results showed that the ANN model without feature selection produced an accuracy of 89.3%. After feature selection, the model's performance improved significantly. The Chi-Square method produced 8 selected features with the highest accuracy of 97.3%, followed by Information Gain with 5 features and an accuracy of 97.3%, and Pearson Correlation with 3 features and an accuracy of 88.0%. The results of this study demonstrate that selecting appropriate features can significantly enhance an ANN's ability to categorize sleep problems. The proposed approach is expected to be a reference in the development of a more accurate sleep disorder diagnostic aid system.

Keywords: Artificial Neural Network, Sleep Disorder Classification, Multiclass Classification, Sleep Health Dataset, Feature Selection

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1. INTRODUCTION

Sleep is essential for keeping the body and mind healthy, not only as a passive sleep time, but also as an active period when the brain processes emotions, consolidates memories, and restores overall bodily functions[1]. However, sleep disorders are one of the health problems that are often overlooked, even though they can really affect how well someone sleeps. Sleep disorders are characterized by symptoms such as difficulty sleeping, breathing disorders during sleep, excessive daytime sleepiness, and irregular sleep patterns. Over time, the illness may lead to more severe sleep abnormalities, such as sleep apnea and insomnia[2].

Sleep Foundation data shows that 50 million to 70 million people suffer from sleep disorders that have a long-term health impact[3]. Despite the magnitude of the impact, many Individuals are unaware of the condition of their sleep disorder due to a lack of awareness, limited polysomnography examination facilities, and the complexity of diagnosis. Therefore, early detection is essential so that Intervention can be carried out before the condition worsens. In addition to technological advancements, integrating computer science with the health industry enables automated identification of sleep problems through data mining and machine learning[4].

Data mining and machine learning techniques are commonly employed in the health sector to identify a variety of disorders. For the classification of various diseases, predictive models including Neural Networks, Support Vector Machine (SVM), Linear Regression, and Decision Trees are frequently utilized[5],[6]. In line with these developments, studies that specifically use the Sleep Health and Lifestyle dataset also show consistent results. Artificial Neural Networks (ANNs) are effective, as research has shown. T. S. Alshammari observed a significant difference in performance among the tested algorithms. 83.19% for KNN, 92.04% for SVM, 88.50% for Decision Tree, 91.15% for Random Forest, and 92.92% for ANN[7].

Research by Sari shows that Neural Networks can achieve an accuracy of up to 91.2%, higher than SVM, which reaches 90.1% in classifying sleep disorders[8]. Another study, according to M. Maulidah et al., reported that the Gradient Boosting algorithm produced an accuracy of about 91%, followed by Random Forest and SVM with an accuracy of up to 88%[9]. Another study by Khansa et al. also noted that a neural network was able to achieve an accuracy of up to 93.08% in the classification of three categories of sleep disorders (None, Insomnia, and Sleep Apnea) using a cross-validation approach[10]. Based on previous studies that used the same dataset for the classification of sleep disorders, no application of feature selection techniques has been found. Therefore, the main contribution of this study lies in the integration of feature selection methods in the classification process to improve model performance.

Nonetheless, ANN deployments often face challenges when all features in a dataset are used without initial selection. Not all features contribute positively to classification, and some attributes even introduce noise that degrades the model's performance[11]. Therefore, to reduce dimensionality, retain pertinent characteristics, and improve ANN training effectiveness, feature selection is an essential step[12].

Various feature selection techniques are widely used in health data analysis, including Chi-square, Information Gain (IG), and Pearson Correlation. To filter out characteristics that don't have a significant impact right away, the Chi-square test is employed to assess the strength of the link between categorical data and class labels[13]. Information Gain helps select informative features in lifestyle-based health datasets by evaluating each feature's contribution to reducing entropy for the target class[14]. In the meantime, features with a high correlation might be given priority for prediction by using Pearson Correlation to determine the linear relationship between numerical features and target classes[15].

In addition, previous studies have shown that ANNs perform well when combined with feature selection methods. An ANN and Chi-Square feature selection were employed by Jayadinanta et al. in a survey to classify heart disease. Depending on the number of characteristics and the tested model setup, it attained an accuracy of 86%[16]. Similar findings were reported by Yücelbaş et al., who showed that integrating the Information Gain feature selection method with the K-Nearest Neighbor (KNN) model significantly improved classification performance, achieving 97.48% accuracy when only the most informative features were used[17]. In addition, Apriza et al. demonstrated that applying feature selection to health data can improve the accuracy of prediction models, with the

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Information Gain and Relief methods achieving better performance than without feature selection[18].

