Improving Sleep Quality Monitoring with IoT and Machine Learning

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***Abstract*— Proper sleep is necessary lack of which brings stress and trauma. There are a lot of reasons that cause it, and we are going to measure how their sleep is so that they can prevent such things. We are going to measure using an IoT device and analyze using Machine learning. The IoT device includes some sensors, an accelerometer, a pulse oximeter, and a microphone amplifier—integrated with an ESP32 microcontroller. The ADXL345 accelerometer captures precise body movement, while the MAX30102 pulse oximeter monitors heartbeat and SPO2 levels. The MAX9814 microphone amplifier facilitates snoring detection, which is held by a person during sleep later the data is backed up to the AWS cloud platform where we are going to implement some algorithms like renal neural network (RNN) with some hyper tuning in regularization, learning rate, and architecture which helps in making the accuracy of the prediction higher which enables the person to track and detect the what kind of sleep he was having and what was lacking which helps in making his sleep better day by day.**

I. Introduction

Sleep, a fundamental pillar of holistic well-being, is intricately interwoven with the fabric of our overall health. Its profound impact on both the physical and mental aspects of our lives cannot be overstated. Disruptions in sleep patterns, influenced by a myriad of factors encompassing biology, psychology, and the environment, can significantly contribute to various health issues. Among these, the intricate relationship between sleep disturbances and mental health problems, such as depression and anxiety, has gained substantial attention from researchers and healthcare professionals alike.

Current paradigms in sleep monitoring predominantly rely on an array of sensing methods, ranging from conventional wrist-attached sensors to the gold standard of polysomnography (PSG). However, this study takes a pioneering step by exploring an innovative approach to sleep monitoring. It delves into the potential of utilizing temperature monitors and passive infrared (PIR) sensors strategically placed within residential spaces to comprehensively monitor ambient sleep conditions.

Addressing the existing gaps in sleep monitoring technologies, our proposed method introduces the integration of a diverse set of sensors, including the cost-effective yet powerful combination of an accelerometer, microphone, and pulse oximeter. This holistic sensor array aims to provide a nuanced and detailed understanding of sleep patterns and quality.

What distinguishes our approach is not just the array of sensors but the intelligent application of machine learning methodologies to forecast sleep quality accurately. By combining these emerging technologies, we strive to create a monitoring system that is not only precise and insightful but also accessible and cost-effective. Whether implemented in a home or hospital setting, our innovative fusion of machine learning and the Internet of Things (IoT) is poised to revolutionize the landscape of sleep monitoring, ensuring a new era of personalized and efficient healthcare practices. This novel intersection not only augments the efficiency of sleep monitoring but also lays the foundation for broader applications, promising advancements in health technology and enhanced well-being for individuals across diverse demographics.

II. Literature Review

Sleep analysis methods play a pivotal role in monitoring individuals' health and fitness, contributing valuable insights into overall well-being. According to [1], utilizing an electrocardiogram-based EDR (electrocardiographically derived respiration) p signal aids in determining both heartbeat and respiration during apnea. However, the accuracy of actual respiratory signals stands at approximately 85%. Chest movement is another crucial factor, offering insights into breathing patterns and even the breathing phase, providing information on ontogenetic alteration [2]. The continuity of sleep, measured through noninterrupted sleep phases, further enhances the evaluation of a person's physical movement during sleep, considering factors like movement time (MT) and movement events (ME).

Polysomnography (PSG) stands out as the "medical gold standard" for monitoring sleep stages and patterns [3]. Conducted in a controlled atmosphere, PSG employs sensors attached to the patient's body, recording psychological and biological parameters such as brain activity, heartbeat, and oxygen saturation during sleep. However, PSG has limitations, primarily being restricted to short-term sensing in a lab setting, possibly deviating from a patient's typical sleep habits.

Contrastingly, WatchPAT offers an easily portable alternative, recording Peripheral Arterial Tone (PAT) and nervous system signals during sleep without requiring a lab [4]. Although this device allows home monitoring of sleep apnea, wearing it during the night may be perceived as inconvenient by users. Other alternatives include EEG, a reliable sleep monitor, and user-friendly sleep sensors like Zeo, which calculates brain signals, providing information on the nervous system during sleep. Despite its effectiveness, Zeo's headband may cause discomfort, leading to the introduction of less intrusive devices.

