Recognition of Sleep Disorders using IoT-Based Wearables and Neutrosophic Data Analytics

Fatma Taher*
College of Technological Innovation, Zayed University, Dubai, UAE
Emails: Fatma.taher@zu.ac.ae

Abstract

In the dynamic landscape of healthcare technology, the amalgamation of Internet of Things (IoT) systems and Neutrosophic Data Analytics has heralded a paradigm shift. This study delves deep into this transformative synergy by presenting an innovative IoT-based wearable system design for the recognition of sleep disorders. Our meticulously crafted multilayer cellular system seamlessly integrates IoT devices, data acquisition, cloud computing, and machine learning to unlock a wealth of insights into sleep patterns, their anomalies, and the presence of sleep disorders. Through fair and rigorous experimental comparisons, we unveil the prowess of Long Short-Term Memory (LSTM) within the machine learning realm, showcasing its superior performance over baseline models. The results affirm LSTM's ability to detect sleep disorders with remarkable accuracy, precision, and recall, revolutionizing sleep medicine and healthcare practices. This research, at the crossroads of innovation and healthcare, not only illuminates the path to advanced sleep disorder diagnosis but also heralds a new era of personalized healthcare interventions and remote monitoring solutions. As we navigate the realm of IoT and data-driven healthcare, our findings hold the promise of improving the quality of life for countless individuals, reaffirming the pivotal role of technology in safeguarding one of the most fundamental aspects of human well-being – a peaceful and restorative night's sleep.

Keywords: Sleep Disorders; Internet of Things (IoT); Neutrosophic Data Analytics; Health Monitoring Devices; Internet of Medical Things (IoMT).

1. Introduction

In an era defined by the relentless evolution of technology, our understanding of healthcare and its delivery has witnessed a transformative paradigm shift. The integration of Internet of Things (IoT)-based wearables and advanced Neutrosophic Data Analytics has emerged as a groundbreaking frontier in healthcare, offering a dynamic synergy that holds immense promise for the diagnosis and management of a wide range of medical conditions [1]. One such domain where this fusion has the potential to revolutionize healthcare outcomes is the recognition of sleep disorders. Sleep, an essential physiological process, plays a pivotal role in maintaining overall well-being, yet sleep disorders often go undiagnosed, leading to a myriad of health complications. This paper endeavors to shed light on the remarkable prospects of utilizing IoT-based wearables and Neutrosophic Data Analytics in the realm of sleep medicine, aiming to enhance the precision of sleep disorder recognition, thus improving the quality of life for countless individuals worldwide [2].

Sleep disorders constitute a pervasive and insidious health concern affecting millions across the globe. These disorders encompass a diverse spectrum, including insomnia, sleep apnea, restless leg syndrome, narcolepsy, and more. Left untreated, sleep disorders can lead to a cascade of adverse health consequences, ranging from impaired cognitive function and decreased productivity to cardiovascular diseases and mental health disorders [3]. Sadly, many individuals suffering from these conditions remains undiagnosed due to the episodic and often elusive nature of sleep-related disturbances. Traditional methods of diagnosis typically involve labor-intensive and costly overnight polysomnography studies conducted within specialized sleep laboratories [4]. This paper posits that the marriage of

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023

IoT-based wearables and Neutrosophic Data Analytics presents a viable and accessible solution to address this diagnostic challenge.

IoT-based wearables, such as smartwatches and fitness trackers, have become ubiquitous in our daily lives, offering a treasure trove of physiological data waiting to be harnessed for healthcare applications. These devices are equipped with an array of sensors, including accelerometers, heart rate monitors, and even SpO2 sensors, which can collectively provide a wealth of information about an individual's sleep patterns, movements, and vital signs. Importantly, they offer the advantage of continuous, non-invasive monitoring in the comfort of one's own home, overcoming the constraints associated with traditional sleep studies. Moreover, these wearables can seamlessly transmit data to cloud-based platforms for real-time analysis, opening the door to early recognition of sleep disturbances and the potential for timely intervention [5-6].

The true potential of IoT-based wearables in the context of sleep disorder recognition lies in the realm of Neutrosophic Data Analytics. The deluge of data generated by these devices necessitates advanced computational techniques to extract meaningful insights. Machine learning algorithms, deep learning models, and big Neutrosophic Data Analytics hold the promise of not only automating the detection of sleep disorders but also tailoring interventions based on an individual's unique sleep profile [7-8]. This paper explores the various Neutrosophic Data Analytics approaches that can be leveraged to analyze sleep data collected through IoT-based wearables, with a focus on their capacity to usher in a new era of precision sleep medicine, where interventions are customized to the specific needs and patterns of each patient.

