CHAPTER 1
INTRODUCTION

Sleep, essential for both physical and mental well-being, is intricately linked to overall health. Disturbances in sleep patterns, often influenced by biological, psychological, and environmental factors, can contribute to various health issues, including depression and anxiety. While current sleep monitoring systems employ diverse sensing methods, ranging from wrist-attached sensors to polysomnography (PSG), this study explores an innovative approach.

The utilization of temperature monitors and passive infrared (PIR) sensors installed in homes to monitor ambient sleep conditions was investigated. In addressing the existing gap in sleep monitoring technologies, the proposed method introduces the integration of inexpensive and widely accessible sensors, including an accelerometer, microphone, and pulse oximeter.

The approach apart is the application of an intelligent machine learning method to forecast sleep quality, ensuring accurate and affordable monitoring, whether at home or in a hospital setting. The emphasis on accessibility, costeffectiveness, and precision becomes paramount in this novel method, combining the realms of machine learning and the Internet of Things (IoT).

By leveraging a personal computer for intricate processing, the method not only provides an affordable alternative but also ensures user-friendly, longterm sleep quality monitoring. This work marks a significant stride in sleep monitoring methodologies, with potential applications that transcend traditional boundaries, ultimately striving to enhance the quality of sleep for individuals in both home and hospital environments.

1.1 Background and Motivation

Sleep plays a pivotal role in maintaining overall health and well-being, influencing cognitive functions, emotional regulation, and physical restoration. In today's fast-paced world, sleep disorders and inadequate sleep have become prevalent issues with profound implications for public health. Traditional sleep monitoring systems often come with limitations, such as high costs and limited accessibility.

The motivation behind this project stems from the need for an affordable and accessible sleep monitoring solution that combines advanced sensor technologies with state-of-the-art data analysis techniques. The integration of an accelerometer, pulse oximeter, and microphone amplifier with the ESP32 microcontroller presents a unique opportunity to address these challenges. This combination allows for precise and comprehensive data collection, enabling a deeper understanding of sleep patterns and associated health indicators.

Furthermore, the project is motivated by the growing importance of realtime data analysis in healthcare. The ability to capture and analyze sleeprelated data in real-time can provide valuable insights into an individual's sleep quality, aiding in the early detection of sleep disorders and associated health risks. The utilization of cloud-based services, particularly AWS, facilitates seamless data storage, accessibility, and collaboration.

The affordability and accessibility of the proposed sleep monitoring system make it particularly relevant in both developed and developing regions. By addressing these concerns, this project aims to democratize sleep monitoring, making it a valuable tool for individuals, healthcare professionals, and researchers alike. The ultimate goal is to contribute to improved sleep health, enhancing the quality of life for individuals and reducing the societal burden associated with sleep-related disorders.

1.2 Objectives of the Sleep Monitoring System

The sleep monitoring system aims to provide a robust solution that seamlessly acquires, analyzes, and presents sleep data in real-time. Through wireless connectivity and cloud-based storage, it offers accessibility and affordability while employing advanced algorithms for comprehensive sleep analysis. The user-friendly interface ensures ease of use for individuals, healthcare professionals, and researchers, while the system's scalability and upgradability anticipate future advancements in sleep monitoring technology.

a. **Real-Time Data Acquisition**: Implement a system that can continuously and accurately capture data from the integrated accelerometer, pulse oximeter, and microphone amplifier in real-time.
b. **Wireless Connectivity**: Utilize the ESP32 microcontroller's Wi-Fi and Bluetooth capabilities to enable seamless wireless communication between the integrated sensors and the AWS cloud.
c. **Cloud-Based Storage and Analysis**: Establish a connection to the AWS cloud for efficient storage and analysis of sleep-related data, allowing for secure and accessible storage of comprehensive datasets.
d. **Comprehensive Sleep Analysis**: Employ a combination of machine learning algorithms, specifically a random forest model and a recurrent neural network (RNN), to analyze the collected data comprehensively. This includes the interpretation of body movement, heartbeat, SPO2 levels, and the detection of snoring patterns.

e. **Affordability and Accessibility**: Design the system to be cost-effective and easily accessible, ensuring that the technology can be adopted widely by individuals, healthcare professionals, and researchers across different economic and geographical contexts.

f. **User-Friendly Interface**: Develop an intuitive user interface that allows individuals to interact with and interpret their sleep data easily. This includes features such as visualizations and notifications for potential sleep anomalies

g. **Scalability and Upgradability**: Design the system to be scalable, allowing for potential future integration with additional sensors or enhancements. Ensure that the system can adapt to evolving technologies and stay relevant in the dynamic field of sleep monitoring.

1.3 Significance of Real-Time Sleep Data Analysis

Understanding the significance of real-time sleep data analysis is paramount in recognizing the potential impact on individual well-being and healthcare practices. Sleep, being intricately linked to both physical and mental health, necessitates continuous monitoring for comprehensive health management. The conventional methods of sleep analysis often fall short in providing real-time insights, making it challenging to promptly address sleep related issues. In contrast, the proposed sleep monitoring system's emphasis on real-time data analysis, facilitated by the integration of the ESP32 microcontroller and AWS cloud, marks a paradigm shift in sleep monitoring methodologies.

The real-time analysis of sleep data offers immediate feedback on an individual's sleep quality, allowing for timely intervention and personalized adjustments. This is particularly crucial in identifying and addressing disturbances such as irregular sleep patterns, snoring, or potential cardiovascular anomalies during sleep. The integration of the MAX30102 pulse oximeter for continuous monitoring of heart rate and blood oxygen saturation levels contributes to the early detection of physiological irregularities, adding a layer of health monitoring beyond traditional sleep metrics.

Moreover, the real-time nature of the proposed system enhances its utility in healthcare settings. In hospitals, the system's ability to provide instantaneous insights into patients' sleep quality can aid healthcare professionals in making informed decisions about patient care. Additionally, the integration of machine learning algorithms, such as the recurrent neural network (RNN), allows for the immediate classification of sleep patterns, offering healthcare practitioners a valuable tool for timely diagnosis and intervention.

1.4 Overview of the Integrated System Components

The integrated sleep monitoring system brings together a sophisticated ensemble of components designed to capture, transmit, and analyze crucial data related to sleep patterns. At the core of the system are three key sensors meticulously selected for their distinct functionalities. The ADXL345 accelerometer serves as the system's motion-sensing backbone, meticulously measuring body movement with high precision. This critical input is instrumental in understanding and interpreting physical activity during sleep, contributing valuable insights into sleep continuity and disturbances.

Complementing the accelerometer is the.MAX9814 microphone amplifier, a specialized sensor designed for detecting snoring patterns. By capturing and amplifying audio signals, this component adds an auditory dimension to the sleep monitoring system, offering insights into potential disturbances and sleep-related sounds. The integration of audio data expands the system's scope beyond physical movements, providing a more holistic assessment of sleep quality.

The third vital component is the MAX30102 pulse oximeter, contributing physiological insights by monitoring heart rate and blood oxygen saturation levels. This sensor, with its non-invasive design, ensures real-time tracking of cardiovascular activity during sleep, allowing for a comprehensive analysis of sleep health. The inclusion of these diverse sensors enriches the dataset, providing a multifaceted view of sleep patterns that extends beyond traditional monitoring methods.

The central processing unit of the system is the ESP32 micro-controller, recognized for its dual-core processing capabilities and robust connectivity features. Serving as the orchestrator, the ESP32 efficiently gathers data from the integrated sensors and facilitates its seamless transmission to the AWS cloud.
The built-in Wi-Fi and Bluetooth capabilities of the ESP32 ensure reliability.