Actigraphy proves to be a simple yet effective method, measuring body movement through accelerometers, offering ease of calculating sleep quality based on physical movement [5]. Additionally, mobile phones equipped with gyroscopes facilitate accelerometer recordings categorized into different classes, such as rotation, sitting, and twisting. However, limitations arise from the need for the user to wear a band during sleep, along with the necessity of having a mobile phone. While actigraphy is suitable for adults, its application becomes limited for children, older individuals, and those with sleep abnormalities.

Recent developments in sleep monitoring focus on noncontact methods, minimizing intrusiveness, and addressing privacy concerns. Lullaby, introduced in [6], incorporates environmental sensors and physical movement recorders to monitor factors influencing sleep quality. iSleep [7] records sound patterns and physical activity using a built-in microphone amplifier. Sleep Hunter, developed by Gu et al. [8], employs a smartphone to monitor physiological and environmental factors using a built-in microphone, accelerometer, and light sensor.

Privacy concerns related to recording sleep-related parameters have led to the exploration of non-intrusive methods. Various researchers embed sensors in smartphones for sleep monitoring. iSleep, for instance, captures sound patterns and physical activity using a built-in microphone amplifier. In contrast, Sleep Hunter monitors physiological and environmental factors using a smartphone's built-in microphone, accelerometer, and light sensor [8]. Despite the advantages, privacy issues arise due to the inherently private nature of sleep.

Understanding that fundamental signals during sleep vary among individuals, recent sensors like Aura, which consists of a pressure-sensitive bed, record both physical movements and biological parameters. However, these advanced sensors are often costly and not easily accessible. Figure 2 provides a comprehensive comparison of various sleep sensing technologies [9-12].

In conclusion, the field of sleep monitoring has witnessed significant advancements, offering a range of methods from traditional PSG to modern noncontact sensors. While each method has its merits and limitations, ongoing research aims to strike a balance between accuracy, user comfort, and privacy concerns. These diverse approaches contribute to the evolving landscape of sleep monitoring technologies, ensuring a tailored solution for individuals with varying needs and preferences. In this, a smart sleep monitoring system has been proposed which monitors the patient’s vital elements like heartbeat, oxygen saturation, body movement, and snoring patterns along with time stamps. Classifying these data into different sleep classes and getting insights about sleep. Hypertuning the RNN algorithm increases result accuracy and performance efficiency compared to other devices and systems.

III. Design and Implementation

An affordable sleep analysis technique was implemented, with an ESP32 controller serving as the main microcontroller. Real-time data was gathered by the system from sensors and sent to the AWS cloud through the WiFi in ESP32 with account credentials where a random forest model was used for analysis. ADXL345 accelerometer measured body movement, the MAX30102 pulse oximeter measured heartbeat and SPO2 levels, and the I2S MEMS microphone amplifier detected snoring. These sensors were utilized in the suggested sleep monitoring technology.

ESP32, a powerful microcontroller known for its dual-core processing, built-in Wi-Fi, and Bluetooth connectivity, served as the central processing unit for sensor data acquisition and communication. Its efficient handling of tasks and connectivity features made it an excellent choice for this IoT project.

