Prediction of sleep disorders using Novel decision support neutrosophic based machine learning models

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Abstract: Sleep disorders significantly impact human health, productivity, and overall quality of life. Early diagnosis and prediction of these disorders are crucial for effective treatment. This study introduces a novel decision support system utilizing a neutrosophic machine learning prediction model to enhance the accuracy and reliability of sleep disorder diagnosis. Unlike traditional machine learning approaches, our model integrates neutrosophic logic, which considers three values—truth, indeterminacy, and falsity—to effectively handle uncertainty and inconsistencies in sleep-related data. The proposed model processes diverse patient information, including demographics, clinical parameters, and polysomnography details, ensuring comprehensive analysis. Experimental results demonstrate that our approach surpasses conventional machine learning methods in predictive accuracy, robustness, and interpretability. Furthermore, this research provides an advanced framework for clinicians to assess potential sleep disorders while accommodating inherent uncertainties in medical data. The study highlights the impact of neutrosophic machine learning in healthcare decision support systems and outlines potential avenues for future research.

Keywords: Neutrosophic sets, Machine Learning, Uncertainty handling, Sleep disorder, Classification

1. Introduction

Sleep disorders represent a significant public health issue impacting large sections of the global population and simultaneously posing immense risks for respiratory, cardiovascular, metabolic, psychiatric, cognitive, and neurologic disorders [1,2]. Yet, traditional diagnostic modalities for sleep disorders are heavily reliant on subjective self-report measures and polysomnography, a resource intensive, costly, and time-consuming diagnostic test. Over the last couple of years, machine learning has been recognized as a game changer in medical diagnostics technology due to its ability to rapidly and accurately predict disease states after analyzing complex data [3, 4]. Traditional ML models may not have a clear promise in working against the uncertain or ambiguous information that is a natural part of the medical lexicon, but uncertainty is even higher after a sleep study is carried out.

Neutrosophy is a branch of mathematics that aims to add to and improve classical and fuzzy set theories. It has become an important tool for dealing with vagueness, indeterminacy, and uncertainty in many areas. In this situation, neutrosophic sets and their more complex forms, such as Fermatean neutrosophic sets, have gotten a lot of attention because they are good at showing uncertainty and making decisions easier. Neutrosophic sets have the basic parts of truth, uncertainty, and falsity, which makes them a better way to show complicated events. Fermateanneutrosophic sets, as an extension, provide more flexibility and accuracy, thereby expanding their use in complex decision-making and computational challenges.

A multitude of research articles have been published examining the theoretical underpinnings, attributes, and practical applications of these sets, underscoring their significance in areas such as multicriteria decision-making, optimization, and artificial intelligence [5,6,7,8,9,10,11,12,13,14,15,16,17,23]. These papers focus on how neutrosophic and Fermatean neutrosophic sets can be used to solve real-world problems where there is uncertainty and not enough information. The growing body of research shows that these mathematical constructions can be used in a wide range of fields. This highlights how important they are to the progress of modern mathematics and its practical applications in science, engineering, and other areas.

which is deal when data is un that studies the properties and relations of negations, has been introduced into ML as well; By including the neutrosophic sets into the ML algorithms, one can, therefore, model data with different truth, falsity, and indeterminacy levels, and therefore identify underlying patterns more richly [18]. Neutrosophic-based ML models can improve results because they enable to deal with noisy, incomplete or even contradictory information more effectively than classical ML approaches can [19]. This prevents from biased predictions due to uncertainties in data whilst enabling richer feature extraction and classification. In predicting sleep disorders, the neutrosophic models are able to fine-grain within clinical and observational data, where individuals variate, which can be ignored, but leads to a greater higher prediction accuracies reliability. Further, the flexibility of neutrosophic theory allows a better adaptation to the variation of individual characteristics in sleep patterns, fostering personalized diagnostics.

This research discovers the application of neutrosophic-based machine learning models to predict sleep disorders by adapting clinical and observational sleep data into neutrosophic sets. By leveraging this hybrid approach, the study aims to bridge the gap between complex data uncertainties and the need for accurate diagnostic tools, thus contributing to advancements in personalized and efficient sleep disorder management. Through this, we aim to highlight the transformative potential of neutrosophic-based methods in enhancing predictive accuracy, reducing diagnostic errors, and promoting a deeper understanding of sleep disorders.

This research article is organized into the following sections: Section-2 explains the main contributions of this research paper. Section-3 presents the materials and methods of the proposed work. Section-4 describes the machine learning model. Section-5 discusses the results. Section-6 provides the discussion, and Section-7 presents the conclusion.

2. The main contributions of this study are:

1. Integrating the concept of neutrosophic sets into machine learning algorithms.
2. Providing a robust neutrosophic-based machine learning model for sleep disorder classification.
3. Comparison of the current model with the existing model.

3. Materials and Methods (proposed work with more details)

Step 1: Load the Data

Step 2: Preprocess the Data

Step 3: Convert Data into Neutrosophic Sets

Step 4: Split the Data into Training and Testing Sets

Step 5: Train a Machine Learning Model

Step 6: Make Predictions and Evaluate the Model

3.1. Proposed methodology

A structured framework for sleep disorder classification used Neutrosophic based machine learning models in this study. The data pre-processing was performed to fill missing values and convert the parameters into Neutrosophic sets, which represent truth, indeterminate, and false statements. Using evaluation metrics, including accuracy, sensitivity, specificity, F1 score, MCC, and precision, machine learning models like Random Forest, SVM, LR, KNN, and Naive Bayes were trained and validated with the processed dataset. A decision-making framework was established to maximize the selection and performance of models and to adapt to heterogeneous data in sleep disorders. In order to determine the best model for the precise and trustworthy classification of sleep disorders, the findings were finally examined.