Research related to the classification of sleep disorders using the Artificial Neural Network (ANN) algorithm has been widely carried out, but until now, no research has been found that specifically applies a multimethod feature selection approach on the Sleep Health and Lifestyle dataset to improve the performance of the classification model. Therefore, this study proposes the integration of Chi-Square, Information Gain, and Pearson Correlation feature selection methods to identify the most relevant attributes in the sleep disorder classification process. By choosing more useful characteristics, this study seeks to maximize the prediction accuracy and stability of the ANN model. It is anticipated that this research will result in a better classification model and offer a fresh strategy for using multimethod feature selection in machine learning-based sleep disorder analysis.

2. METHODS

This study builds an ANN model using the best feature selection techniques: Chi-Square, Information Gain, and Pearson Correlation. The research steps are shown in Figure 1.

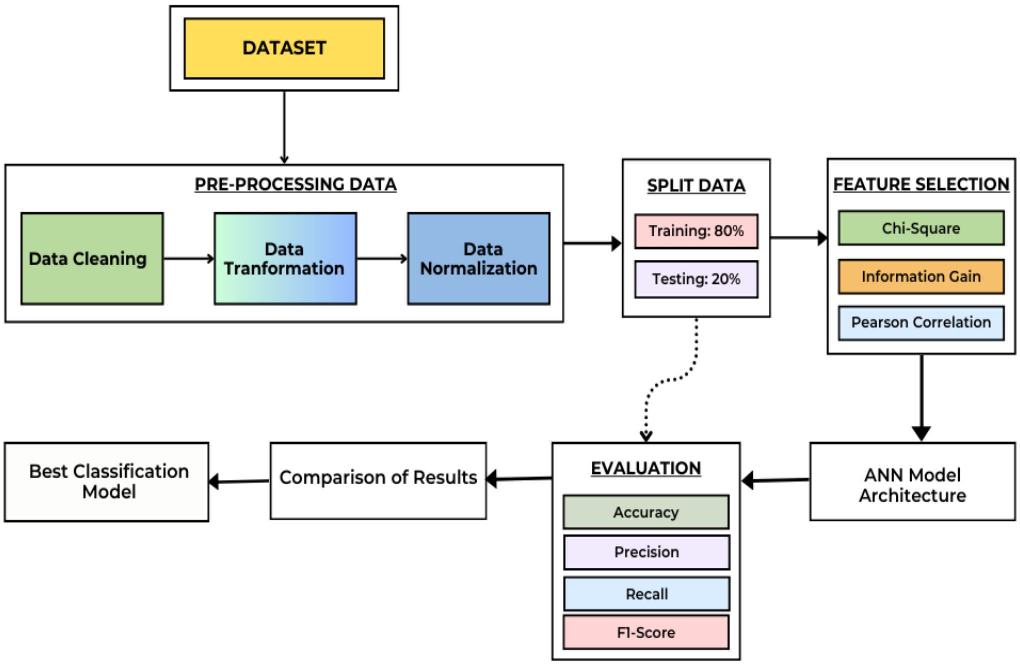

Figure 1. ANN Method Flowchart with Feature Selection

2.1. Dataset

The Sleep Health and Lifestyle Dataset used in this work was provided by Laksika Thamalingam at the dataset link on Kaggle.com, a publicly accessible data repository for research. The dataset contains information on sleep habits, lifestyle factors, and demographic characteristics that can affect a person's sleep quality. Overall, the dataset consisted of 12 attributes and 374 records. "Insomnia," "Sleep Apnea," and "None" are the three classes of the target variable "sleep disorder." Including the target variable, this yields 13 columns in total. The dataset's properties are listed in Table 1.