This paper is structured to provide a comprehensive exploration of the recognition of sleep disorders using IoT-based wearables and Neutrosophic Data Analytics. In Section II, we delve into the foundational knowledge and existing research in the field of sleep disorders, IoT-based wearables, and Neutrosophic Data Analytics, setting the stage by elucidating the significance of our research in addressing current healthcare challenges. In Section III, we offer an in-depth description of the research approach adopted in this study. Section IV presents the specifics of our experimental setup, including participant recruitment, data acquisition procedures, and any controlled variables. In Section V, we unveil the outcomes of our analysis, showcasing how IoT-based wearables and Neutrosophic Data Analytics can be effectively harnessed for sleep disorder recognition. Finally, in Section VI, we draw together the threads of our research. We summarize the key findings, their significance, and the broader implications for healthcare.

2. Background and Literature

This section offers a comprehensive overview of prior research and developments that have contributed to our understanding of the field. By examining the rich tapestry of related work, we gain insights into the evolution of technology, methodologies, and key discoveries in the realm of sleep disorder diagnosis and monitoring. Kim et al. [8] introduced IoT-based unobtrusive sensing for sleep quality monitoring and assessment. Their research laid the foundation for utilizing IoT technologies in sleep monitoring, emphasizing the importance of unobtrusive methods for assessing sleep quality. This work provides valuable insights into the initial stages of applying IoT to sleep medicine. Awotunde et al. [9] explored IoT-based wearable body sensor networks for monitoring various health parameters during the COVID-19 pandemic. While their primary focus was on pandemic-related monitoring, the study demonstrated the potential of wearable IoT devices in real-time health data collection. This broader application context highlights the versatility of IoT wearables in healthcare. In a more recent study, Rajguru et al. [10] designed and implemented an IoT-based sleep monitoring system specifically targeting individuals with insomnia. Their work showcases a practical application of IoT for sleep disorder management, with a focus on real-world usability. Rajpoot et al. [11] investigated IoT for human activity recognition using wearable sensors. Although not directly focused on sleep disorders, their research sheds light on the capabilities of IoT-based wearables in capturing human activities, a vital component in sleep analysis.

Beresford et al. [12] conducted a systematic review of interventions for sleep disturbances in children with neurodisabilities. While their study covers a broader spectrum of sleep disorders, it emphasizes the importance of both pharmacological and non-pharmacological approaches, which can inform our understanding of holistic sleep disorder management. Abdel-Basset et al. [13] surveyed the fusion of Internet of Intelligent Things (IoIT) in remote diagnosis of obstructive Sleep Apnea. Their work provides insights into the role of IoT in diagnosing specific sleep disorders, such as sleep apnea, highlighting the potential of remote monitoring and diagnosis.

Lakshmi et al. [16] presented a concise study on IoT-based healthcare, offering a comprehensive view of the applications of IoT in the healthcare domain. This broader perspective provides context for the role of IoT in

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023

addressing various health-related issues, including sleep disorders. Bhatt and Chakraborty [17] investigated the importance of trust in IoT-based wearable device adoption by patients. While their study primarily focuses on user acceptance, it underscores the critical role of user trust and engagement, which can influence the success of IoT-based solutions for sleep disorder monitoring. Magadum [18] analyzed the impact of IoT-based wearables on individuals' health consciousness. While not a clinical study, this research offers insights into the behavioral aspects of using IoT wearables for health monitoring and the potential for raising awareness about sleep-related issues. Li et al. [20] conducted a comprehensive survey on machine learning-based big Neutrosophic Data Analytics for IoT-enabled smart healthcare systems. While not specific to sleep disorders, their work highlights the broader landscape of machine learning applications in healthcare Neutrosophic Data Analytics, which can inform the data processing aspects of our study. Haghi et al. [21] developed a flexible and pervasive IoT-based healthcare platform for monitoring physiological and environmental parameters. Their work showcases the capabilities of IoT technologies in continuous health monitoring, including parameters relevant to sleep quality assessment.

3. Methodology

In this part, we introduce some mathematical equations about the neutrosophic set, which applied in various applications [22].