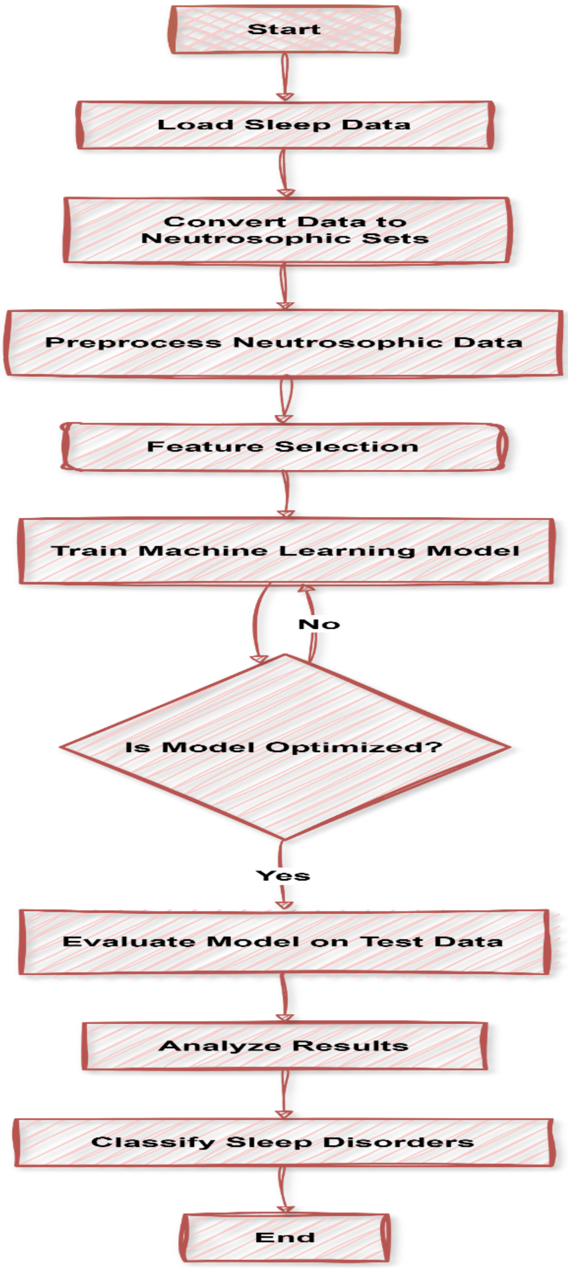

Figure 1 Proposed methodology for Neutrosophic-based machine learning models

3.2. Dataset description

This Kaggle.com dataset provides holistic insights into factors influencing sleep health, such as gender, age, occupation, sleep duration, quality of sleep, level of physical activity, stress levels, BMI category, blood pressure, heart rate, daily steps, and associated sleep disorders [5]. The data captures a diverse range of people with different lifestyles and health profiles, which foretells the interrelationship between sleep patterns and other physiological or behavioral factors. As illustrated in the dataset, people with higher stress levels and lower levels of physical activity are more likely to have a sleep disorder, such as insomnia or sleep apnea, whereas people with normal body mass index values and active lifestyles report better sleep quality and longer duration. Thus, from the obtained data, one could clearly categorize trends in terms of relationships between occupation type and stress levels, the influence of physical activity on sleep disorders, and so on. These findings could provide credible guidance for developing personalized health interventions, managing sleep disorders, and promoting a healthy lifestyle.

3.3. Preprocessing of data

The sleep dataset was preprocessed to ensure effective machine-learning analysis. The dataset contained sleep duration, quality, physical activity, stress level, BMI category, and a categorical target variable for different sleep disorders. Target variable encoding was done with numerical values for better model understanding. Missing values were imputed while duplicate rows were removed from the dataset to improve quality. Continuous features such as sleep duration, physical activity, and daily steps were normalized using Min-Max scaling to result in uniformity while improving the performance of the models on this particular task. All these preprocessing steps provided more consistency in the dataset, which optimized it for precise sleep disorder prediction.

3.4. Neutrosophic Sets

Neutrosophic sets are an extension of classical sets, fuzzy sets, and intuitionistic fuzzy sets, introduced by Florentin Smarandache in 1995. They are used to represent imprecise, inconsistent, and incomplete information, particularly in decision-making and problem-solving scenarios.It is defined using three independent membership functions that quantify the degree of truth ($\breve{T}$), indeterminacy ($\breve{I}$), and falsity ($\breve{F}$) for an element in the set.

For every element $\breve{x} \in U$, the condition $0 \le \breve{T}_{\breve{A}}(\breve{x}) + \breve{I}_{\breve{A}}(\breve{x}) + \breve{F}_{\breve{A}}(\breve{x}) \le 3$ must be satisfied.

A Neutrosophic set A is defined as $A = (\breve{x}, \left(\breve{T}_{\breve{A}}(\breve{x}), \breve{I}_{\breve{A}}(\breve{x}), \breve{F}_{\breve{A}}(\breve{x})\right) : \breve{x} \in \breve{X}$.