Table 1. Dataset Attributes and Descriptions

No	Attribution	Description
1	Person ID	Each participant was given an identification number
2	Gender	The person's biological sex
3	Age	Age measured in years
4	Occupation	Type of work performed by the individual
5	Sleep Duration	The average amount of time spent sleeping each day
6	Quality of Sleep	Self-reported sleep quality score (1–10)
7	Physical Activity Level	Daily amount of time spent exercising (minutes)
8	Stress Level	Perceived stress level score (1–10)
9	BMI Category	Classification based on body mass index
10	Blood Pressure	Measurement of systolic and diastolic pressure
11	Heart Rate	Heart rate at rest in beats per minute
12	Daily steps	Total number of steps taken each day
13	Sleep Disorder	Type of sleep condition (None, Insomnia, Sleep Apnea)

2.2. Preprocessing

The initial steps in data pre-processing include data cleansing, transformation, and normalization. In addition, categorical features are converted to numeric values to be compatible with subsequent stages[19]. Data Cleaning is carried out to handle incomplete and inconsistent data. Missing values on numerical attributes are imputed using statistical measures such as 'mean' or 'median', while the missing value in the categorical attribute is imputed using the mode[20]. Transformation data is performed by converting categorical attributes to numerical values using the 'encoding' method[19]. Data normalization applied to numeric attributes using the 'Min-Max Scaling'. This

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normalization maps data values to the range 0 to 1, preventing the dominance of certain features[21].

2.3. Feature Selection

Feature Selection is required to select the attributes that most strongly influence prediction results, thereby improving the model's efficiency and classification accuracy [22]. The following are the selection features used:

1) Chi-Square

A statistical technique used in feature selection to assess the correlation between category characteristics and target variables is the Chi-Square test. Because they show a strong correlation with the aim, features with high Chi-Square values are regarded as more pertinent. In terms of mathematics[23]. Chi-Square can be formulated in Equation 1.

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

with:

O_i is the frequency of actual observations in the category of i-th,
E_i Is the expected frequency in the category of i-th,
n is the sum of the combination of feature categories and target classes.

2) Information Gain

Information Gain is a measure in information theory that is used in the feature selection process to assess the extent to which a feature can reduce the level of uncertainty for the target variable. The greater the IG value, the greater the feature's contribution to information, as formulated in Equation 2.

$$IG(S,A) = H(S) - H(S|A) \tag{2}$$

where:

$IG(S, A)$ is the information gain between feature A and dataset S,
$H(S)$ is the initial entropy of the dataset,
$H(S \mid A)$ is conditional entropy after the dataset is divided by feature A.

Entropy is calculated using Equation 3.

$$H(s) = -\sum_{j=1}^{c} P(y_j)\, log_2\, P(y_j) \tag{3}$$

where c is the number of target classes and p(y_j) is the probability of the j-th class [24].

3) Pearson Correlation

The Pearson Correlation is used to evaluate how strongly and linearly a feature and a target variable are related. Features with large correlation values (positive or negative) are considered to have a strong linear relationship with the target and may be necessary for prediction[9]. Mathematically, the Pearson coefficient (r_xy) is formulated in Equation 4.

$$\mathrm{r_{xy}} = \frac{\sum(\mathrm{x_i}-\bar{\mathrm{x}})(\mathrm{y_i}-\bar{\mathrm{y}})}{\sqrt{\sum(\mathrm{x_i}-\bar{\mathrm{x}})^2}\sqrt{\sum(\mathrm{y_i}-\bar{\mathrm{y}})^2}} \tag{4}$$

with:

x_i and y_i represent the i observed values of the feature and the target,

$\bar{x}$dan $\bar{y}$ is the average value of features and targets,

n is the number of samples.

2.4. Artificial Neural Network

The Artificial Neural Network (ANN) approach was employed in this study to categorize sleep disorders. Because ANN performs well on classification problems based on health data and can model nonlinear interactions between features, it was selected [7]. Here is the ANN architecture in Figure 2.

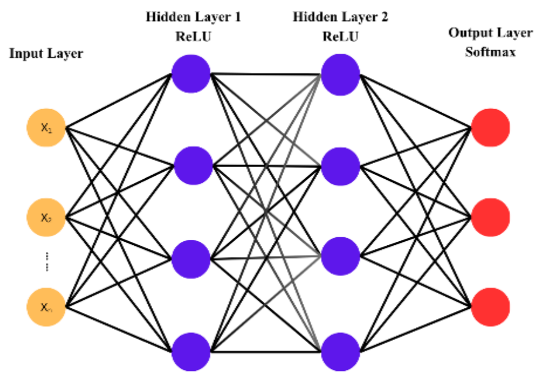

Figure 2. ANN Algorithm Architecture

Figure 2 shows the architecture of the Artificial Neural Network (ANN) model used, with the input layer consisting of 11 attributes. The model has two hidden layers totaling 128 and 64 neurons, respectively, with a ReLU activation function to improve data pattern learning capabilities. The output layer consists of 3 neurons representing the classes none, sleep apnea, and insomnia using the Softmax activation function.