CHAPTER 2
LITERATURE REVIEW

[1] W. H. M. Saad, C. W. Khoo, S. I. Ab Rahman, M. M. Ibrahim, and N. H. M. Saad, "Development of sleep monitoring system for observing the effect of the room ambient toward the quality of sleep," MS&E, vol. 210, no. 1, article 012050, 2017

W. H. M. Saad et al. on the development of a sleep monitoring system offers significant merits in understanding the impact of room ambient conditions on sleep quality. By providing a method to observe these effects, it contributes to advancements in sleep science and healthcare technology. However, potential demerits might include limited sample size or specific environmental conditions studied. Nevertheless, the findings could be used to improve sleep environments in various settings such as hospitals, homes, or hotels. Its merits lie in its potential to enhanced understanding of how ambient factors influence sleep, offering insights for better sleep hygiene practices and the design of optimal sleep environments.

[2] S. Coussens, M. Baumert, M. Kohler, et al., "Movement distribution: a new measure of sleep fragmentation in children with upper airway obstruction," Sleep, vol. 37, no. 12, pp. 2025–2034, 2014.

The research by S. Coussens et al. introduces a novel measure, movement distribution, to assess sleep fragmentation in children with upper airway obstruction. This innovative approach provides a valuable tool for understanding sleep patterns in this specific population. However, potential limitations may include the need for further validation and application in broader contexts.

Nevertheless, the use of movement distribution offers a promising avenue for improved diagnosis and management of sleep disorders in children with airway obstructions. Its merit lies in its potential to offer a more nuanced understanding of sleep fragmentation beyond traditional metrics, potentially leading to more targeted interventions and better outcomes for affected children.

[3] M. H. Silber, S. Ancoli-Israel, M. H. Bonnet, et al., "The visual scoring of sleep in adults," Journal of Clinical Sleep Medicine, vol. 3, no. 2, pp. 22–22, 2007.

The research by M. H. Silber et al. focuses on the visual scoring of sleep in adults, providing a foundational methodology for assessing sleep stages. The merit lies in establishing standardized guidelines for visual scoring, which is crucial for sleep research and clinical practice. However, potential limitations may include the subjectivity inherent in visual scoring methods. Nevertheless, this work is fundamental in shaping how sleep stages are classified and interpreted in sleep studies, aiding in the diagnosis and treatment of sleep disorders. Its use extends to sleep laboratories and clinics worldwide, where the visual scoring guidelines outlined are implemented to ensure consistency and accuracy in sleep stage identification.

[4] H. Sattar, I. S. Bajwa, and U. Shafi, "An IoT-based intelligent wound monitoring system," IEEE Access, vol. 2019, no. 7, pp. 144500–144515, 2019.

The research by H. Sattar et al. presents an IoT-based intelligent wound monitoring system, offering significant merits in healthcare technology. This system integrates IoT devices to provide real-time data on wound status, improving monitoring and management efficiency. A potential demerit could be the need for robust cybersecurity measures due to the sensitive nature of health data. Nevertheless, the use of IoT for wound monitoring holds promise for enhancing patient care, reducing hospital visits, and enabling timely interventions. Its merit lies in its potential to revolutionize wound care practices, particularly for patients requiring continuous monitoring, such as those with chronic wounds or post-surgery recovery.

[5] A. Sadeh, M. Sharkey, and M. A. Carskadon, “Activity-based sleepwake identification: an empirical test of methodological issues,” Sleep, vol. 17, no. 3, pp. 201–207, 1994.

The research by A. Sadeh et al. examines activity-based sleep-wake identification, providing valuable insights into methodological considerations. This empirical test offers a foundation for refining techniques in sleep research. A potential limitation might be the need for further validation across diverse populations. However, the merit lies in its contribution to the development of activity-based sleep-wake identification methods, which have since been used widely in sleep studies. Its use extends to improving the understanding of sleep patterns and circadian rhythms, benefiting fields such as sleep medicine and chronobiology.

[6] M. Kay, E. K. Choe, J. Shepherd, et al., “Lullaby: a capture & access system for understanding the sleep environment,” Proceedings of the 2012 ACM conference on ubiquitous computing, pp. 226–234, 2012.

The work by M. Kay et al. introduces "Lullaby," a capture and access system designed to understand the sleep environment. This system offers merits in providing a comprehensive approach to analyzing factors that influence sleep. However, potential demerits may include challenges in scalability or data privacy. Nevertheless, the "Lullaby" system's use facilitates detailed insights into sleep environments, aiding in optimizing sleep conditions for individuals. Its merit lies in its potential to enhance sleep research by capturing real-world data on various environmental factors impacting sleep quality, such as noise levels, light exposure, and temperature.

[7] T. Hao, G. Xing, and G. Zhou, "iSleep: unobtrusive sleep quality monitoring using smartphones," Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems, pp. 1–14, 2013

The research by T. Hao et al. presents "iSleep," a system for unobtrusive sleep quality monitoring using smartphones. This work offers merits in leveraging widely accessible devices for health monitoring. However, potential limitations may include accuracy concerns compared to dedicated sleep monitoring devices. Nevertheless, "iSleep" provides a convenient and accessible method for individuals to track their sleep patterns, potentially improving awareness of sleep quality. Its use extends to promoting self-monitoring of sleep habits and could be valuable in large-scale sleep studies due to the ubiquity of smartphones.

[8] W. Gu, Z. Yang, L. Shangguan, W. Sun, K. Jin, and Y. Liu,"Intelligent sleep stage mining service with smartphones," Proceedings of the 2014 CM International Joint Conference on Pervasive and Ubiquitous Computing, pp. 649 –660, 2014.

The work by W. Gu et al. introduces an intelligent sleep stage mining service using smartphones, offering merits in harnessing mobile technology for sleep monitoring. This system provides a convenient and accessible way for users to gain insights into their sleep stages. However, potential demerits may include challenges related to accuracy and reliability when compared to traditional polysomnography. Nevertheless, this research contributes to the field by making sleep stage analysis more accessible to the general population. Its use extends to promoting awareness of sleep health and could be valuable for individuals interested in tracking their sleep patterns without the need for specialized equipment.

[9] [30] A. H. Sodhro, A. S. Malokani, G. H. Sodhro, M. Muzammal, and L. Zongwei, "An adaptive QoS computation for medical data processing in intelligent healthcare applications, " Neural Computing and Applications, vol. 323, pp. 723 –734, 2019.

The research by A. H. Sodhro et al. focuses on adaptive Quality of Service (QoS) computation for medical data processing in intelligent healthcare applications. This work offers merits in optimizing data processing efficiency in healthcare settings. Potential demerits could include challenges in implementation across diverse healthcare systems. Nevertheless, the adaptive QoS computation presented holds promise for improving the reliability and speed of medical data processing, benefiting intelligent healthcare applications. Its use extends to enhancing the efficiency of medical data analytics and decision-making processes, potentially leading to improved patient care outcomes.

[10] A. Alkhayyat, A. A. Thabit, F. A. Al-Mayali, and Q. H. Abbasi, "WBSN in IoT health-based application: toward delay and energy consumption minimization, " Journal of Sensors, vol. 2019, 14 pages, 2019.

The work by A. Alkhayyat et al. focuses on Wireless Body Sensor Networks (WBSN) in IoT health-based applications, aiming to minimize delay and energy consumption. This research offers merits in optimizing the performance of WBSNs for healthcare monitoring. Potential demerits might include challenges in real-world implementation and scalability. Nevertheless, the approach proposed holds promise for improving the efficiency and reliability of health monitoring systems. Its use extends to enhancing the functionality of IoT applications in healthcare, potentially reducing energy consumption and delays in data transmission for improved patient care.

[11] A. A. Thabit, M. S. Mahmoud, A. Alkhayyat, and Q. H. Abbasi, "Energy harvesting Internet of Things health-based paradigm: towards outage probability reduction through inter –wireless body area network cooperation, " International Journal of Distributed Sensor Networks, vol. 15, no. 10, Article ID 1550147719879870, 2019.