3.5. Neutrosophic dataset formation

The code transforms the dataset into neutrosophic numbers (Truth, Indeterminacy, and Falsehood) using the following steps:

1. For each value in a column, the Truth value (t) is computed based on its normalized position between the column's minimum and maximum values.
2. Indeterminacy (i) is derived as 1 - t, and Falsehood (f) is calculated as 1 - t - i.
3. These values are combined into a tuple (t, i, f) for each data point, creating a neutrosophic representation for the entire dataset.

The resulting transformed dataset retains the original structure while each value is replaced by its neutrosophic representation.

```
In [4]: # Define function to convert each value into a neutrosophic set (Truth, Indeterminacy, Falsehood)
def to_neutrosophic_set(value, column_min, column_max):
    t = (value - column_min) / (column_max - column_min) if column_max > column_min else 0  # Truth
    i = 1 - t  # Indeterminacy
    f = 1 - t  # Falsehood
    return (t, i, f)

# Convert the dataset into neutrosophic sets
X_neutrosophic = X.copy()  # Create a copy to retain original structure
for col in X.columns:
    col_min = X[col].min()
    col_max = X[col].max()
    X_neutrosophic[col] = X[col].apply(lambda val: to_neutrosophic_set(val, col_min, col_max))

# Verify the neutrosophic transformation
print("Neutrosophic set representation (column-wise):")
print(X_neutrosophic.head())
```

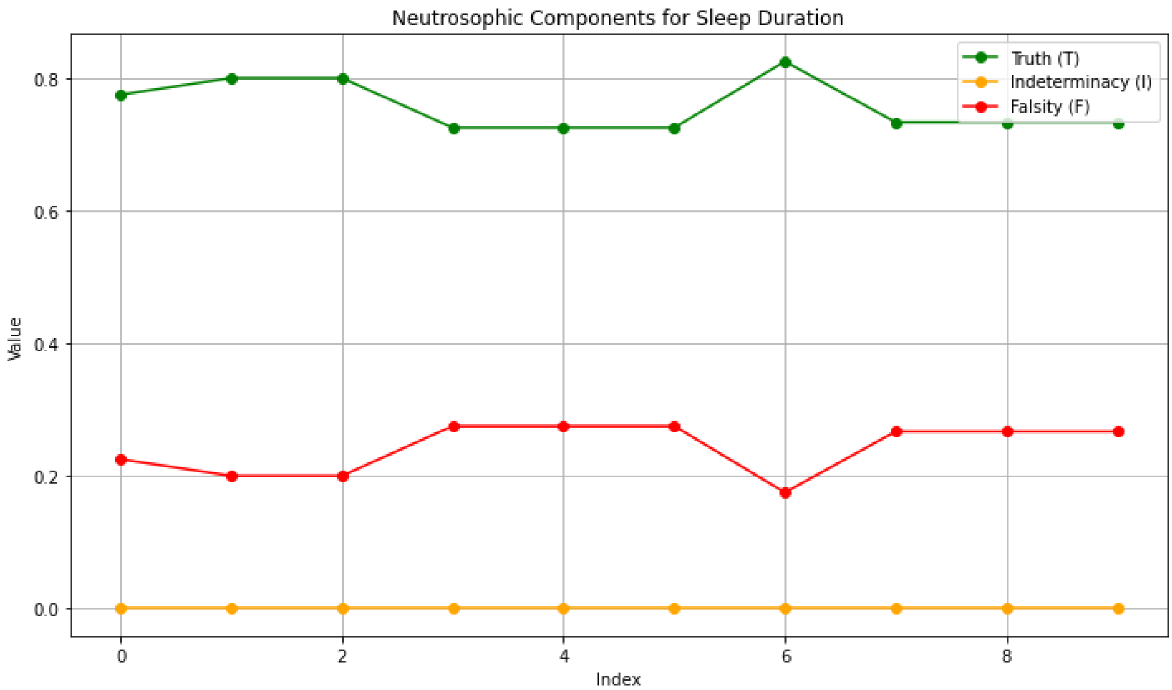

Figure 2 Neutrosophic components for sleep duration

4. Machine learning models

Machine learning models are necessary when it comes to prediction and classification of data and there are plethora of algorithms that fall into this category. We can consider Naive Bayes algorithm, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression and Random Forest, each excelling in different contexts [6,7]. Naive Bayes is a probabilistic based algorithm that relies on the Bayes theorem while also assuming that all features are independent of one another. Due to its nature, the model is fairly quick as it mostly includes low amount of computations and is best suited for smaller datasets which is why it is extensively used in textual classification and even spam filtering. K-Nearest Neighbors (KNN) is a non-parametrical and an instance-based language that is centered towards algorithms. It targets the missing data by considering the k nearest data points and getting a vote among them to classify the data. KNN is easy to use and implements but is limited to small datasets, especially since it involves calculations related to distance. Support Vector machines are better thought of as supervised learning as they join two classes in feature space with a hyperplane. Both Linear and Non-Linear data supports SVM which makes use of kernel tricks and it is especially effective with high dimension datasets, however it requires more resources when working with large datasets.