The input, hidden, and output layers are the three primary layers of an ANN. The results of feature selection are sent to the input layer, where they are processed in the hidden layer to extract nonlinear patterns. The output layer generates a probability for the sleep disorder class[25]. This process is formulated with Equation 5.

$$z_j^{(h)} = \sum_{i=1}^{n} w_{ij}^{(h)}\, x_i^{(h-1)} + b_j^{(h)} \tag{5}$$

where $x_i^{(h-1)}$ is the output of the neuron in the previous layer, $w_{ij}^{(h)}$ is the weight of the connection, and $b_j^{(h)}$ This is the bias.

The activation function Z is then used to process the values. As stated in equation 6, the Rectified Linear Unit (ReLU) function, which is computationally efficient and accelerates convergence, is employed in the hidden layer.

$$f(z) = \max(0, z) \tag{6}$$

As stated in Equation 7, on the output layer, the softmax activation function is used to generate the prediction probability for each sleep disorder class:

$$\text{Softmax}(z_k) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}} \tag{7}$$

To measure the prediction error of the model, a categorical cross-entropy function was used, as in Equation 8.

$$L = -\left(\frac{1}{N}\right) \Sigma_{i=1}^{N} \Sigma_{k=1}^{K} y_{ik} \log(\hat{y}_{ik}) \tag{8}$$

where y_{ik} is the actual label of the class k for sample i in one-hot encoded form, and $\hat{y}_{ik}$ is the predicted probability produced by the model for class k. The optimization process is carried out using an Adam optimizer because of its ability to adaptively adjust the 'learning rate' and achieve stable training.

2.5. Model Evaluation

Model evaluation assessed the performance of the Artificial Neural Network (ANN) in classifying sleep disorders. In this study, several evaluation metrics commonly used in binary classification problems are employed: accuracy, precision, recall, and F1-score[26]. The following is how the metrics are developed:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

By comparing the number of correct predictions (TP and TN) with the total number of observations (TP, TN, FP, and FN), accuracy is determined as the percentage of correct predictions among all test data.

$$Precision = \frac{TP}{TP+FP} \tag{10}$$

Precision is a comparison between the amount of data predicted positive (TP) against all data predicted positive, which is a combination of (TP) and (FP).

$$Recall = \frac{TP}{TP+FN} \tag{11}$$

Recall, which combines (TP) and (FN), is the percentage of data that are accurately predicted in relation to the total quantity of positive data.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{12}$$

F1-Score is a harmonious average of Precision and Recall used to assess the balance of model performance in predicting positive classes, especially when the data is unbalanced[25].

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3. RESULTS AND DISCUSSION

This chapter covers the pre-processing of the dataset, the application of the first Artificial Neural Network (ANN) algorithm scenario, the second ANN algorithm scenario in conjunction with the Chi-Square feature selection approach, the third ANN algorithm scenario combined with the Information Gain feature selection method, and the fourth ANN algorithm scenario combined with the Pearson feature selection method—the correlation.

3.1. Preprocessing

To get the dataset ready for the ANN algorithm, we must first clean it. Among the pre-processing steps completed are:

1) Data Cleaning

At the data cleansing stage, it was found that the value of the "None" category on the target attribute "sleep disorder" was read as a missing value (NaN). The value was then corrected again because it represented a valid class that indicated the absence of sleep disturbances. After the repair process, the target attributes consist of three classes, namely None, Sleep Apnea, and Insomnia. In addition, the "Person ID" attribute was removed because it only serves as the unique identity of each respondent and has no influence on the analysis or modeling process. The cleanup dataset is then used for the next stage of analysis.