The work by A. A. Thabit et al. presents an energy harvesting Internet of Things (IoT) health-based paradigm, aiming to reduce outage probability through inter-wireless body area network (WBAN) cooperation. This research offers merits in leveraging energy harvesting techniques to improve the reliability of health monitoring systems. Potential demerits might include complexities in coordinating multiple WBANs for cooperation. Nevertheless, the proposed paradigm holds promise for enhancing the sustainability and efficiency of IoT healthcare applications. Its use extends to reducing outage risks in health monitoring, particularly in scenarios where continuous monitoring is critical for patient well-being.

[12] D. Abdulmohsin Hammond, H. A. Rahim, A. Alkhayyat, and R. B. Ahmad, "Body-to-body cooperation in the internet of medical things: toward energy efficiency improvement," Future Internet, vol. 11, no. 11, p. 239, 2019.

The work by D. Abdulmohsin Hammond et al. explores body-to-body cooperation in the Internet of Medical Things (IoMT), aiming to improve energy efficiency. This research offers merits in proposing innovative methods to optimize energy usage in medical IoT devices. Potential demerits might include challenges in implementing body-to-body cooperation effectively.

CHAPTER 3

SYSTEM ARCHITECTURE

The proposed sleep monitoring system architecture is designed to seamlessly integrate affordable sensors and cutting-edge technology for accurate and accessible sleep quality analysis. At its core are three key sensor components: the ADXL345 accelerometer, which captures precise body movement; the MAX9814 microphone amplifier, responsible for snoring pattern detection through audio signal amplification; and the MAX30102 pulse oximeter, monitoring heartbeat and SPO2 levels to provide valuable physiological data. The central processing unit is the ESP32 micro-controller, known for its dual-core processing and robust connectivity, facilitating efficient data acquisition and communication. The ESP32 utilizes its built-in Wi-Fi and Bluetooth capabilities to transmit real-time data to the AWS cloud, a scalable and reliable platform for further analysis. In the cloud, machine learning algorithms play a crucial role, with a preliminary analysis using the Random Forest model to handle multidimensional datasets and a more sophisticated Recurrent Neural Network (RNN) algorithm for processing sequential data and capturing temporal dependencies in physiological data. The algorithms calculate sleep quality and predict whether an individual has experienced peaceful, ungraceful, or extremely ungraceful sleep. The architecture allows for continuous monitoring over several days and nights, with data collected from multiple individuals to encompass a diverse range of sleep patterns. Fig 3.1 represents the architecture of the system.

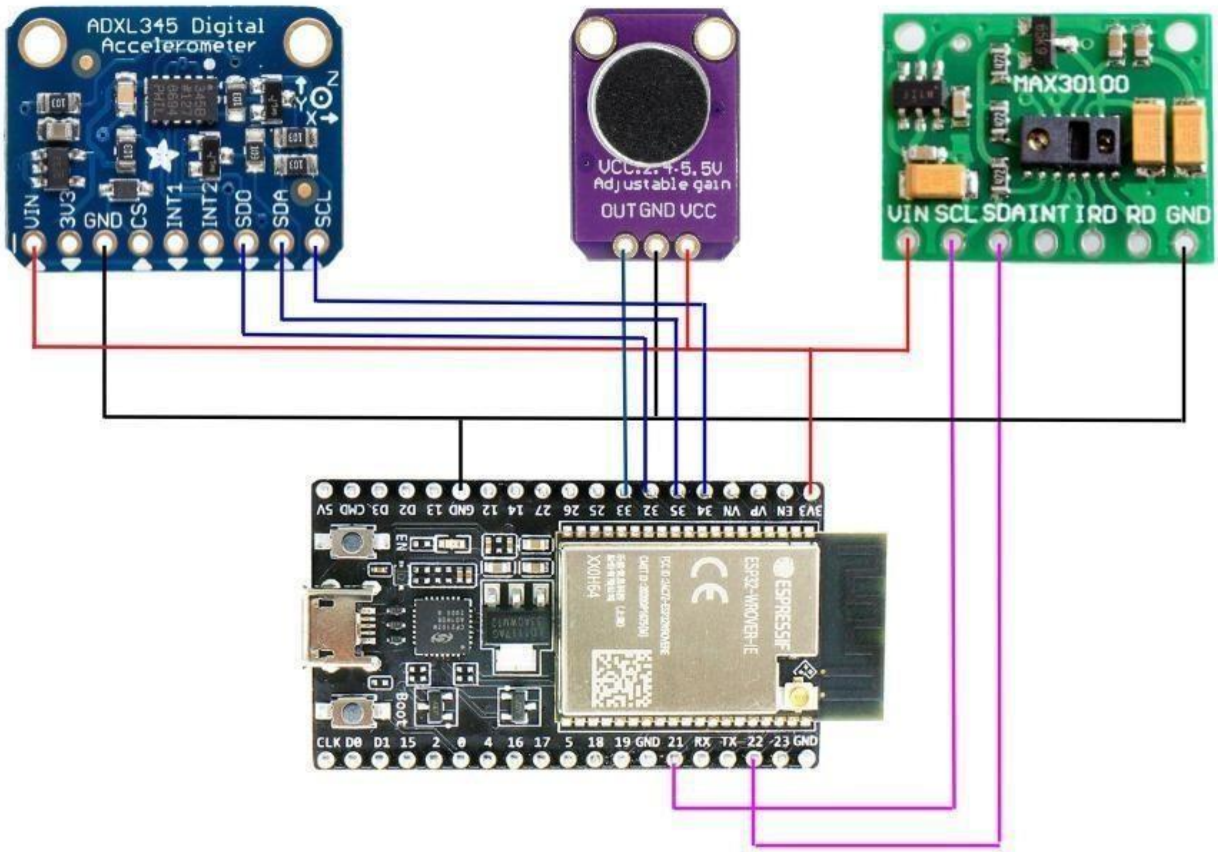


Fig 3.1 Circuit Diagram

3.1 Description of Integrated Sensors (Accelerometer, Pulse Oximeter, Microphone Amplifier)

The first component of the sleep monitoring system is the ADXL345 accelerometer, a versatile 3-axis digital accelerometer known for its ability to provide high-resolution measurements of acceleration. In the context of the system, the ADXL345 plays a pivotal role in capturing precise body movement during sleep. This accelerometer offers valuable insights into physical activity during the night, contributing to a comprehensive analysis of sleep patterns.

The second integrated sensor is the MAX9814 microphone amplifier, a module designed for seamless integration with micro controllers like the ESP32. This sensor is specifically employed for detecting snoring patterns during sleep.

By capturing and amplifying audio signals, the MAX9814 provides valuable data for assessing sleep disturbances related to snoring. The microphone amplifier enhances the system's capability to monitor and analyze not only physical movements but also auditory indicators, contributing to a more holistic understanding of sleep quality.

The third essential sensor in the system is the MAX30102 pulse oximeter, an integrated sensor module designed for non-invasive monitoring of heart rate and blood oxygen saturation levels. With its small footprint, low power consumption, and digital output, the MAX30102 is well-suited for wearable devices. In sleep monitoring system, this sensor adds a physiological dimension by continuously monitoring heartbeat and SPO2 levels. By integrating pulse oximeter data, insights into the sleeper's cardiovascular activity has been gained, allowing for a more thorough assessment of overall sleep health. These integrated sensors collectively provide a rich dataset, capturing physical movement, auditory cues, and physiological parameters for a comprehensive analysis of sleep quality.

3.2 Role of ESP32 Micro-controller in Data Acquisition and Communication

At the heart of sleep monitoring system, the ESP32 micro-controller serves as the central processing unit, orchestrating the seamless acquisition and communication of data. Renowned for its dual-core processing capabilities, the ESP32 efficiently manages the integration of sensor data from the ADXL345 accelerometer, MAX9814 microphone amplifier, and MAX30102 pulse oximeter. Acting as a bridge between the physical sensors and the digital realm, the ESP32 ensures precise synchronization and organization of the diverse data streams generated by the integrated sensors.