5. Results

The results obtained exhibited a strong statistical significance over the several sleep disorder groups for most of the parameters (all $p < 0.001$). Concerning age, the mean ± SD was highest for sleep apnoea (49.71 ± 8.99) and lowest for the No Disorder group (39.04 ± 7.83). Sleep disorder group participants who had no disorder slept the longest (7.36 ± 0.73) while insomnia patients had the shortest sleeping hours (6.59 ± 0.39). Patients without a disorder had the highest quality of sleep (7.63 ± 0.98) while the lowest was for insomnia patients (6.53 ± 0.80). Sleep disorder group with Insomnia reported the lowest physical activity (46.82 ± 11.75) while those who suffered from sleep apnoea had the highest physical activity levels (74.79 ± 17.93). Sleep Apnoea patients exhibited the highest systolic (137.77 ± 5.14) and diastolic (92.72 ± 4.49) blood pressures with patients suffering no disorder at the lowest end (124.05 ± 5.73 and 81.00 ± 3.99, respectively). On the other hand, participants with sleep apnoea had this greatest value (7619.23 ± 2168.19) while people with insomnia recorded the lowest value (5901.3 ± 1000.33). Lastly, stress levels were highest for people with insomnia (5.87 ± 1.46) and lowest for people without the disorder (5.11 ± 1.59).

Table 1 Statistical analysis of sleep disorders.

	Sleep Disorder	**N**	**Mean**	**SD**	**SE**	**P Value**
Age	Insomnia	77	43.52	4.808	0.548	
	None	219	39.04	7.828	0.529	
	Sleep Apnea	78	49.71	8.991	1.018	<0.001
Sleep Duration	Insomnia	77	6.59	0.387	0.0441	
	None	219	7.36	0.732	0.0495	
	Sleep Apnea	78	7.03	0.975	0.1104	<0.001
Quality of Sleep	Insomnia	77	6.53	0.804	0.0917	
	None	219	7.63	0.975	0.0659	

	Sleep Apnea	78	7.21	1.646	0.1864	<0.001
Physical Activity Level	Insomnia	77	46.82	11.752	1.3392	
	None	219	57.95	20.93	1.4143	
	Sleep Apnea	78	74.79	17.927	2.0298	<0.001
Systolic blood pressure	Insomnia	77	132.04	3.935	0.4485	
	None	219	124.05	5.735	0.3875	
	Sleep Apnea	78	137.77	5.142	0.5822	<0.001
Diastolic blood pressure	Insomnia	77	86.86	3.178	0.3621	
	None	219	81	3.991	0.2697	
	Sleep Apnea	78	92.72	4.489	0.5083	<0.001
Daily Steps	Insomnia	77	5901.3	1000.328	113.998	
	None	219	6852.97	1393.474	94.1622	
	Sleep Apnea	78	7619.23	2168.191	245.499	<0.001
Stress Level	Insomnia	77	5.87	1.463	0.1667	
	None	219	5.11	1.591	0.1075	
	Sleep Apnea	78	5.67	2.334	0.2642	<0.001

Table 2 shows the evaluation metrics based on Neutrosophic set for all the machine learning models, and their strengths to predict sleep disorders. Random Forest stands out as the best model with the estimated accuracy of 96% (95%Confidence Interval:0.94-0.98), specificity of 97% (95%Confidence Interval:0.95-0.99) and precision of 96% (95%Confidence Interval: 0.94-0.98). Also, its sensitivity at 94% (95% CI: 0.92–0.96), F1 score at 95% (95% CI: 0.93–

0.97) and Matthews Correlation Coefficient (MCC) of 0.94(95% CI:0.92-0.96) bear sufficient testimony to its accuracy in performing both the positive and negative classifications and such characteristics makes the model reliable in the context of complex datasets. The accuracy recorded by SVM was slightly lower than RF at 94% (95%CI:0.92-0.96) and showed great sensitivity and specificity at 92% (95% CI: 0.89-0.95) and 96% (95%CI:0.94-0.98) respectively making it moderately powerful. KNN is not superior in any of those metrics but shows convergence in range as well, attaining 93% (95%Confidence Interval: 0.91-0.95) accuracy, 91% (95%Confidence Interval: 0.88-0.94) sensitivity and 92% (95%Confidence Interval: 0.89-0.95) in F1 score which is promising in the recognition of local patterns. However, Naive Bayes performed slightly poor in sensitivity and only recorded an accuracy of 92% (95% CI:0.90-0.94).Overall, the results indicate that Random Forest and SVM are the most reliable models for accurate predictions