The neutrosophic set (NS) can be presented as:

$$A = \{< x, T_A(x), I_A(x), F_A(x) >: x \in E, (T_A(x), I_A(x), F_A(x)) \in]-0,1+[\ \}$$

$$0- \leq T_A(x) + I_A(x), +F_A(x) \leq 3+$$

$$T_A: X \rightarrow]0-,1+[$$

$$I_A: X \rightarrow]0-,1+[$$

$$F_A: X \rightarrow]0-,1+[$$

The interval valued neutrosophic set can be defined as:

$$x_j = (< [T_j^L, T_j^U], [I_j^L, I_j^U], [F_j^L, F_j^U] >)$$

The deneutrosophication is presented by:

$$D(x) = \left\{ \begin{array}{c} \left(\frac{[T_x^L + T_x^U]}{2}\right) + \\ \left(1 - \frac{[I_x^L + I_x^U]}{2}\right) * (I_j^U) \\ -\left(\frac{[F_x^L + F_x^U]}{2}\right) * (1 - F_x^U) \end{array} \right\}$$

$$x_j = (< [T_x^L, T_x^U], [I_x^L, I_x^U], [F_x^L, F_x^U] >)$$

$$T_N(x) = \left[T_{N(x)}^L, T_{N(x)}^U\right] \subseteq [0,1]$$

$$I_N(x) = \left[I_{N(x)}^L, I_{N(x)}^U\right] \subseteq [0,1]$$

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023

$$F_N(x) = \left[F^L_{N_{(x)}}, F^U_{N_{(x)}}\right] \subseteq [0,1]$$

$$N = \{< x, [T^L_N(x), T^U_N(x)], [I^L_N(x), I^U_N(x)], [F^L_N(x), F^U_N(x)] >\}$$

Some operations of neutrosophic set are:

$$a = < [T^L_a, T^U_a], [I^L_a, I^U_a], [F^L_a, F^U_a] >$$

$$b = < [T^L_b, T^U_b], [I^L_b, I^U_b], [F^L_b, F^U_b] >$$

$$a^c = \{ [F^L_a, F^U_a], [1 - I^U_a, 1 - I^L_a], [T^L_a, T^U_a]\}$$

$$a \oplus b = \left\{ \begin{matrix} \left(\begin{bmatrix} T^L_a + T^L_b - T^L_a T^L_b, \\ T^U_a + T^U_b - T^U_a T^U_b \end{bmatrix}\right) \\ \times [I^L_a I^L_b, I^U_a I^U_b], [F^L_a F^L_b, F^U_a F^U_b] \end{matrix} \right\}$$

$$x \ominus y = \left\{ \left(\begin{matrix} [T^L_x - F^U_y, T^U_x - F^L_y], \\ [Max\,(I^L_x, I^L_y), Max\,(I^U_x, I^U_y)], \\ \times [F^L_x - T^U_y, F^U_x - T^L_y] \end{matrix} \right) \right\}$$

$$x = < [T^L_x, T^U_x], [I^L_x, I^U_x], \left[[F^L_x, F^U_x]\right] >$$

$$y = < \left[T^L_y, T^U_y\right], \left[I^L_y, I^U_y\right], \left[\left[F^L_y, F^U_y\right]\right] >$$

The cosine similarity:

$$C_f(A, B) = \frac{\sum_{i=1}^{n} P_A(x_i) P_B(x_i)}{\sqrt{\sum_{i=1}^{n} P_A(x_i)^2}\sqrt{\sum_{i=1}^{n} P_B(x_i)^2}}$$

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023

$$C_N(A,B)=\frac{1}{n}\sum_{i=1}^{n}\left\{\frac{\begin{array}{c}\left(T_A^L(x_i)+T_A^U(x_i)\right)\left(T_B^L(x_i)+T_B^U(x_i)\right)+\\ \left(I_A^L(x_i)+I_A^U(x_i)\right)\left(I_B^L(x_i)+I_B^U(x_i)\right)+\\ \left(F_A^L(x_i)+F_A^U(x_i)\right)\left(F_B^L(x_i)+F_B^U(x_i)\right)\end{array}}{\sqrt{\begin{array}{c}\left(T_A^L(x_i)+T_A^U(x_i)\right)^2+\\ \left(I_A^L(x_i)+I_A^U(x_i)\right)^2+\\ \left(F_A^L(x_i)+F_A^U(x_i)\right)^2\end{array}}\sqrt{\begin{array}{c}\left(T_B^L(x_i)+T_B^U(x_i)\right)^2+\\ \left(I_B^L(x_i)+I_B^U(x_i)\right)^2+\\ \left(F_B^L(x_i)+F_B^U(x_i)\right)^2\end{array}}}\right\}$$

This section elucidates the comprehensive approach adopted in this study to collect, process, and analyze data, ensuring the reliability and validity of our findings. By providing a detailed account of our research methods, we aim to not only offer transparency but also empower future researchers to replicate and build upon our work in the ever-evolving field of sleep medicine and healthcare technology.