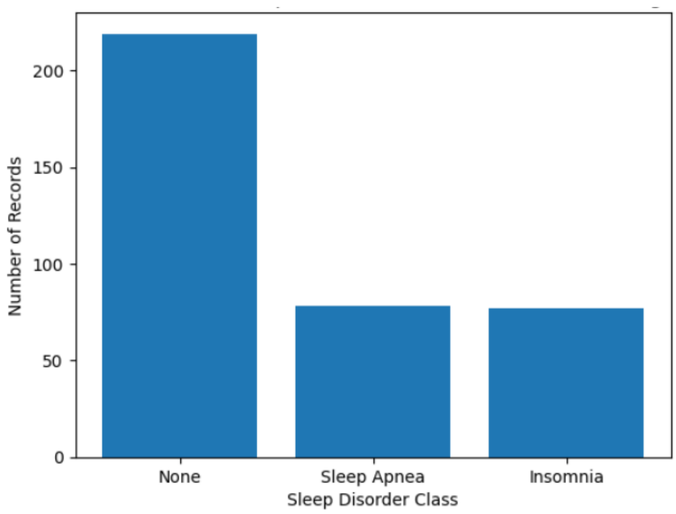

Figure 3. Distribution of Sleep Disorder Classes After Data Cleaning

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2) Data Transformation

The data transformation results in all attributes being numerical. The 'Occupation' attribute is transformed by 'one-hot encoding', while the 'Gender and BMI Category' is numerically encoded. The 'Blood Pressure' attribute is represented using systolic values, and the sleep disorder label is converted into three numerical classes.

3) Data Normalization

The "Min–Max Scaling method" is used to standardize all numerical features to the range 0-1 during data normalization. The target label of sleep disorder is not normalized because it is a discrete class in a multiclass classification.

3.2. Feature Selection

A collection of features is obtained as input to the ANN model through feature selection utilizing Chi-Square, Information Gain, and Pearson Correlation.

1) Chi-Square for Feature Selection

Eight features were selected using the Chi-Square feature selection process, with a p-value cutoff of 0.05. These features, along with the Chi-Square score and p-value, are shown in Table 2.

Table 2. Features Selected Based on Chi-Square

No	Fitur	Chi-Square Score	p-value
1	BMI Category	124.9226	7.47×10^{-28}
2	Occupation	33.8330	4.50×10^{-8}
3	Blood Pressure	31.6408	1.35×10^{-7}
4	Gender	26.8626	1.47×10^{-6}
5	Physical Activity Level	17.7781	1.38×10^{-4}
6	Age	13.8281	9.94×10^{-4}
7	Sleep Duration	9.6372	8.08×10^{-3}
8	Heart Rate	8.8702	1.19×10^{-2}

The 'BMI Category' feature has the highest Chi-Square value, indicating the most dominant influence on this classification. All selected features have *p-values below the significance threshold, making them suitable* as model inputs and improving the accuracy of predictive analysis.

2) Feature Selection Using Information Gain

Based on IG values over the 0.4377 threshold, the top six features are selected using Information Gain. Table 3 lists the IG traits and values.

Table 3. Information Gain-Based Features Selected

No	Fitur	Information Gain
1	Blood Pressure	0.4745
2	Sleep Duration	0.4732
3	Daily Steps	0.4638
4	Age	0.4617
5	Occupation	0.4475

The 'Blood Pressure' feature has the highest Information Gain, indicating the most significant influence on this classification. All selected features meet the threshold criteria, making them suitable for use as model inputs and improving the accuracy of predictive analysis.

3) Feature Selection Using Pearson Correlation

The results of the feature selection using Pearson Correlation show that only three features have the highest absolute correlation value to the target class. These features are shown in Table 4.

Table 4. Features Selected Based on Pearson Correlation

No	Fitur	Nilai Korelasi Absolut (|r|)
1	Physical Activity Level	0.4332
2	Daily Steps	0.3421
3	Gender	0.2534

The 'Physical Activity Level' feature has the highest Pearson correlation, indicating the most significant influence on this classification. To ensure they are appropriate as model inputs and to increase the precision of predictive analysis, all features were selected based on their highest correlations.

3.3. Artificial Neural Network (ANN) Modeling Classification

The modeling process of Artificial Neural Networks (ANN) is performed in multiple scenarios with varying feature counts and feature selection techniques. The classification accuracy value varies depending on the situation. Table 5 illustrates the accuracy.