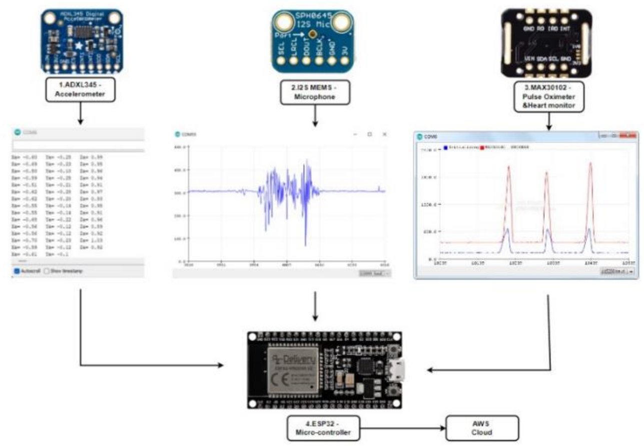

Fig 1 Smart Sleep Design

ADXL345, a versatile 3-axis digital accelerometer that provided high-resolution measurements of acceleration, was employed for precise motion sensing and, in this context, for monitoring physical body movement. MAX9814, a microphone amplifier module designed for easy integration with microcontrollers like the ESP32, was utilized for capturing and amplifying audio signals. 3.MAX30102, an integrated sensor module designed for non-invasive monitoring of heart rate and blood oxygen saturation levels, provided accurate and real-time physiological data. With its small footprint, low power consumption, and digital output, it was well-suited for wearable devices like the project. Integration with microcontrollers, such as the 4.ESP32 was facilitated through I2C communication. These sensors were integrated into a sleep quality monitoring system that was linked to a 4.ESP32 controller in the design of the suggested system. Heart rate, SPO2, body movement, and snoring patterns were among the ambient parameters that were monitored utilizing a pulse sensor, microphone amplifier, and triple-axis accelerometer. In a regulated setting, the system captured real-time data and used that information to calculate sleep quality.

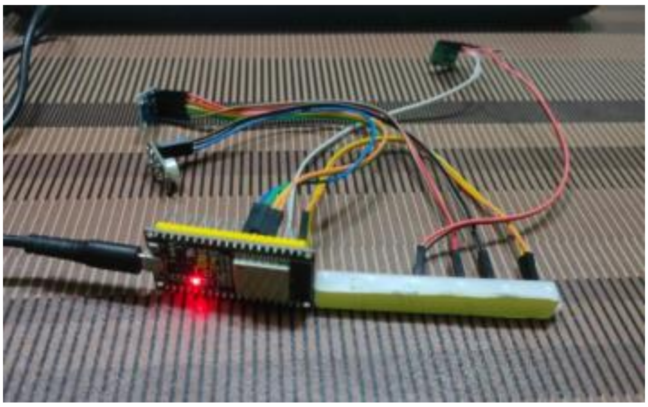

Fig 2 Hardware of smart sleep

Data collected from these sensors were transmitted to the AWS cloud using the ESP32's built-in Wi-Fi and Bluetooth capabilities. In the cloud, random forest and Recurrent Neural Network (RNN) algorithms were employed to analyze the sensor data. The random forest algorithm was utilized for its ability to handle multidimensional datasets, while the Hyper RNN algorithm, known for sequential data processing, was employed to capture temporal dependencies in the physiological data. The model then calculates the result from the calculated data to anticipate whether a person sleeps peacefully or not. It also calculates the un-peaceful and very peaceful night sleep of a patient.

To evaluate the performance of the algorithms, rigorous testing methodologies, including cross-validation and other techniques, were applied. Through these analyses, the accuracy of the algorithms in interpreting the sensor data and providing meaningful insights into the monitored physiological parameters was determined. This integration of sensor data acquisition, cloud computing, and machine learning algorithms showcased a comprehensive approach to health monitoring in real-time, leveraging the capabilities of state-of-the-art sensors and cloud infrastructure.

To allow the model to predict sleep patterns that were peaceful, ungraceful, and extremely ungraceful at night, data collection was spread out over several days and nights. The system's efficacy stemmed from its precise outcomes and economical nature with current gadgets and frameworks, thereby propelling the progress of sleep monitoring technologies. For improved sleep quality assessment in both home and hospital settings, the suggested intelligent sleep monitoring system offered a complete solution.

IV. Methodology

The sleep analysis system utilized a 4.ESP32 controller for real-time data collection from sensors measuring body movement, heartbeat, SPO2 levels, and snoring. Sensors like the 1.ADXL345, 3.MAX9814, and 3.MAX30102 was integrated, capturing real-time data transmitted to AWS The data set transferred to the cloud consists of 4 columns of data containing the accelerometer data, pulse oximeter data, the microphone data, and the time at which all these data have been collected. The dataset contains more than 2,20,000 rows of data to give a high accuracy to the training modal. This data set also consists of the sleep patterns of multiple humans to get a vast variety of sleep pattern analysis, since each person's sleep differs greatly. Random forest and recurrent neural network algorithms analyzed the data, showcasing a comprehensive approach to real-time health monitoring.