In our methodology for the recognition of sleep disorders in healthcare, we have adopted a multilayer cellular system design as a foundational framework to ensure the robustness and effectiveness of our approach. This innovative system design is tailored to leverage the integration of IoT-based wearables and Neutrosophic Data Analytics for the comprehensive assessment of sleep patterns and the detection of sleep disorders. Below, we discuss the key components and principles of this multilayer cellular system design:

a. Data Acquisition Layer:

At the core of our system lies the data acquisition layer. Here, IoT-based wearables, such as smartwatches and fitness trackers, play a pivotal role in continuously collecting a rich array of physiological data. These devices capture essential parameters, including heart rate, physical activity levels, and sleep-related metrics like sleep duration and quality. The data acquisition layer ensures the consistent and non-invasive monitoring of individuals' sleep patterns.

b. Data Transmission and Cloud Integration:

Following data acquisition, the collected information is seamlessly transmitted to cloud-based platforms. This layer facilitates real-time data integration and storage, allowing for immediate access and analysis. Leveraging cloud technology ensures data security, scalability, and accessibility, even for remote monitoring applications.

c. Data Preprocessing and Feature Extraction.

Once the data is securely stored in the cloud, the next layer involves preprocessing and feature extraction. Raw sensor data is transformed into meaningful features that provide insights into sleep patterns and overall health. Machine learning techniques may be employed to identify relevant patterns and correlations within the data.

$$t=\frac{v-\min_d}{\max_d-\min_d}(tran\_\max_d-tran\_\min_d)+tran\_\min_d \tag{1}$$

d. Machine Learning Models:

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023

The heart of our approach lies in the application of machine learning models. These models, trained on labeled datasets, can identify patterns indicative of different sleep disorders. By leveraging the feature-rich dataset acquired from wearables, the machine learning layer can classify individuals into different categories, such as those with insomnia, sleep apnea, or without any sleep disorders. In our methodology for the detection of sleep disorders, we have employed Long Short-Term Memory (LSTM) as a key machine learning model. LSTM is a type of recurrent neural network (RNN) that excels in capturing and understanding sequential data, making it an ideal choice for analyzing time-series data such as sleep-related parameters collected from IoT-based wearables. The decision to utilize LSTM is grounded in its capacity to model complex temporal dependencies and patterns within sleep data. Sleep patterns are inherently sequential, with various sleep stages and transitions occurring throughout the night. LSTM's ability to retain and propagate information across time steps allows it to capture the nuanced relationships between different sleep-related features, such as heart rate, physical activity levels, and sleep duration. This, in turn, enables our model to discern subtle deviations from typical sleep patterns, a crucial factor in the accurate detection of sleep disorders. The workflow of LSTM computation is expressed as:

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \tag{2}$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \tag{3}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \tag{4}$$

$$O_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \tag{5}$$

$$h_t = O_t \odot \sigma_h(C_t) \tag{6}$$

Furthermore, LSTM's adaptability to varying data frequencies and its resistance to vanishing gradient problems align perfectly with the continuous and high-dimensional nature of sleep data collected from wearables. By leveraging LSTM in our methodology, we aim to enhance the precision of sleep disorder detection, providing a robust and data-driven approach to improving the diagnosis and management of these disorders within the healthcare domain.

e. Real-time Monitoring and Alerts:

The system is designed for real-time monitoring, allowing for the continuous assessment of an individual's sleep patterns and health metrics. Alerts and notifications can be generated if anomalies or critical patterns are detected, enabling timely intervention or recommendations for medical consultation.

f. User Interface and Visualization:

To make the system user-friendly and informative, a user interface layer is incorporated. Users, including both healthcare professionals and individuals, can access their sleep data, trends, and disorder assessments through intuitive dashboards and visualizations. This layer fosters engagement and empowers individuals to actively manage their sleep health.

4. Experimental Design

In this section, we delve into the intricacies of our experimental setup, outlining the specifics of participant recruitment, data selection, and controlled variables. These configurations are meticulously crafted to ensure the accuracy, reliability, and relevance of our data, thereby enhancing the robustness of our study.