Table 5. Comparison of ANN Model Accuracy in Each Scenario

No	Scenario Model ANN	Feature Methods	Features	Acc (%)
1	ANN Baseline	No Feature Selection	All features	**89.3**
2	ANN + Chi-Square	Chi-Square	8	**97.3**
3	ANN + Information Gain	Information Gain	5	**97.3**
4	ANN + Pearson Correlation	Pearson Correlation	3	**88.0**

The test results demonstrate that feature selection significantly improves the performance of the ANN model. Chi-Square, Information Gain, and Pearson Correlation feature selection improved the accuracy to 97.3%, 97.3%, and 88.0%, respectively, compared to the baseline model's accuracy of 89.3%. When categorizing sleep disorders, the ANN with Chi-Square feature selection performs best across all scenarios.

3.4. Evaluation

Figures 3 to 6 present the confusion matrices for four Artificial Neural Network (ANN)-based models: ANN, ANN + Chi-Square, ANN + Information Gain, and ANN + Pearson Correlation.

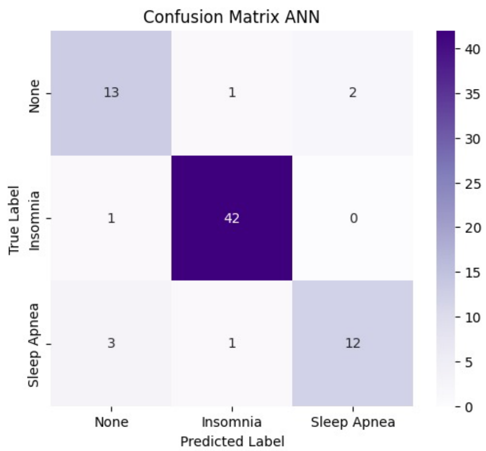

Figure 4. ANN

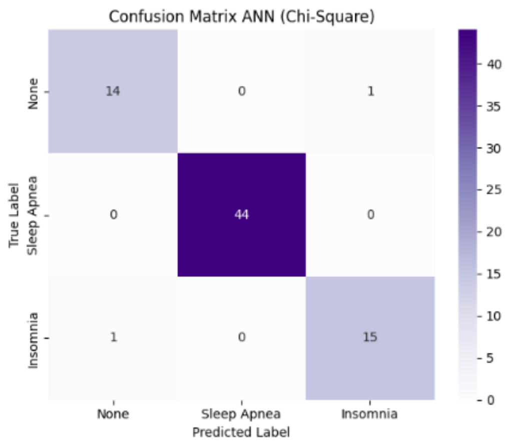

Figure 5. Chi-Square + ANN

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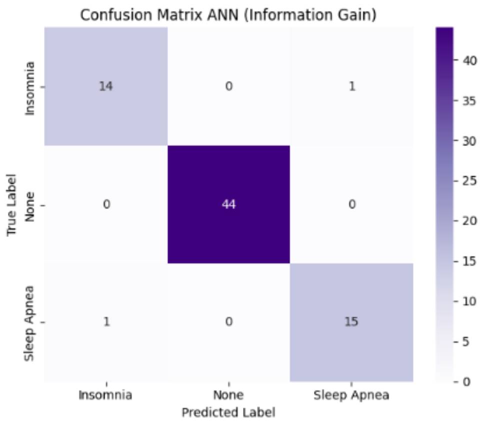

Figure 6. Information Gain + ANN

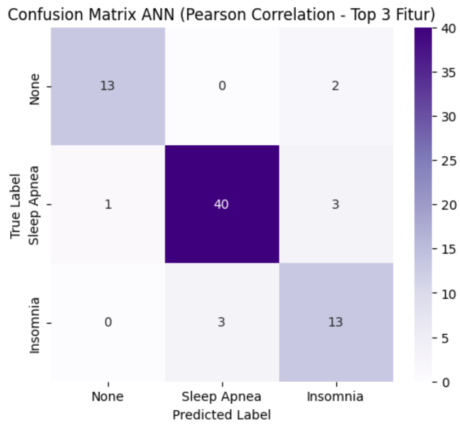

Figure 7. Pearson Correlation + ANN

Based on the confusion matrix in Figure 4, the ANN model without feature selection shows a fairly good classification performance, but there are still some prediction errors between the None, Insomnia, and Sleep Apnea classes. After the feature selection was applied using Chi-Square in Figure 5, the model's performance improved significantly with a very minimal number of misclassifications. Almost similar results are also shown by the Information Gain method in Figure 6, which is able to maintain a high level of classification across the entire class. Meanwhile, the use of Pearson Correlation (Top 3 features) in Figure 7 produces good performance, but is relatively lower than the Chi-Square and Information Gain methods. Overall, Chi-Square feature selection and Information Gain methods were shown to be more effective in improving the performance of ANN models in sleep disorder classifications compared to no feature selection or Pearson Correlation.