Parameters	Range
Heat Beat	65 - 67

Noise	1700 - 1900
Body Movement	150 - 250
SpO2 %	90 - 96

Table 1 Optimal values of the parameters

The system utilizes optimal sensor values for SpO2 (90-96), heart rate (65-67), noise level (1700-1850), and body motion (200-250). The ESP32 microcontroller efficiently acquires and transmits real-time data to the AWS cloud.

Parameters/Algorithm	Random Forest	Hyper RNN
Estimators	50	40
Random State	42	42
Time Steps	5	4
RMSE	0.017	0.064
Variance	0.170	0.168
MSE	0.0002	0.004
F1 Score	0.999	0.996

Table 2 Parameters of algorithms

From Table 2 the Random Forest algorithm is implemented with 50 estimators and a random state of 42. In comparison, the Hyper RNN outperformed is implemented by using 40-time steps and the same random state. The Root Mean Squared Error (RMSE) for Random Forest and Hyper RNN were 0.017 and 0.064, respectively. Both algorithms exhibited similar variance (Random Forest: 0.170, HyperRNN: 0.168) and Mean Squared Error (Random Forest: 0.0002, Hyper RNN: 0.004). The F1 Score for both algorithms is not provided in the provided information.

The traditional core formula of an RNN encapsulated this temporal understanding, as exemplified by the equation, which combined with the tuning was the key difference for accuracy from the random forest:

1. Hidden State Update :

h(t) = activation(W(hh).h(t-1) + W(hx).x(t) + b(h)) (1)

i) h(t) represented the hidden state at time t

ii) W(hh) and W(hx) were weight matrices for the hidden state and the input

iii) x(t) denoted the input at time t,

iv) b(h) was the bias term.

2. Output Calculation :

y(t) = activation(W(yh).h(t) + b(y)) (2)

i)y(t) represented the output at time t

ii) h(t) represented the hidden state at time t,

iii)W(yh) was the weight matrix connecting the hidden state to the output

iv)b(y) was the output bias term.

3. Hyper Tuning :

a)CLR (Cyclic Learning Rate) :

Cyclical Learning Rates involve cyclically changing the learning rate during training. This technique is based on the idea that using a high learning rate for a short period can help the model escape local minima and converge faster.

Learning_rate = base_learning_rate + 1/2.amplitude.(1+cos((current_iteration/step_size).pie)) (3)

i)base_learning_rate- minimum learning rate amplitude

ii)Amplitude- amplitude of the learning rate cycle.

iii)current_iteration- current iteration in the training process.

iv)step_size- iterations it takes to complete one cycle.

The learning rate oscillates between base_learning_rate + 1/2.amplitude and base_learning_rate - 1/2.amplitude throughout one cycle. The cyclical behavior allows the model to explore different regions of the loss landscape.

b)Adaptive regularization :

Base Regularization - Traditional regularization term (e.g., L2 regularization term).Confidence Factor: A value indicating the model's confidence or certainty. It can be derived from metrics like prediction entropy, prediction variance, or other measures of uncertainty.

Adaptive Regularization Term = Base Regularization * Confidence Factor (4)

An optimal value for the confidence factor is 0.1 to 1.0, where we have used 0.4 in the algorithm to get better accuracy. This is to dynamically adjust the regularization strength based on the current confidence of the model. When the model is more confident (lower uncertainty), the regularization strength is reduced, allowing the model to rely more on the data. It is not to prevent overfitting.

c)Residual Connection (Architecture):

This introduces shortcut connections that bypass one or more layers. The input to a layer is added to the output of a later layer, creating a shortcut connection.

Output = activation(input + dropout_function(layer_output)) (5)

This application of hypertuning in the traditional RNN Alleviates the vanishing gradient problem. Allows easier training of very deep networks. Enhances information flow through the network.