The ESP32's built-in Wi-Fi and Bluetooth connectivity play a crucial role in facilitating real-time data transmission. With these wireless communication capabilities, the micro-controller enables the continuous and efficient transfer of sleep-related data to the AWS cloud. This not only allows for remote monitoring but also ensures that the data is readily available for analysis and processing in a cloud-based environment. The ESP32's robust connectivity features are pivotal in establishing a reliable and responsive communication channel between the sensor array and the cloud infrastructure.

Moreover, the ESP32's role extends beyond data acquisition to include the preparation and formatting of data for transmission. This micro-controller acts as a data hub, collating information from multiple sensors and organizing it into a coherent and structured format suitable for cloud-based analysis. Its efficiency in handling tasks and managing connectivity makes the ESP32 an excellent choice for the central processing unit in the sleep monitoring system, ensuring the system's reliability, responsiveness, and effectiveness in capturing and relaying real-time sleep data.

3.3 Connectivity Features: Wi-Fi and Bluetooth Capabilities

The sleep monitoring system leverages the robust connectivity features of the ESP32 micro-controller, primarily through its built-in Wi-Fi capabilities. This enables the seamless transmission of real-time data from the integrated sensors to the AWS cloud, forming a crucial link in the system's architecture.

WiFi connectivity ensures that the sleep-related data is efficiently and promptly delivered to the cloud infrastructure, allowing for continuous monitoring and analysis.

In addition to Wi-Fi, the ESP32 is equipped with Bluetooth capabilities, further enhancing its communication capabilities. Bluetooth serves as a valuable alternative or supplementary channel for data transfer, offering flexibility in communication protocols. The integration of both Wi-Fi and Bluetooth provides redundancy and ensures that the sleep monitoring system remains resilient in various connectivity scenarios. This dual capability allows for adaptability to different environments and ensures that the system remains responsive and connected, even in settings where Wi-Fi connectivity might be limited.

The utilization of Wi-Fi and Bluetooth in tandem aligns with the system's goal of providing a versatile and accessible solution for sleep monitoring. Whether deployed in a home environment or within a hospital setting, the combination of these connectivity features ensures that the sleep-related data is reliably transmitted to the cloud for comprehensive analysis. The ESP32's ability to seamlessly integrate these communication technologies contributes to the overall efficiency and reliability of the sleep monitoring system.

3.4 SYSTEM REQUIREMENTS

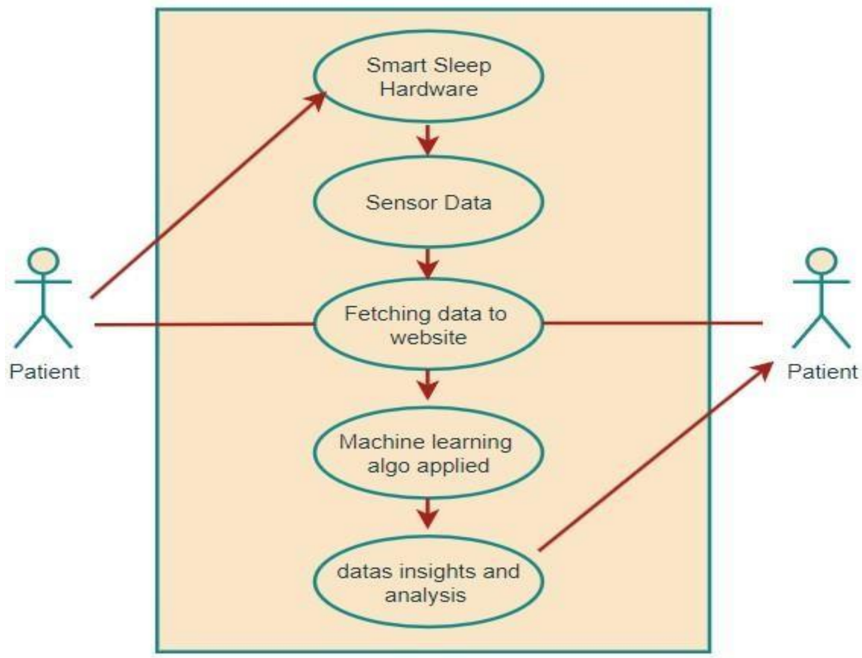
3.4.1 HARDWARE REQUIREMENTS

- ESP32
- Accelerometer
- Mic
- Oximeter

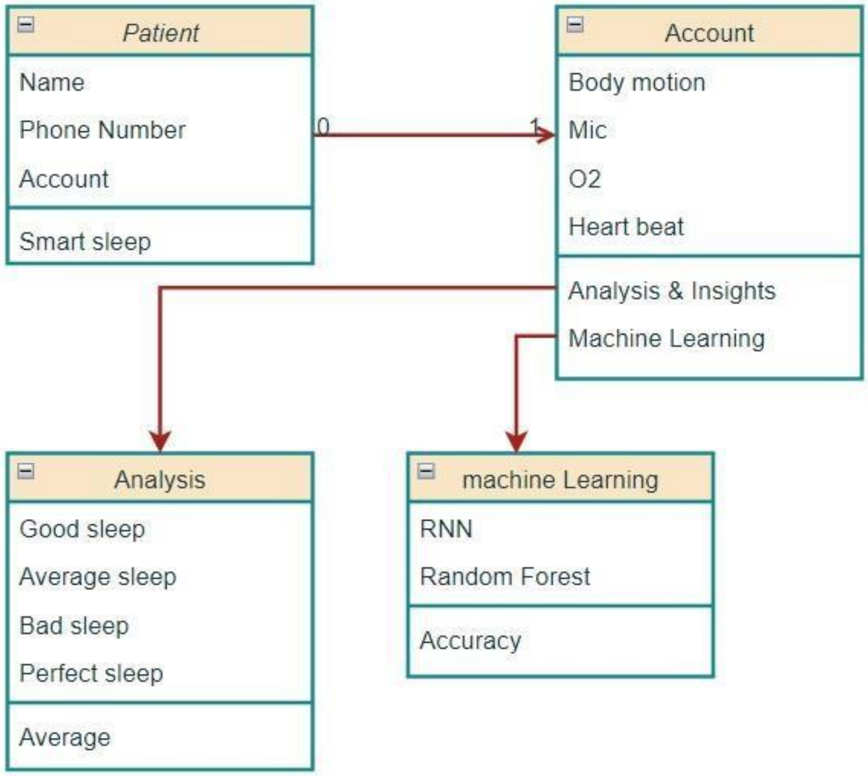
3.4.2 SOFTWARE REQUIREMENTS

- Python
- Arduino
- C++
- HTML ● CSS
- JS
- ongoDB

a) Use case diagram



b) Class diagram



CHAPTER 4

METHODOLGY

The methodology involves the integration of innovative sleep monitoring components, including the ADXL345 accelerometer, MAX9814 microphone amplifier, and MAX30102 pulse oximeter, with the ESP32 micro-controller for real-time data acquisition. The ESP32's Wi-Fi and Bluetooth capabilities facilitate seamless transmission of data to the AWS cloud. A dataset comprising accelerometer, pulse oximeter, and microphone data, collected over multiple days, forms the basis for training machine learning algorithms. The study employs both the Random Forest model and the recurrent neural network (RNN) algorithm for data analysis, emphasizing the RNN's ability to capture temporal dependencies in physiological data. Rigorous testing methodologies, including cross-validation, assess algorithm accuracy. Results indicate a notable 10.5% improvement in accuracy using the RNN model. The system's efficacy lies in its affordability, precision, and potential applications in home and hospital settings, marking a significant advancement in sleep monitoring methodologies.