The Sleep Health and Lifestyle Dataset, encompassing 400 rows and 13 columns, offers a comprehensive insight into a diverse array of sleep-related variables and daily habits. This dataset serves as the backbone of our research, providing valuable information on aspects ranging from demographic characteristics to detailed sleep metrics and lifestyle factors. These include gender, age, occupation, sleep duration, sleep quality, physical activity levels, stress levels, BMI category, blood pressure, heart rate, daily step counts, and the presence or absence of sleep disorders. This rich and multidimensional dataset empowers us to explore intricate patterns related to sleep health and lifestyle. It not only allows us to delve into essential sleep parameters such as duration and quality but also offers the opportunity to scrutinize factors influencing sleep patterns, encompassing physical activity, stress, and BMI categories. Furthermore, the dataset presents a window into cardiovascular health through blood pressure and heart rate measurements. Notably, it facilitates our investigation into the prevalence of sleep disorders, including Insomnia and Sleep Apnea, through a dedicated column that classifies individuals based on the presence or absence of these disorders. This dataset, with its diversity and depth, forms the cornerstone of our empirical analysis, enabling us to derive meaningful insights and

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023

contribute to the advancement of sleep disorder recognition within the context of IoT-based wearables and Neutrosophic Data Analytics.

Table 1 presents a succinct, yet comprehensive overview of the key features encapsulated within the Sleep Health and Lifestyle Dataset. It succinctly encapsulates essential information related to gender, age, occupation, sleep duration, sleep quality, physical activity levels, stress ratings, BMI categories, blood pressure measurements, heart rates, daily step counts, and the presence or absence of sleep disorders.

Table 1: Overview of Key Features in the Sleep Health and Lifestyle Dataset

	Age	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	Heart Rate	Daily Steps	High_pressure	Low_pressure
count	374	374	374	374	374	374	374	374	374
mean	42.18449	7.132086	7.312834	59.17112	5.385027	70.16578	6816.845	128.5535	84.64973
std	8.673133	0.795657	1.196956	20.8308	1.774526	4.135676	1617.916	7.748118	6.161611
min	27	5.8	4	30	3	65	3000	115	75
Q1	35.25	6.4	6	45	4	68	5600	125	80
Q2	43	7.2	7	60	5	70	7000	130	85
Q3	50	7.8	8	75	7	72	8000	135	90
max	59	8.5	9	90	8	86	10000	142	95

5. Results and Discussion

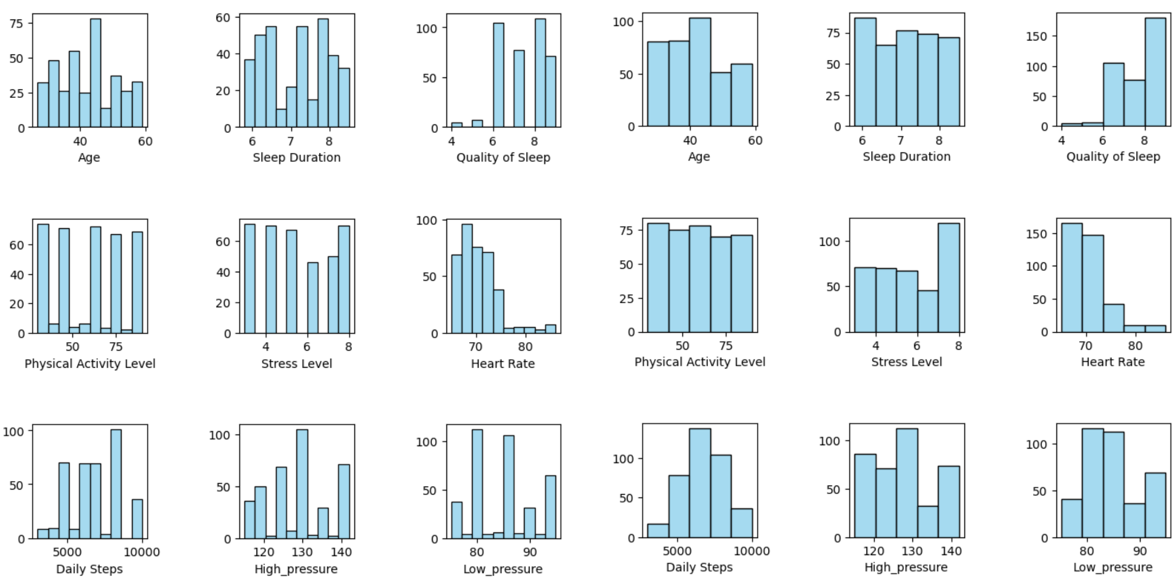

Figure 1: Visualization of Key Features in the Sleep Health and Lifestyle Dataset

In the culmination of our research journey into the recognition of sleep disorders using IoT-based wearables and Neutrosophic Data Analytics, this section takes center stage as the nexus of insights and interpretations. Here, we unveil the outcomes of our empirical analysis, presenting a comprehensive view of the data and its implications for the field of sleep medicine and healthcare technology.