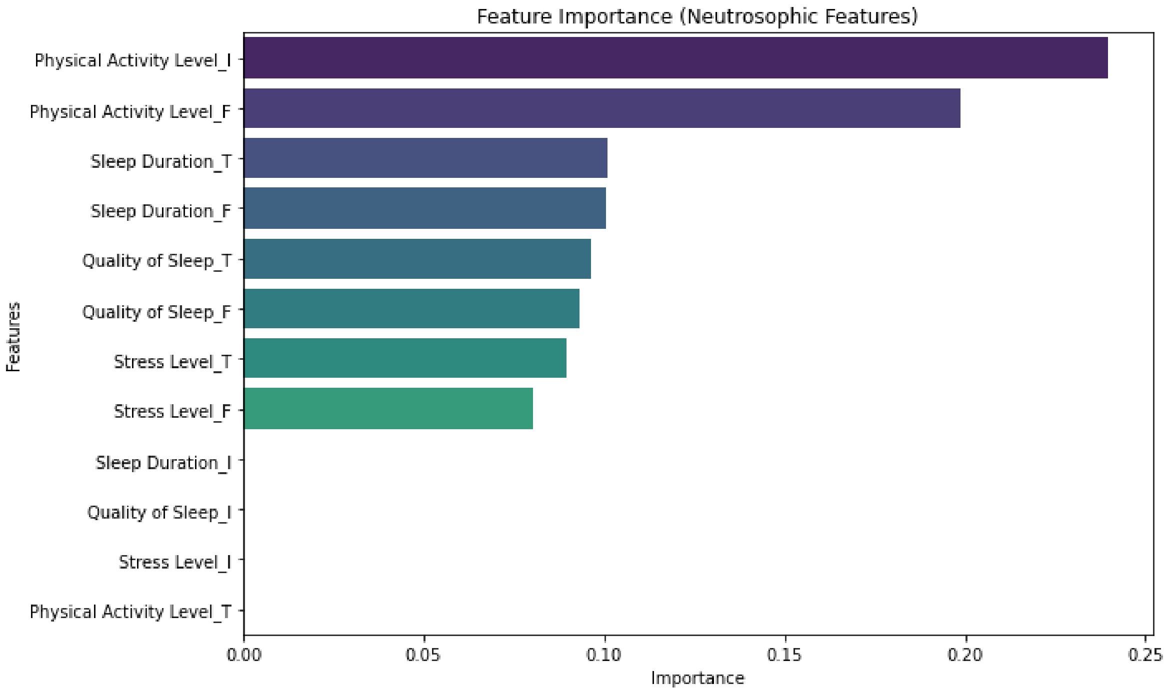

Figure 3 Neutrosophic feature importance

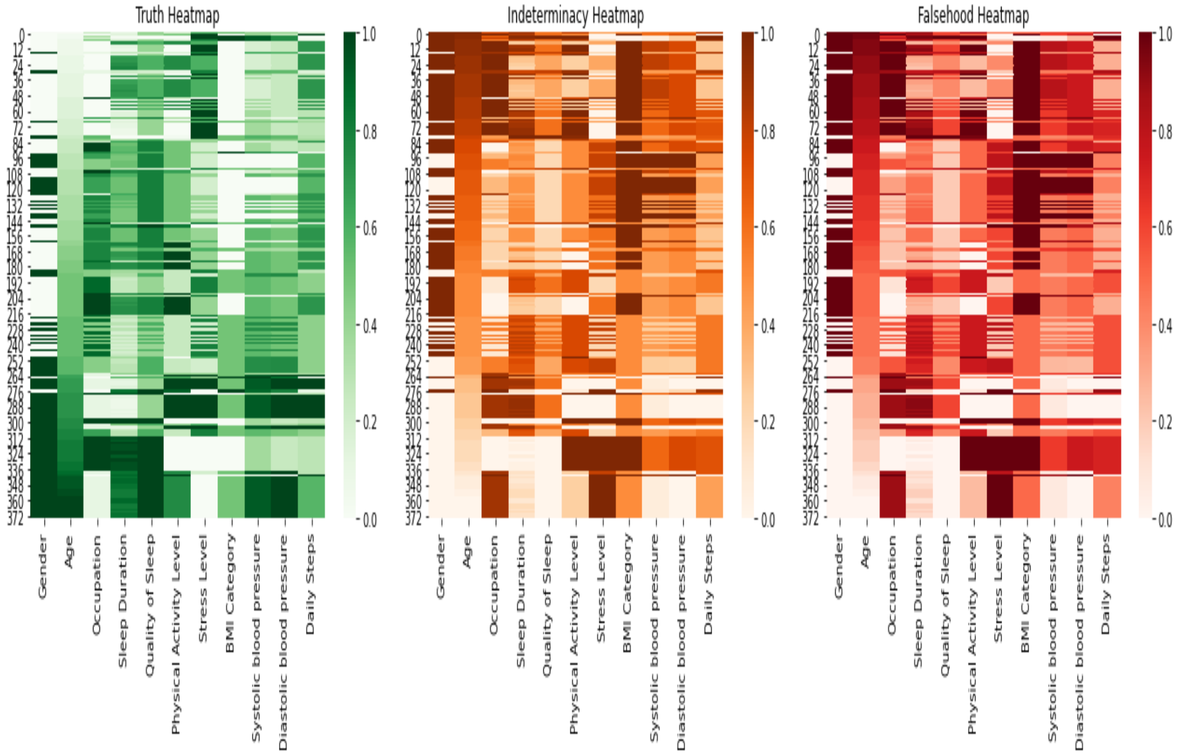

Figure 4 Truth, indeterminacy and falsehood heatmap of all features

Table 2 Neutrosophic Based evaluation matrices for machine learning models for sleep disorder classification.