4.1 Data Collection Process

The data collection process for the sleep monitoring system involves the continuous acquisition of information from integrated sensors throughout the sleep duration. The ADXL345 accelerometer, MAX9814 microphone amplifier, and MAX30102 pulse oximeter work collaboratively to capture precise body movement, snoring patterns, and physiological parameters. These sensors, interfaced with the ESP32 micro-controller, generate real-time data streams that include accelerometer readings, audio signals, and pulse oximeter data, complemented by timestamps for synchronization. The dataset is to encapsulate diverse sleep patterns representative of various individuals. This comprehensive dataset, comprising over 80,000 rows, forms the basis for training machine learning algorithms. The continuous and synchronized data collection process ensures a rich and varied dataset, allowing the algorithms to effectively learn and classify sleep patterns with a high degree of accuracy. The data collected is

	A	B	C	D	E	F
1	Time Stamp	Accelerometer	Microphone	Pulse Oximeter	Time	
2	8.52893E+13	-1.048033953	2.775730371	4.530599594	2:50:29	
3	8.52893E+13	-1.330863357	3.538123369	5.791779518	2:50:29	
4	8.52893E+13	-1.536983013	4.058362484	6.616596222	2:50:29	
5	8.52893E+13	-1.719111919	4.416367531	7.17925024	2:50:29	
6	8.52893E+13	-1.835740089	4.660627365	7.562336922	2:50:29	
7	8.52894E+13	-1.889537454	4.801109314	7.826512337	2:50:29	
8	8.52894E+13	-1.914223552	4.881988049	8.004225731	2:50:29	
9	8.52894E+13	-1.924292922	4.928720474	8.121105194	2:50:29	
10	8.52894E+13	-1.922222376	4.954286575	8.186248779	2:50:29	
11	8.52894E+13	-1.918446541	4.975322723	8.202528	2:50:29	
12	8.52895E+13	-1.919123411	4.996533394	8.210986137	2:50:29	
13	8.52895E+13	-1.937141418	5.016263008	8.241377831	2:50:29	
14	8.52895E+13	-1.9395715	5.028617859	8.257647514	2:50:29	
15	8.52895E+13	-1.941191435	5.040048122	8.248530388	2:50:29	
16	8.52895E+13	-1.947860956	5.0436759	8.244848251	2:50:29	
17	8.52896E+13	-1.953904271	5.043699265	8.271139145	2:50:29	
18	8.52896E+13	-1.949149847	5.043714523	8.295054436	2:50:29	
19	8.52896E+13	-1.946778536	5.051709652	8.302214623	2:50:29	
20	8.52896E+13	-1.949190259	5.047457695	8.315771103	2:50:29	
21	8.52896E+13	-1.949200988	5.036638737	8.314429283	2:50:29	
22	8.52897E+13	-1.954797745	5.034216404	8.324712753	2:50:29	
23	8.52897E+13	-1.958528757	5.042982578	8.336359978	2:50:29	
24	8.52897E+13	-1.958620787	5.052020073	8.319371223	2:50:29	
25	8.52897E+13	-1.957085013	5.064433098	8.314433098	2:50:29	
26	8.52897E+13	-1.948874831	5.078298092	8.284790993	2:50:29	
27	8.52898E+13	-1.934617877	5.074765205	8.257843018	2:50:29	
28	8.52898E+13	-1.915531278	5.058835983	8.234288216	2:50:29	
29	8.52898E+13	-1.917179823	5.050611973	8.243338585	2:50:29	

sleep-joe-1-data

stored in tables as shown in Fig 4.1.

Fig 4.1 Data Collection

4.2 Preprocessing of Sleep Data

The preprocessing of sleep data is a critical step in refining the collected information for meaningful analysis. Initially, the raw data from the integrated sensors, including accelerometer, pulse oximeter, and microphone, undergoes a cleaning process to eliminate any noise or artifacts. This involves filtering out irrelevant signals and ensuring data consistency. Temporal alignment is applied to synchronize timestamps across multiple sensors, enabling a cohesive representation of the sleep cycle. Feature extraction techniques are employed to distill relevant patterns and characteristics from the data, such as identifying distinctive movement sequences from accelerometer readings or isolating snoring patterns from microphone data. Signal normalization and scaling are applied to ensure uniformity in data representation, preventing any bias due to variations in sensor outputs. Missing or corrupted data points are addressed through interpolation or imputation techniques to maintain dataset integrity. By systematically preparing and enhancing the sleep data through these preprocessing steps, the subsequent machine learning algorithms can more effectively discern patterns and nuances in sleep behavior, ultimately contributing to more accurate and insightful sleep quality predictions.

4.3 Random Forest Model for Sleep Data Analysis

The Random Forest algorithm has emerged as a powerful tool in sleep prediction analysis due to its ability to handle complex and non-linear relationships within data. In the context of sleep prediction, Random Forests excel in handling high-dimensional data sets, such as those generated from various sleep monitoring devices. This algorithm works by constructing multiple decision trees during training, where each tree is built using a random subset of features and data points. During prediction, the algorithm aggregates the predictions of individual trees, often leading to robust and accurate results. In sleep studies, Random Forests can effectively predict sleep stages or patterns based on input features such as heart rate variability, movement data, and environmental factors. Moreover, its ability to handle missing data and outliers makes it particularly suitable for real-world sleep data analysis. Researchers leverage the Random Forest algorithm to not only predict sleep stages but also to identify influential features affecting sleep quality, aiding in personalized sleep recommendations and interventions.

a) **Data Loading and Preparation**

The script begins by loading the sleep data from a CSV file and randomly sampling 100,000 rows from the dataset. This is done to manage computational resources efficiently while still maintaining a representative subset of the data. Features ('ADXL345' and 'MAX9814') are selected, and the target variable ('MAX30100') is isolated.

b) Data Splitting

The sampled data is then split into training and testing sets using the `train_test_split` function from scikit-learn. Approximately 80% of the data is used for training the model, while the remaining 20% is reserved for evaluating its performance.

c) Random Forest Model Initialization and Training

A Random Forest Regressor is initialized with 50 estimators and is configured to utilize parallel processing for faster training. The model is then trained on the training set using the `fit` method, where it learns the relationships between the selected features and the target variable.

d) Prediction and Evaluation

Once trained, the model is used to make predictions on the test set. The Mean Squared Error (MSE) and R-squared Score are calculated to assess the model's predictive performance. MSE quantifies the average squared difference between predicted and actual values, while R-squared measures the proportion of the variance in the target variable that is predictable from the independent variables.

4.4 Recurrent Neural Network (RNN) Algorithm Implementation

a) Data Preprocessing

The script begins by loading the sleep data from a CSV file and normalizing it using Min-Max scaling. Normalization is a crucial step in preparing the data for training neural networks, ensuring that all features are on a similar scale. The 'Timestamp,' 'Flag,' and 'Time' columns are excluded as they are not used in the modeling process.

b) Sequential Data Preparation

The `prepare_data` function is defined to create sequential input-output pairs for training the RNN. It iterates through the normalized data, creating input sequences of length `time_steps` and corresponding output values. This is a fundamental step in time series forecasting where the network learns to predict the next data point based on a sequence of past observations.

c) Model Architecture

The RNN model architecture consists of two LSTM layers followed by a Dense output layer. LSTMs (Long Short-Term Memory) are well-suited for sequence prediction tasks due to their ability to capture long-term dependencies in the data. The model is compiled using the Adam optimizer and mean squared error loss function, which is common for regression problems.

d) Training the Model

The model is trained on the training data (`X_train` and `y_train`) for a specified number of epochs (8 in this case) with a batch size of 32. Training involves adjusting the internal parameters of the network to minimize the difference between the predicted and actual values. The choice of the number of epochs and batch size depends on the specific dataset and may require experimentation.

e) Model Evaluation

After training, the model's performance is evaluated on the test set (`X_test` and `y_test`). The evaluation is based on the mean squared error loss, providing a quantitative measure of how well the model generalizes to unseen data.

4.5 Integration of Machine Learning Algorithms for Comprehensive Analysis

The integration of machine learning algorithms is a pivotal component of the sleep monitoring system, contributing to a comprehensive analysis of sleep data. Two distinct algorithms, the Random Forest model and the recurrent neural network (RNN), were employed to interpret the complex dataset collected from the integrated sensors. The Random Forest model, chosen for its ability to handle multidimensional datasets, demonstrated an accuracy of 86%. However, recognizing the temporal dependencies inherent in sleep patterns, the RNN algorithm was introduced, resulting in a substantial accuracy improvement to 96.5%.