Implementing advanced hyperparameter tuning techniques enhances the traditional RNN model. Cyclic Learning Rates (CLR) equation 3 dynamically adjusts learning rates during training, enabling faster convergence by exploring different regions of the loss landscape. Adaptive regularization equation 4 tailors regularization strength based on the model's confidence, preventing overfitting with a confidence factor. Equation 5 Residual Connection in the architecture alleviates the vanishing gradient problem, facilitating the training of deeper networks and enhancing information flow. These hyperparameter tuning components, integrated into the core RNN formulae, contribute to substantial accuracy improvements, surpassing the capabilities of the traditional RNN.

The increase in accuracy from the Random Forest model to the Hyper RNN model can be attributed to architectural considerations and hyperparameter tuning. Recurrent Neural Networks (RNN) excel at capturing sequential dependencies within data due to their dynamic recurrent connections. This allows them to discern patterns crucial for predicting outcomes in sequential data. Hyperparameter tuning, including adjusting learning rates, hidden layer numbers, and selecting activation functions, also plays a vital role. Hyper RNN offers nuanced control over model architecture, enabling better adaptation to dataset intricacies. The combination of RNNs' sequential learning capability and flexible hyperparameter tuning contributes significantly to accuracy enhancement.

V. Results and Discussion

The utilization of an RNN algorithm with hyper-tuning demonstrated a substantial improvement in accuracy compared to the previously employed Random Forest technique. The Random Forest model achieved an accuracy of 86%, while the Hyper RNN model achieved an impressive 96.5% accuracy using the same set of sensor data. This enhancement in accuracy by 10.5 percentage points highlighted the efficacy of employing Hyper RNN for the given dataset.

Fig 3 Random Forest graph Accuracy

Fig 3 graph displayed the comparison between the actual values of the dataset and the prediction of the random forest method. The random forest method showed an accuracy of up to 86.0%. Since sleep is subjective to each and random forest uses multiple decision trees to train the model, the maximum accuracy obtained was limited. The difference in the blue line and yellow line shows that it is only 86% accurate and the lines go almost in parallel. As the number of epochs increases they start to come together, which we try to close in the Hyper RNN algorithm.

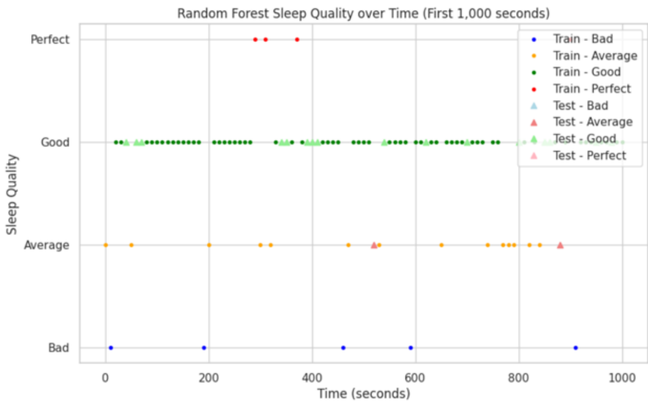

Fig 4 Random Forest Sleep Quality Test Train Graph

Fig 4 graph is plotted between sleep quality and time for the Random Forest algorithm. The data is recorded every 3 seconds thus the dot represents the train data points and the triangle represents the train data points. The sleep is categorized into perfect, Good, Average, and bad. The categorization is done based on the number of parameters in the optimal value range at a particular point. The time is represented only for 1000 seconds but the data is recorded for 34,000 seconds. As you can see the number of dots is in the order Good - > Average - > Bad - > Perfect, which tells us what type of sleep it was on average thus it makes it easier for the person to control the sleep. In the same line in the grid, two different colors are used to differentiate the test and train data.