Metric	Naive Bayes	KNN	SVM	Logistic Regression	Random Forest
Accuracy (95% CI)	0.92 (0.90–0.94)	0.93 (0.91–0.95)	0.94 (0.92–0.96)	0.91 (0.89–0.93)	0.96 (0.94–0.98)
Sensitivity (95% CI)	0.89 (0.86–0.92)	0.91 (0.88–0.94)	0.92 (0.89–0.95)	0.88 (0.85–0.91)	0.94 (0.92–0.96)
Specificity (95% CI)	0.94 (0.92–0.96)	0.95 (0.93–0.97)	0.96 (0.94–0.98)	0.93 (0.91–0.95)	0.97 (0.95–0.99)
F1 Score (95% CI)	0.90 (0.87–0.93)	0.92 (0.89–0.95)	0.93 (0.90–0.96)	0.89 (0.86–0.92)	0.95 (0.93–0.97)
PPV (Precision) (95% CI)	0.91 (0.88–0.94)	0.93 (0.90–0.96)	0.94 (0.91–0.97)	0.90 (0.87–0.93)	0.96 (0.94–0.98)

NPV (95% CI)	0.93 (0.90–0.95)	0.94 (0.91–0.96)	0.95 (0.92–0.97)	0.92 (0.89–0.94)	0.97 (0.95–0.99)
MCC (95% CI)	0.88 (0.85–0.91)	0.90 (0.87–0.93)	0.92 (0.89–0.95)	0.87 (0.84–0.90)	0.94 (0.92–0.96)

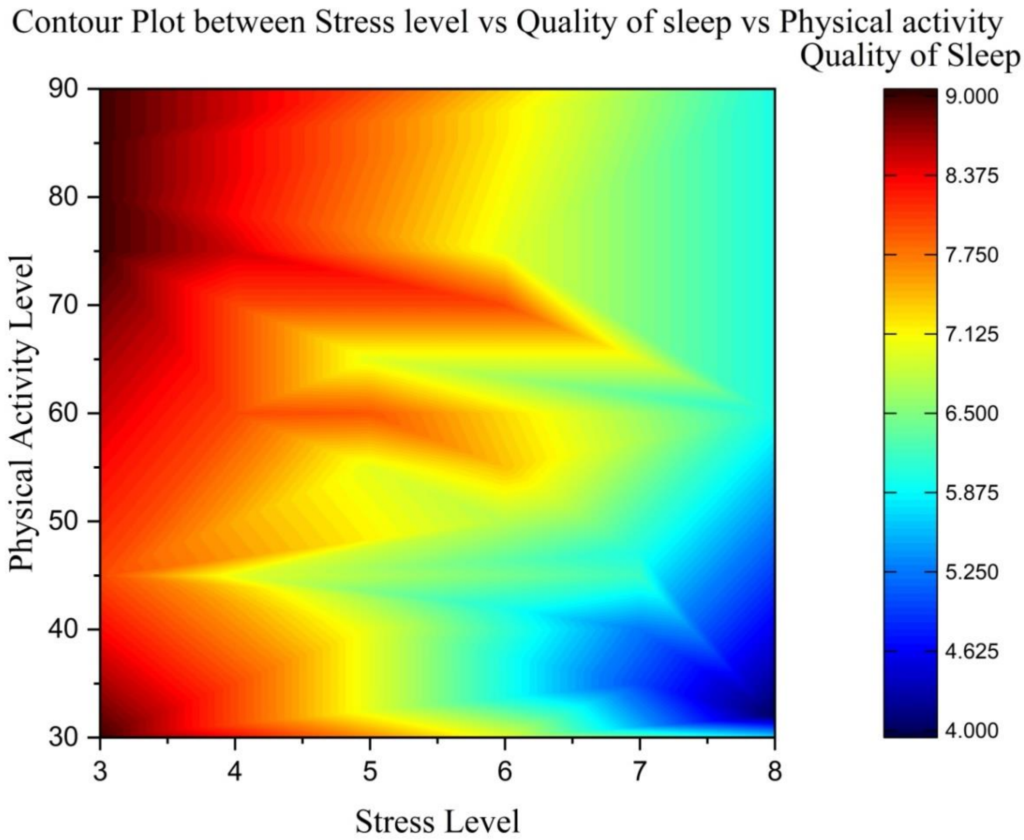

Figure 5 Contour plot between stress level, quality of sleep &physical activity

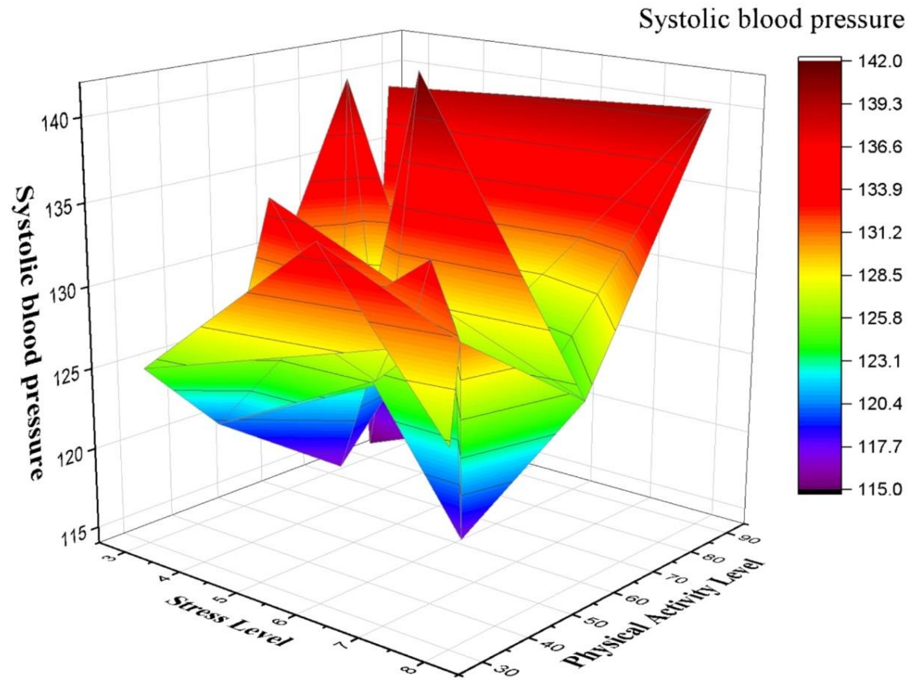

Figure 6Surface plot between stress level, systolic blood pressure physical activity