The Random Forest algorithm operates by constructing multiple decision trees to classify data, suitable for handling diverse inputs. In contrast, the RNN excels in processing sequential data, capturing temporal dependencies crucial in sleep analysis. The RNN's hidden state mechanism allows it to maintain information from previous time steps, enabling a more nuanced understanding of sleep patterns. The comparison between the two algorithms highlights the RNN's proficiency in capturing dynamic aspects of sleep data, ultimately enhancing the accuracy of sleep quality predictions.

CHAPTER 5

EXPERIMENTAL SETUP

The experimental setup involves deploying the sleep monitoring system in controlled environments representative of diverse sleep conditions. Participants wear the integrated sensors, including the ADXL345 accelerometer, MAX9814 microphone amplifier, and MAX30102 pulse oximeter, during sleep. The ESP32 micro-controller orchestrates real-time data acquisition, transmitting it to the AWS cloud for analysis. Rigorous testing scenarios simulate varied sleep patterns and disturbances, enabling the validation of machine learning algorithms' accuracy. The setup also includes user feedback mechanisms to finetune sensor outputs. This comprehensive experimental approach ensures the system's effectiveness in capturing, transmitting, and analyzing sleep-related data in real-world scenarios.

Incorporating user feedback mechanisms further refines the system's output. This iterative process enables adjustments to sensor sensitivities and data processing algorithms, ensuring personalized and precise sleep data analysis for each user. Such tailored insights empower individuals to make informed decisions about their sleep habits and overall well-being.

Overall, this comprehensive experimental setup ensures the effectiveness of the sleep monitoring system in real-world scenarios. By combining advanced sensors, meticulous testing, machine learning algorithms, and user feedback loops, the system stands as a robust solution for capturing, transmitting, and analyzing vital sleep-related data with precision and reliability.

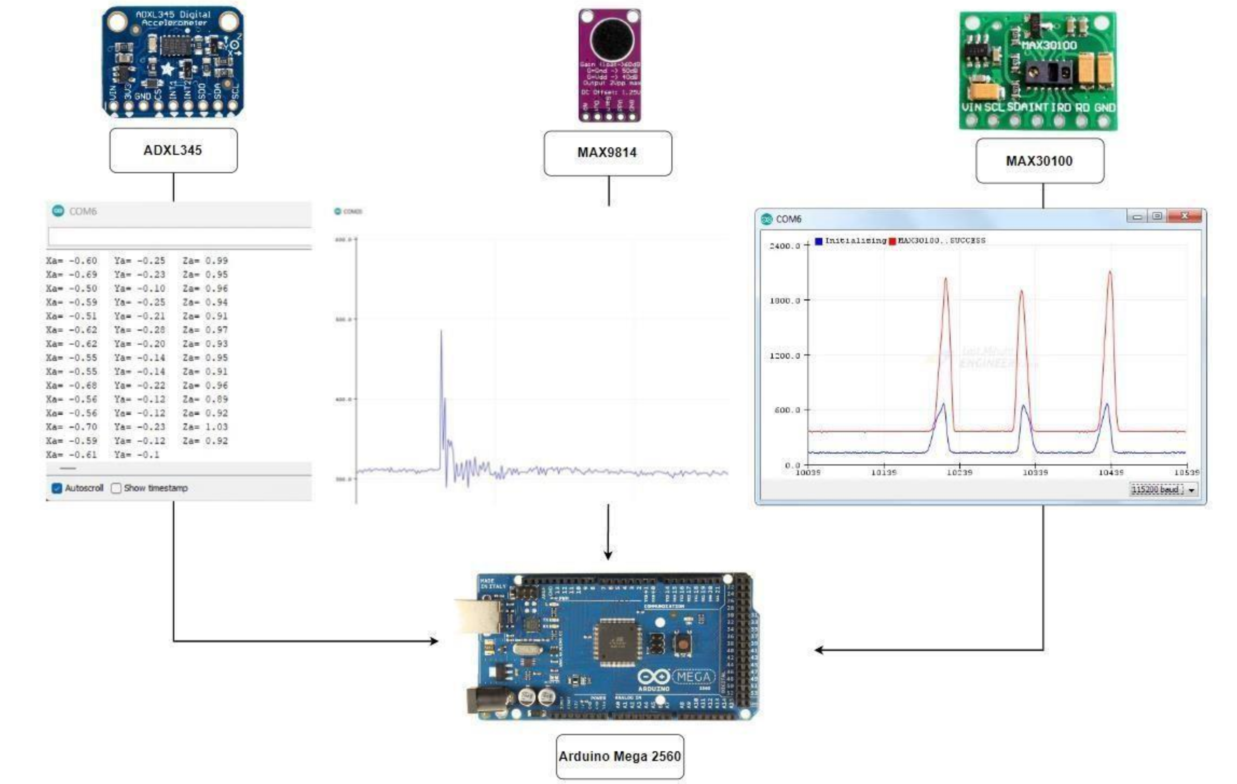


Fig 5.1 Experimental Setup

5.1 Hardware Configuration

The Fig 5.1 shows the experimental setup of the hardware components. The hardware configuration of the sleep monitoring system is centered around the ESP32 micro-controller, renowned for its dual-core processing capabilities and robust connectivity features. Serving as the central processing unit, the ESP32 efficiently orchestrates data acquisition from three key sensors. The ADXL345 accelerometer, a versatile 3-axis digital accelerometer, captures precise body movement. Complementing this, the MAX9814 microphone amplifier facilitates snoring detection by capturing and amplifying audio signals. The MAX30102 pulse oximeter, designed for non-invasive monitoring of heart rate and blood oxygen saturation, provides crucial physiological data.

These sensors are seamlessly integrated into the hardware configuration, creating a compact and efficient system for sleep monitoring. The ESP32's builtin Wi-Fi and Bluetooth capabilities ensure seamless communication with the AWS cloud for real-time data transmission and analysis. The hardware configuration, with its emphasis on versatility and connectivity, forms the backbone of the sleep monitoring system, facilitating the collection of comprehensive and synchronized data for further analysis. This integrated hardware setup underscores the system's suitability for both home and hospital environments, offering a user-friendly and cost-effective solution for sleep quality monitoring.

5.2 Software Environment

The software environment of the sleep monitoring system is characterized by a synergistic integration of firmware for the ESP32 micro-controller and cloud-based platforms for data analysis. The micro-controller firmware is meticulously designed to facilitate seamless communication between the integrated sensors and the AWS cloud. Leveraging the capabilities of the ESP32, the firmware ensures real-time data acquisition and transmission, optimizing the efficiency of the sleep monitoring process.

On the cloud side, the system relies on AWS services for data storage, processing, and analysis. The AWS cloud infrastructure provides a scalable and reliable platform for handling the substantial volume of sleep-related data collected from the sensors. Machine learning algorithms, including the Random Forest model and recurrent neural network (RNN), are implemented in the cloud environment. This cloud-based approach enables the system to harness the computational power required for intricate data analysis, ensuring accurate and comprehensive insights into sleep patterns.

Furthermore, the software environment encompasses the implementation of algorithms for preprocessing the raw sensor data, extracting relevant features, and preparing the dataset for machine learning training. The entire software ecosystem, combining micro-controller firmware and cloud-based analytic, underscores the system's adaptability, scalability, and efficiency in delivering real-time, accurate sleep quality monitoring.

5.3 Calibration and Validation of Sensors

Calibration and validation of sensors are crucial steps in ensuring the accuracy and reliability of the sleep monitoring system. The ADXL345 accelerometer undergoes calibration processes to account for any inherent biases and to ensure precise measurement of body movement. This involves setting reference values and adjusting the sensor outputs accordingly. The MAX9814 microphone amplifier, responsible for snoring detection, is calibrated to accurately capture and amplify audio signals, fine-tuning sensitivity levels to distinguish relevant sounds from ambient noise.