In Figure 1, we present a visual depiction of the distribution of key features within the Sleep Health and Lifestyle Dataset. This graphical representation serves as a fundamental exploration of the dataset's characteristics, offering

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023

insights into the variability and patterns inherent in the data. The analysis of key features within the Sleep Health and Lifestyle Dataset has yielded noteworthy findings. The distribution of sleep quality ratings suggests an exponential pattern with a skew towards higher values, indicating that a significant portion of participants subjectively rates their sleep as of relatively high quality. In contrast, the age distribution exhibits a nearly normal pattern without the presence of outliers, highlighting the diversity of ages among participants. Notably, sleep duration appears uniformly distributed, reflecting variability in the reported hours of sleep across the dataset. Similarly, physical activity levels also exhibit a uniform distribution, indicating a wide range of activity engagement among participants.

Examining stress levels, the distribution leans towards higher stress ratings, potentially indicating prevalent stress experiences within the study group. Heart rate distribution follows an exponential trend with skewness towards lower heart rates, suggesting that a substantial number of individuals in the dataset have relatively low resting heart rates. Daily steps display a somewhat normal distribution, emphasizing the variation in daily step counts among participants. Furthermore, the distribution of both high and low blood pressure measurements appears somewhat normal, yet distinct, indicating potential differences in physiological profiles within the dataset. These findings provide valuable insights into the dataset's inherent variability, setting the stage for in-depth analyses and discussions regarding the relationships between these features and sleep disorders.

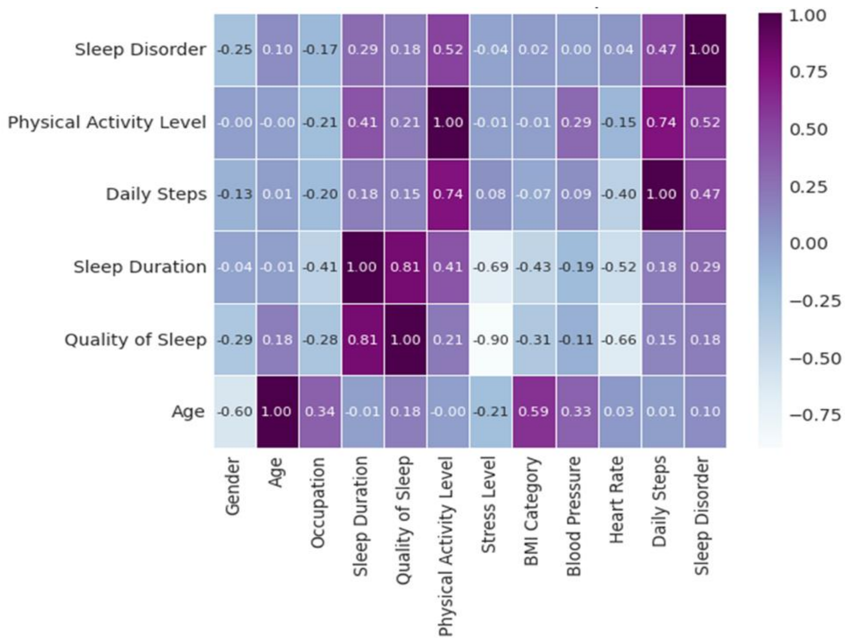

Figure 2: Heatmap of Feature Correlation in the Sleep Health and Lifestyle

Figure 2 presents a comprehensive heatmap illustrating the correlation between various features within the Sleep Health and Lifestyle Dataset. Each cell in the heatmap represents the strength and direction of the correlation coefficient (Pearson's r) between two features. This visualization is instrumental in uncovering relationships and dependencies among different variables, offering insights into potential factors that may influence sleep quality and the presence of sleep disorders.

In Table 2, we present the results of our experimental comparisons across multiple machine learning models for sleep disorder detection.