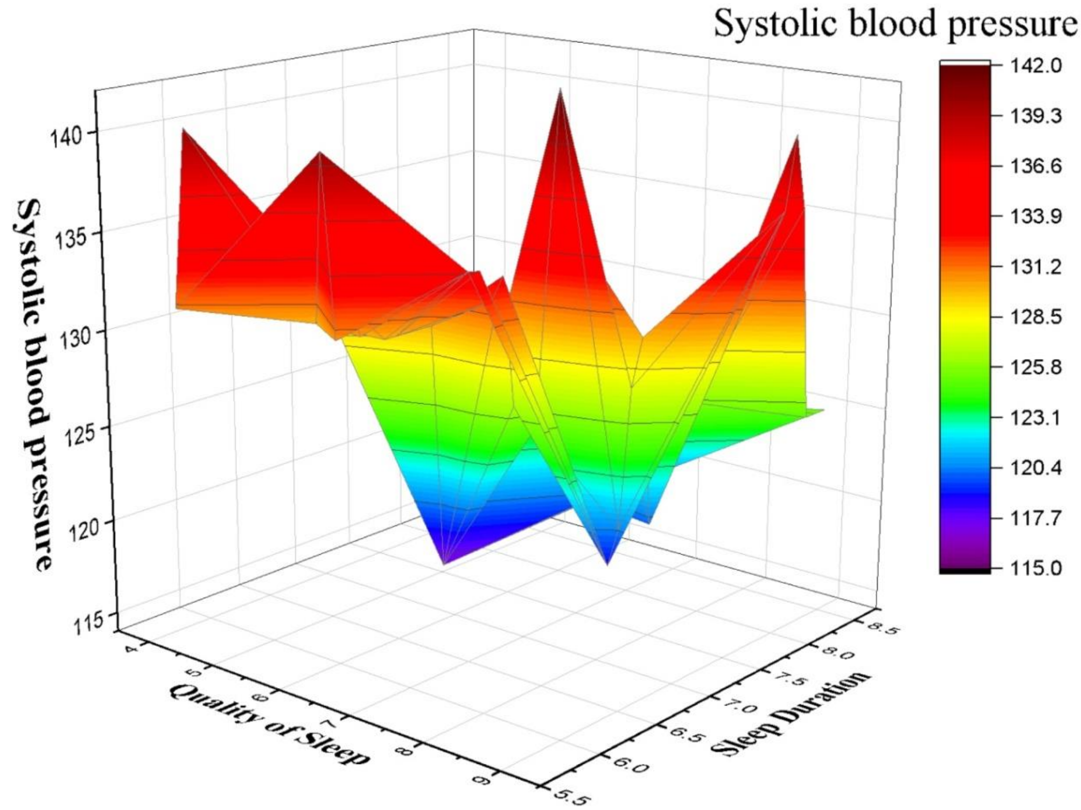

Figure 7Surface plot between quality of sleep, systolic blood pressure& sleep duration