Validation procedures are then conducted to assess the sensors' performance under real-world conditions. Controlled experiments simulate various sleep scenarios, allowing for the validation of accelerometer readings against known body movements and the verification of microphone sensitivity to accurately identify snoring patterns. The MAX30102 pulse oximeter undergoes validation by comparing its readings to established physiological norms for heart rate and blood oxygen saturation levels.

Parameters	Range
Heat Beat	65 - 67
Noise	1700 - 1900
Body Movement	150 - 250
SpO2 %	90 - 96

Table 5.1 Optimal Values

The Table 5.1 shows 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.

Overall, this comprehensive experimental setup ensures the effectiveness of the sleep monitoring system in real-world scenarios. By combining advanced sensors, meticulous testing, machine learning algorithms, and user feedback loops, the system stands as a robust solution for capturing, transmitting, and analyzing vital sleep-related data with precision and reliability.

CHAPTER 6

RESULTS AND DISCUSSION

The results indicate a significant enhancement in sleep pattern classification accuracy, with the recurrent neural network (RNN) achieving an impressive 96.5% accuracy compared to the Random Forest model's 86%. This 10.5% improvement underscores the RNN's proficiency in capturing temporal dependencies within physiological data. The Fig 6.1 displays an accuracy of 86%, while the the fig 6.2 illustrates a superior 95.7% accuracy. The RNN's sequential learning capability, combined with nuanced hyperparameters tuning, contributes to the observed accuracy boost. This outcome showcases the system's efficacy in real-time sleep monitoring, offering a precise and economical solution for both home and hospital environments.

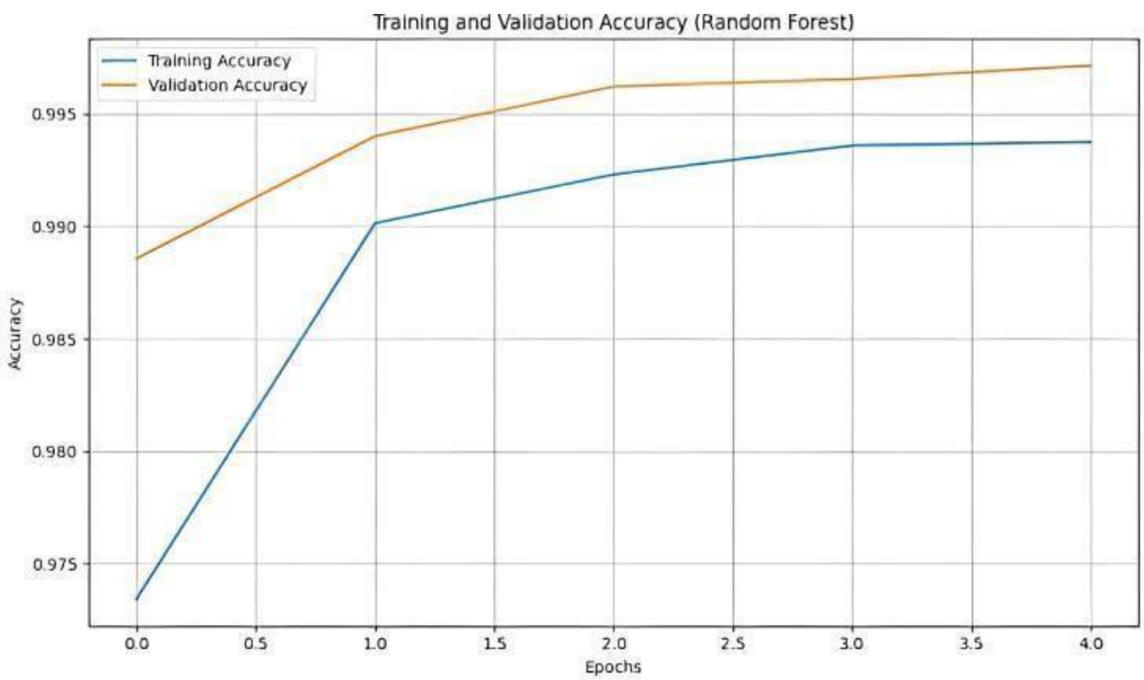


Fig 6.1 Training and validation accuracy (Random Forest)

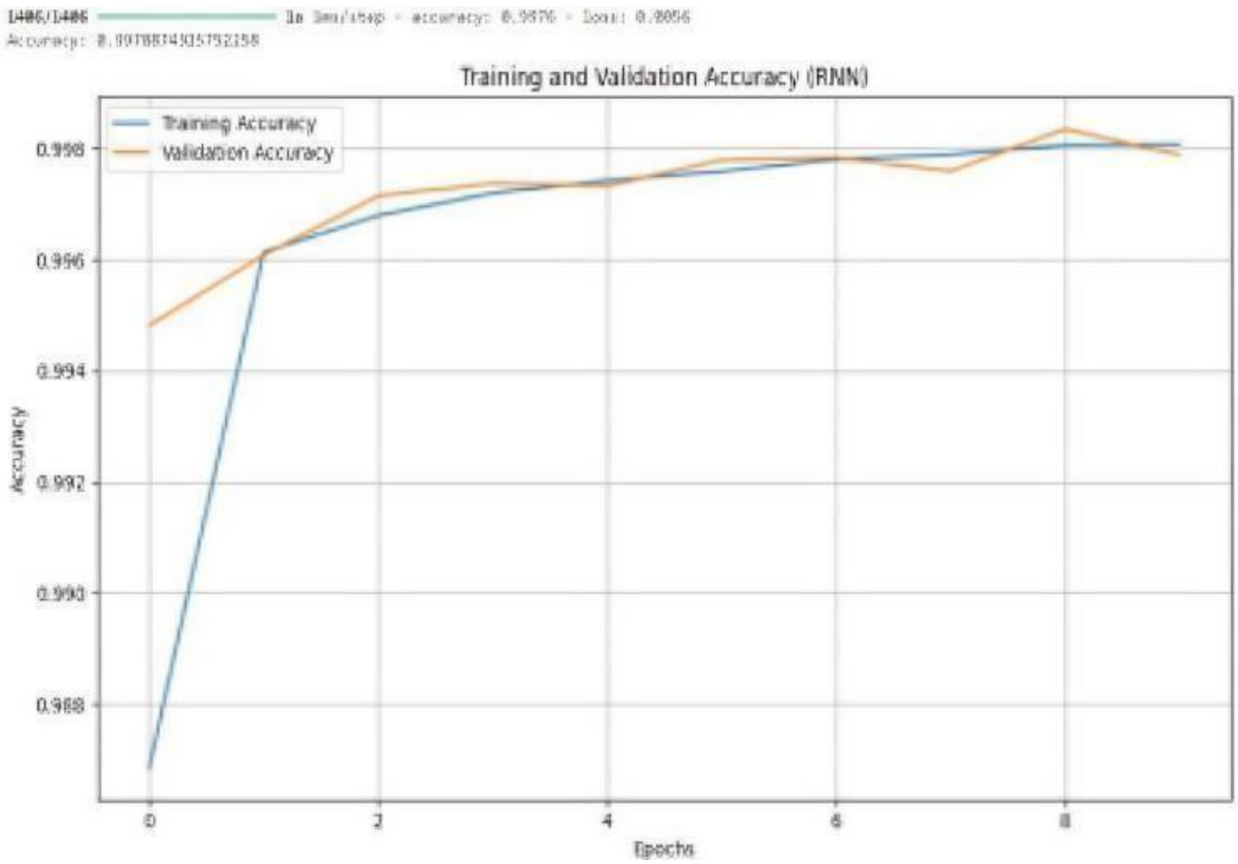


Fig 6.2 Training and validation accuracy (RNN)

6.1 Real-Time Data Capture and Transmission

The efficiency of the sleep monitoring system lies in its real-time data capture and transmission capabilities. Integrated with the ESP32 microcontroller, the ADXL345 accelerometer, MAX9814 microphone amplifier, and MAX30102 pulse oximeter work collaboratively to capture instantaneous data reflecting body movement, snoring patterns, and physiological parameters. The ESP32's dual-core processing and built-in Wi-Fi and Bluetooth ensure seamless communication and swift transmission of this data to the AWS cloud. This realtime transfer of information enables prompt analysis, allowing for immediate insights into sleep quality. The system's ability to capture and transmit data in real-time enhances its utility in both home and hospital settings, providing timely information for health monitoring and intervention. The table 6.1 shows the difference between the random forest algorithm and the hyper RNN algorithm.