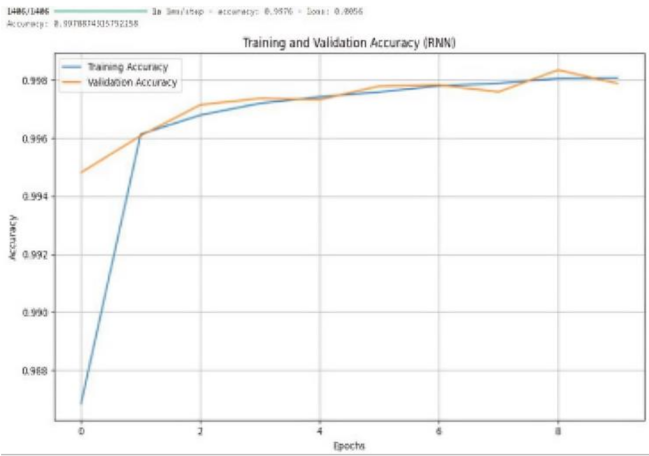

Fig 5 Hyper RNN graph Accuracy

Fig 5 graph illustrates the RNN model's training data by comparing the actual sleep values to the predicted sleep analysis. The graph represents the training and validation accuracy of a Hyper RNN over eight epochs. Since the data was collected over some time, this method provided a better outcome of 95.7% accuracy. As the blue line and yellow line start to collide early and travel along with each other as the number of epochs increases which explains why we got more accuracy in this algorithm.

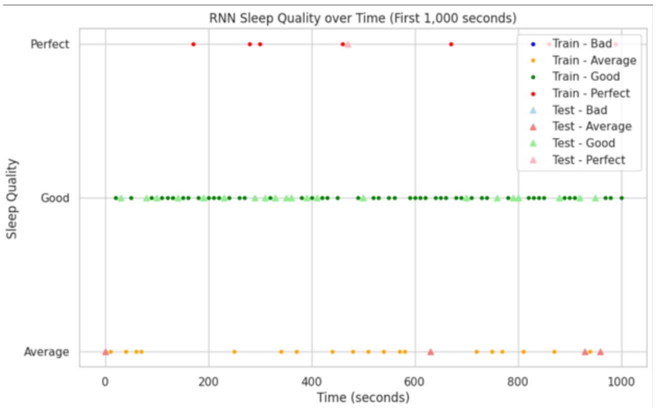

Fig 6 Hyper RNN Sleep Quality Test Train Graph

Fig 6 graph is plotted between sleep quality and time for the Hyer RNN algorithm. The data is recorded every 3 seconds thus the dot represents the train data points and the triangle represents the train data points. The sleep is categorized into perfect, Good, Average, and bad. The categorization is done based on the number of parameters in the optimal value range at a particular point. The time is represented only for 1000 seconds but the data is recorded for 34,000 seconds. As you can see the number of dots are in the order Good - > Average - > Perfect, which tells us what type of sleep it was in average thus it makes it easier for the person to control the sleep. In the other data, we got no bad sleep at all. In the same line in the grid, two different colors are used to differentiate the test and train data.

After the prediction of results through the Hyper RNN algorithm, the machine learning model calculates the result from the calculated data to anticipate whether a person sleeps peacefully or not. It also calculates the un-peaceful and very peaceful night sleep of a patient.

VI. Conclusion

In this study, the devised system employed cost-effective and user-friendly sensors, including an accelerometer, pulse oximeter, and microphone amplifier, to monitor patients' sleep patterns. Utilizing ESP32, the collected data was transmitted to a server for analysis, yielding impactful outcomes at a minimal cost. This data set included four columns of data, consisting of the accelerometer data, pulse oximeter data, microphone data, and the time at which all these data were collected. This data set has nearly 2,20,000 rows of data used for training the set and produces nearly accurate results. The accelerometer, ADXL345, tracked body movement, providing valuable insights for advanced analysis by specialists. Snoring detection relied on the MAX30100 sensor, contributing to the intelligent random forest classification method for precise predictions. The system showcased a notable 96.5% accuracy in classifying sleep quality, emphasizing its accuracy, affordability, and user-friendliness. The study acknowledged limitations, suggesting future enhancements with additional sensors for more comprehensive sleep pattern recognition. The potential integration of Raspberry Pi was proposed for independent system operation, possibly displaying results on a mobile app for improved accessibility and monitoring instead of the cloud.

VII. References

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