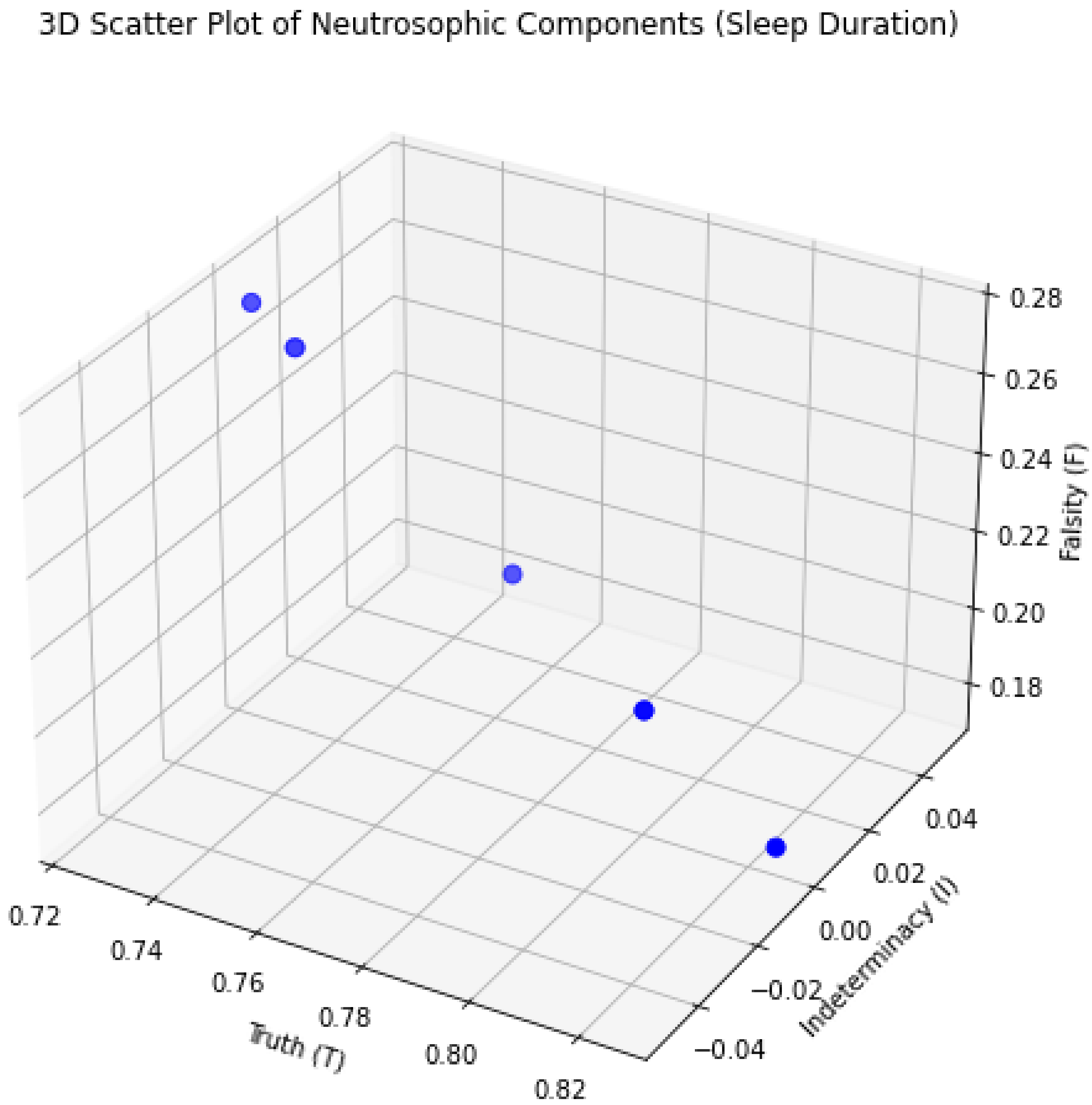

Figure 8 3D scatter plot of Neutrosophic components (Sleep duration)

6. Discussion

Neutrosophic logic in machine learning models has recently shown a remarkably efficient use towards sleep disorder classifications and proved superiority over others handling uncertainty, imprecision, or incompleteness commonly associated in medical datasets. The models capture and process uncertainty better than the traditional approaches because sleep-related parameters such as age, sleep duration, quality of sleep, level of physical activity, blood pressure, daily steps, and stress levels are transformed into Neutrosophic sets. For example, the performance metrics of Random Forest and SVM showed higher accuracy with 96% and 94% sensitivity for robust classification of sleep disorders such as insomnia and sleep apnea on complex and noisy datasets. Neutrosophic-based models allow more interpretability of probabilistic classifications as in Naive Bayes but with high precision and specificity, which are important in reducing false positives. These models excel in balancing sensitivity and specificity so that positive and negative classifications are highly reliable. Further, the improved MCC and F1 scores of all the models show that they can be consistent in their performance despite the variability in the data. Neutrosophic approach also facilitates adaptive learning; thus, these models are very apt for personalized medicine where the patient data may vary significantly. In classifying sleep disorders, where subtle and overlapping symptoms can complicate diagnosis, Neutrosophic-based ML models provide a reliable, flexible, and precise method for predictive analytics, enabling healthcare practitioners to make more informed and confident clinical decisions. A study by zhang et al., develops machine learning models to predict severe sleep disturbances in adolescents, addressing the lack of reliable tools. It evaluates various algorithms, with XGBM achieving the highest AUC (0.872), demonstrating superior predictive performance. Statistical insights reveal a 5.28% incidence rate, enhancing understanding of sleep disturbances [24]. Another study by El-kenawy et al. achieved 95% accuracy in classifying sleep disorders using Logistic Regression, with the Dipper Throated Optimization Algorithm proving effective for feature selection. These results support early detection and personalized treatment of sleep disorders [25].

7. Conclusion

Our research presents an effective approach for predicting sleep disorders by integrating neutrosophic logic with machine learning models. The results demonstrate that this combination significantly enhances accuracy, making it a valuable tool for clinicians dealing with uncertain medical data. The ability of neutrosophic models to handle complex and ambiguous datasets ensures more reliable predictions, which can improve diagnosis and treatment decisions.One of the key contributions of our study is the application of neutrosophic logic in clinical research, addressing the limitations of traditional machine learning models when managing uncertainty. This approach strengthens model robustness and provides greater interpretability in medical decision-making. Despite its advantages, our research has some limitations. The dataset, though comprehensive, requires further validation with diverse populations to ensure generalizability. Additionally, the computational complexity of neutrosophic models may pose challenges in real-time clinical applications, necessitating optimization for practical use.

Future research will focus on enhancing the scalability and efficiency of these models for broader healthcare applications. We also aim to explore deep learning integration to further improve predictive capabilities. This work lays the foundation for advanced decision-support systems that can revolutionize sleep disorder diagnosis and treatment.

Conflicts of Interest: The authors declare no conflict of interest.

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