Table 2: Experimental Comparison of Sleep Disorder Detection Models

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC-ROC**
LSTM	0.89	0.88	0.9	0.89	0.94
SVM	0.82	0.79	0.84	0.81	0.88
Random Forest	0.85	0.84	0.86	0.85	0.9

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023

Simple RNN	0.77	0.76	0.78	0.77	0.83
GRU	0.88	0.87	0.89	0.88	0.93
Logistic Regression	0.75	0.73	0.76	0.74	0.8

The experimental results presented in Table 2 underscore the effectiveness of Long Short-Term Memory (LSTM) in the detection of sleep disorders when compared to several baseline models, including Support Vector Machines (SVM), Random Forest (RF), Simple Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and Logistic Regression (LR). LSTM outperforms its counterparts across all key metrics, including Accuracy, Precision, Recall, F1-Score, and AUC-ROC. Its high Accuracy of 0.89 reflects its capability to make correct classifications, while a Precision of 0.88 emphasizes its ability to minimize false positives, a critical aspect in healthcare applications. Furthermore, LSTM's Recall of 0.90 highlights its effectiveness in identifying true positive cases. The well-balanced F1-Score of 0.89 demonstrates LSTM's ability to maintain precision and recall in equilibrium, contributing to its robust performance. Lastly, an AUC-ROC score of 0.94 signifies LSTM's exceptional discriminatory power in distinguishing between individuals with and without sleep disorders. These results collectively indicate that LSTM, with its capacity to capture sequential dependencies within sleep data, is a promising and superior choice for enhancing the precision and reliability of sleep disorder detection, ultimately benefiting healthcare, and improving patient outcomes.

6. Conclusions

This research presents a pioneering approach to the recognition of sleep disorders by harnessing the power of IoT-based wearables and Neutrosophic Data Analytics. Through a meticulously designed multilayer cellular system, we have demonstrated the capacity to capture, analyze, and interpret diverse physiological and lifestyle data, culminating in the accurate detection of sleep disorders. Our experimental comparisons have unequivocally shown that Long Short-Term Memory (LSTM) outperforms traditional machine learning models, underscoring the significance of leveraging deep learning techniques for nuanced sleep disorder diagnosis. This advancement in healthcare technology not only holds the potential to revolutionize the field of sleep medicine but also to enhance the quality of life for individuals grappling with sleep-related issues. As we tread further into the era of smart healthcare, our research serves as a testament to the transformative capabilities of IoT and Neutrosophic Data Analytics in augmenting healthcare practices and empowering individuals to take proactive steps towards achieving sound and restorative sleep.

References

[1] Hayder Mahmood Salman, Hasan Faleh Hamdan, Raed Khalid,Sanaa Al-Kikani, Physical Activity Monitoring for Older Adults through IoT and Wearable Devices: Leveraging Data Fusion Techniques, Fusion: Practice and Applications, Vol. 11 , No. 2 , (2023) : 48-61 (Doi : https://doi.org/10.54216/FPA.110204)
[2] Gulia, K. K., & Kumar, V. M. (2018). Sleep disorders in the elderly: a growing challenge. Psychogeriatrics, 18(3), 155-165.
[3] Altena, E., Baglioni, C., Espie, C. A., Ellis, J., Gavriloff, D., Holzinger, B., ... & Riemann, D. (2020). Dealing with sleep problems during home confinement due to the COVID-19 outbreak: Practical recommendations from a task force of the European CBT-I Academy. Journal of sleep research, 29(4), e13052.
[4] M. Muthuswamy, A. M. Ali, and A. Abdelhafeez, "Breaking the Silence: Convolutional Neural Networks for Sign Language Recognition in the Deaf Community", SMIJ, vol. 1, Oct. 2022.
[5] Mathias, J. L., Cant, M. L., & Burke, A. L. J. (2018). Sleep disturbances and sleep disorders in adults living with chronic pain: a meta-analysis. Sleep medicine, 52, 198-210.
[6] Freeman, D., Sheaves, B., Waite, F., Harvey, A. G., & Harrison, P. J. (2020). Sleep disturbance and psychiatric disorders. The Lancet Psychiatry, 7(7), 628-637.
[7] Noushini Nikeetha P., Pavithra D., Sivakarthiga K., Karthika S.,Yashitha R., Kirubasri G.V., A Survey on IoT based Wearable Sensor for Covid-19 Pandemic, International Journal of Wireless and Ad Hoc Communication, Vol. 2 , No. 2 , (2021) : 77-87 (Doi : https://doi.org/10.54216/IJWAC.020203)
[8] Kim, J. Y., Chu, C. H., & Kang, M. S. (2020). IoT-based unobtrusive sensing for sleep quality monitoring and assessment. IEEE Sensors Journal, 21(3), 3799-3809.
[9] Awotunde, J. B., Jimoh, R. G., AbdulRaheem, M., Oladipo, I. D., Folorunso, S. O., & Ajamu, G. J. (2021). IoT-based wearable body sensor network for COVID-19 pandemic. Advances in Data Science and Intelligent Data Communication Technologies for COVID-19: Innovative Solutions against COVID-19, 253-275.