Table 6. Model Evaluation

Model	Accuracy	Precision	Recall	F1-Score
Baseline	0.893	0.859	0.846	0.851
Information Gain	0.973	0.958	0.958	0.958
Chi-Square	0.973	0.958	0.958	0.958
Pearson Correlation	0.880	0.860	0.860	0.860

Table 6 of the model performance evaluation shows that the application of the feature selection method has a significant influence on improving the performance of the ANN model classification on sleep disorder data. The baseline ANN model without feature selection produced an accuracy value of 0.893, with a precision of 0.859, a recall of 0.846, and an F1-score of 0.851, which indicates that the model is able to perform classification quite well, but is not optimal. After applying the Information Gain and Chi-Square feature selection methods, the model's performance improved significantly, with an accuracy value of 0.973 in each, and a precision, recall, and F1-score of 0.958, indicating very high and stable classification ability in all classes. Meanwhile, the Pearson Correlation method produced an accuracy value of 0.880, with precision, recall, and F1-score of 0.860 each, which is still good but lower than the other two feature selection methods. Overall, these results show that the Chi-Square feature selection method and Information Gain are the most effective approaches in improving the performance of the ANN model in the classification of sleep disorders compared to baseline and Pearson Correlation.

3.5. Discussion

This study discusses the performance of an Artificial Neural Network (ANN) model for classifying sleep disorders using three different feature configurations: baseline (without feature selection) and best feature selection. The results indicate that feature selection plays a significant role in improving classification performance. The baseline model achieved an accuracy of 89.3%, while both Information Gain and Chi-Square methods increased the accuracy to 97.3%. This improvement can be attributed to the ability of feature selection techniques to eliminate irrelevant and redundant features, thereby allowing the model to focus on the most informative attributes. By reducing noise in the input data, the model becomes more effective in learning meaningful patterns.

Between the two feature selection methods, Chi-Square and Information Gain achieved similar overall accuracy; however, they exhibited different classification behaviors. The Information Gain model showed misclassifications primarily between Insomnia and Sleep Apnea, indicating that these two conditions share similar characteristics in the feature space. In contrast, the Chi-Square model demonstrated confusion between the None and Insomnia classes, suggesting that mild insomnia symptoms may overlap with normal sleep conditions.

Further analysis of the confusion matrices reveals that Sleep Apnea is consistently one of the most challenging classes to classify. This is evident from the lower recall values in the baseline model and the misclassification patterns observed in other models. This

difficulty can be explained by the overlapping symptoms between Sleep Apnea and other conditions, such as general sleep disturbances or fatigue, which are not uniquely represented in the available features. From a clinical perspective, this finding is important because misclassification of Sleep Apnea may lead to delayed diagnosis and treatment.
In terms of evaluation metrics, the ANN model demonstrates strong performance, particularly for the Insomnia class, which achieved the highest precision, recall, and F1-score. However, the performance for the Sleep Apnea class remains relatively lower, indicating the need for further improvement. This could be addressed in future work by incorporating additional domain-specific features or using more advanced modeling techniques.

The findings of this study are consistent with previous research, which suggests that feature selection methods significantly enhance machine learning model performance by reducing dimensionality and improving generalization. The results also highlight the importance of careful feature handling and comprehensive evaluation metrics in developing reliable classification models.

4. CONCLUSION

This study shows that the Artificial Neural Network (ANN) algorithm can be effectively used for classifying sleep disorders, especially when combined with an appropriate feature selection method. The test results showed that the ANN model without feature selection achieved 89.3% accuracy, whereas feature selection provided a significant performance improvement. With an accuracy of 97.3%, the Chi-Square approach performed the best, followed by Information Gain at 97.3% and Pearson Correlation at 88.0%. These results suggest that feature selection is essential to enhancing the model's capacity to reliably and precisely identify sleep disturbance patterns. The impact of this research lies in its contribution to the development of a more reliable artificial intelligence-based sleep disorder classification system, which has the potential to serve as a decision-support system for medical personnel, speeding up and improving the accuracy of sleep disorder diagnosis.

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