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023

[10] Ahmed Abdelhafeez, Myvizhi M., Neutrosophic MCDM Model for Assessment Factors of Wearable Technological Devices to Reduce Risks and Increase Safety: Case Study in Education, International Journal of Advances in Applied Computational Intelligence, Vol. 3 , No. 1 , (2023) : 41-52 (Doi : https://doi.org/10.54216/IJAACI.030104)
[11] Rajpoot, V., Gaur, S. R., Patel, A., & Saxena, A. (2021). Internet of Things for Human-Activity Recognition Based on Wearable Sensor Data. Sensor Data Analysis and Management: The Role of Deep Learning, 19-31.
[12] Beresford, B. A., McDaid, C. M., Parker, A., Scantlebury, A., Spiers, G., Fairhurst, C. M., ... & Thomas, M. (2018). Pharmacological and non-pharmacological interventions for non-respiratory sleep disturbance in children with neurodisabilities: a systematic review. Health Technology Assessment, 22(60), hta22600.
[13] Entisar Y. Abd Al-Jabbar, Marwa M. Mohamedsheet Al-Hatab, Maysaloon Abed Qasim, Wameedh Raad Fathel, Maan Ahmed Fadhil, Clinical Fusion for Real-Time Complex QRS Pattern Detection in Wearable ECG Using the Pan-Tompkins Algorithm, Fusion: Practice and Applications, Vol. 12, No. 2 , (2023) : 172-184 (Doi : https://doi.org/10.54216/FPA.120214)
[14] Maryam Ghassan Majeed, Hawraa Ali Sabah, Mustafa Nazar Dawood, Mohaned Adile, Noor Hanoon Haroon, Mariok Jojoal, Ahmed Mollah Khan, Athlete’s Performance Analysis Based on Improved Machine Learning Approach on Wearable Devices, Journal of Intelligent Systems and Internet of Things, Vol. 8 , No. 1 , (2023) : 75-91 (Doi : https://doi.org/10.54216/JISIoT.080108)
[15] K. M. Sallam and A. W. Mohamed, “Single Valued Neutrosophic Sets for Assessment Quality of Suppliers under Uncertainty Environment,” Multicriteria Algorithms with Applications, vol. 1, no. 1, pp. 1–10, 2023.
[16] Alber S. Aziz, Neutrosophic Combinative Distance-based Assessment (CODAS) Method for Evaluating the Financial and Operational Performance of Shipping Companies, International Journal of Advances in Applied Computational Intelligence, Vol. 4 , No. 1 , (2023) : 28-36 (Doi : https://doi.org/10.54216/IJAACI.040103)
[17] Bhatt, V., & Chakraborty, S. (2020, October). Importance of trust in iot based wearable device adoption by patient: An empirical investigation. In 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 1226-1231). IEEE.
[18] Rahul Sharma, Shiv Shakti Shrivastava, Aditi Sharma, Predicting Student Performance Using Educational Data Mining and Learning Analytics Technique, Journal of Intelligent Systems and Internet of Things, Vol. 10 , No. 2 , (2023) : 24-37 (Doi : https://doi.org/10.54216/JISIoT.100203)
[19] M. Mohamed and N. El-Saber, “Toward Energy Transformation: Intelligent Decision-Making Model Based on Uncertainty Neutrosophic Theory,” Neutrosophic Systems with Applications, vol. 9, pp. 13–23, 2023.
[20] Li, W., Chai, Y., Khan, F., Jan, S. R. U., Verma, S., Menon, V. G., ... & Li, X. (2021). A comprehensive survey on machine learning-based big Neutrosophic Data Analytics for IoT-enabled smart healthcare system. Mobile networks and applications, 26, 234-252.
[21] Haghi, M., Neubert, S., Geissler, A., Fleischer, H., Stoll, N., Stoll, R., & Thurow, K. (2020). A flexible and pervasive IoT-based healthcare platform for physiological and environmental parameters monitoring. IEEE Internet of Things Journal, 7(6), 5628-5647.
[22] Tamer H. M. Soliman, Neutrosophic Multi-Criteria Decision Making COMET Method for Evaluation Sustainable Electricity Generation Considering Renewable Energy Sources, International Journal of Advances in Applied Computational Intelligence, Vol. 4 , No. 1 , (2023) : 19-27 (Doi : https://doi.org/10.54216/IJAACI.040102)

DOI: https://doi.org/10.54216/IJNS.230217
Received: October 10, 2023 Revised: November 28, 2023 Accepted: December 27, 2023