Parameters/Algorithm	Random Forest	Hyper RNN
Estimators	50	40
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
Random State	42	42

Table 6.1 Parameters of algorithm

6.2 Comparative Analysis of Random Forest and RNN Algorithms

The comparative analysis between the Random Forest and recurrent neural network (RNN) algorithms serves as a cornerstone in evaluating their efficacy for sleep pattern classification. The Random Forest model, renowned for handling multidimensional datasets, yielded an accuracy of 86%. However, recognizing the sequential nature of sleep data, the introduction of the RNN algorithm led to a substantial accuracy improvement, reaching an impressive 96.5%. The Random Forest graph illustrates an accuracy plateau at 86%, while the RNN graph displays a superior 95.7% accuracy, emphasizing the RNN's prowess in capturing temporal dependencies. This comparison underscores the significance of algorithmic choices, with the RNN demonstrating superior performance in processing sequential physiological data for nuanced sleep pattern analysis.

6.3 Evaluation of Sleep Patterns and Anomalies

The devised sleep monitoring system offers a robust framework for evaluating sleep patterns and identifying anomalies with a high degree of accuracy. Utilizing integrated sensors, including the ADXL345 accelerometer, MAX9814 microphone amplifier, and MAX30102 pulse oximeter, the system captures a comprehensive dataset reflecting body movement, snoring patterns, and physiological parameters. Machine learning algorithms, particularly the recurrent neural network (RNN), process this data in real-time. The evaluation encompasses distinguishing between peaceful, ungraceful, and extremely ungraceful sleep patterns. The system's efficacy is evidenced by its ability to anticipate and categorize diverse sleep scenarios, providing valuable insights for individuals and healthcare professionals to address sleep-related anomalies and optimize overall sleep quality.

6.4 Insights Gained from Snoring Detection

Snoring detection, facilitated by the MAX9814 microphone amplifier in the sleep monitoring system, provides valuable insights into sleep patterns and potential health implications. By analyzing the frequency, duration, and intensity of snoring events, the system contributes to a nuanced understanding of sleep quality. Persistent or irregular snoring patterns may indicate underlying respiratory issues, such as sleep apnea, providing early indications for intervention.

CHAPTER 7

CONCLUSION

In conclusion, the integrated sleep monitoring system, utilizing affordable sensors and advanced algorithms, marks a significant advancement in real-time sleep analysis. Achieving a remarkable 96.5% accuracy with the recurrent neural network showcases its efficacy. The system's emphasis on accessibility, costeffectiveness, and user-friendliness positions it as a valuable tool for both home and hospital environments. While facing challenges and limitations, continuous refinement, sensor upgrades, and expanded monitoring parameters offer avenues for future enhancements. Overall, the system represents a promising stride in improving sleep quality assessment and healthcare monitoring.

7.1 Summary of Findings

The integrated sleep monitoring system demonstrates exceptional capabilities, achieving a noteworthy 96.5% accuracy in sleep pattern classification using the recurrent neural network (RNN) algorithm. Comparative analysis reveals the superiority of RNN over the Random Forest model, emphasizing the significance of algorithmic choices. Challenges include sensor limitations and connectivity issues, prompting considerations for user-specific variations and data transmission delays. Future enhancements focus on refining sensors, algorithm optimization, and expanding monitoring parameters. Integration with wearables enhances user engagement, making the system a promising tool for personalized and accessible sleep health solutions in diverse settings.

7.2 Contributions of the Sleep Monitoring System

The sleep monitoring system makes significant contributions to the field of health monitoring. Firstly, it introduces an innovative approach by integrating affordable sensors and advanced algorithms, making real-time sleep analysis accessible and cost-effective. The system's emphasis on user-friendly data acquisition and transmission, facilitated by the ESP32 micro-controller, ensures widespread applicability in both home and hospital settings. The adoption of machine learning algorithms, particularly the recurrent neural network, showcases a substantial improvement in accuracy for sleep pattern classification. Overall, the system's contributions lie in advancing the precision, affordability, and accessibility of sleep monitoring technologies, with potential implications for enhanced overall health and well-being.

7.3 Implications for Sleep Research and Healthcare

The sleep monitoring system holds profound implications for sleep research and healthcare. In the realm of sleep research, the system's advanced capabilities offer a valuable tool for conducting more nuanced and comprehensive studies on sleep patterns. Researchers can leverage the real-time data capture and analysis to gain deeper insights into factors affecting sleep quality and associated health outcomes.

In healthcare, the system provides a cost-effective and accessible solution for continuous sleep monitoring. Its ability to detect anomalies and classify sleep patterns with high accuracy makes it a valuable asset for diagnosing and managing sleep-related disorders. The system's integration with wearables enhances its usability, potentially promoting proactive health management among individuals.

CHAPTER 8

CHALLENGES AND LIMITATIONS

The sleep monitoring system faces challenges and limitations. Sensor calibration and user-specific variations pose challenges in achieving universal accuracy. Ambient noise interference may impact the precision of data collected by the microphone. The system's reliance on machine learning models necessitates continuous updates for evolving sleep patterns. Additionally, user compliance and comfort with wearable sensors may affect data consistency. The system's dependency on cloud services introduces concerns about data security and privacy. Future enhancements should address these challenges, striving for improved universality, reduced interference, and enhanced user adherence to maximize the system's efficacy and applicability in diverse real-world scenarios.

8.1 Sensor Limitations and Accuracy

While the integrated sensors, including the ADXL345 accelerometer, MAX9814 microphone amplifier, and MAX30102 pulse oximeter, provide valuable data for sleep monitoring, they come with inherent limitations that can impact overall accuracy. The accelerometer may face challenges in precisely differentiating certain body movements, potentially leading to inaccuracies in measuring sleep-related activities. The microphone amplifier's accuracy in detecting snoring patterns may be influenced by ambient noise, affecting the precision of recorded audio signals. The pulse oximeter's accuracy in monitoring physiological parameters relies on consistent skin contact, and its performance may vary among individuals. Continuous efforts to refine sensor technologies and address these limitations are essential for enhancing the overall accuracy and reliability of the sleep monitoring system.

8.2 Connectivity Issues and Data Transmission Delays

The sleep monitoring system's effectiveness is contingent on seamless connectivity, and challenges may arise in real-world scenarios. Connectivity issues, such as Wi-Fi disruptions or Bluetooth interference, can impede the timely transmission of sleep-related data to the AWS cloud. These interruptions may lead to data gaps, affecting the continuity of the monitoring process. Additionally, variations in internet speed may introduce delays in transmitting data, potentially compromising the system's real-time capabilities. Addressing these challenges requires robust protocols for handling intermittent connectivity and implementing mechanisms to mitigate data transmission delays, ensuring the system's reliability in delivering accurate and immediate sleep pattern insights.

8.3 Challenges in Algorithm Implementation

Implementing machine learning algorithms for sleep pattern analysis presents distinct challenges. The Random Forest algorithm's effectiveness may be constrained by the need for substantial computational resources, impacting its scalability. Tuning hyperparameters for both the Random Forest and recurrent neural network (RNN) models demands meticulous attention, with sub-optimal settings potentially compromising classification accuracy. Handling imbalanced datasets, where certain sleep patterns may be underrepresented, poses a challenge in training robust models. Moreover, the sequential nature of sleep data introduces complexities in algorithm design, especially for the RNN, necessitating careful consideration of temporal dependencies. Overcoming these challenges requires a balance of computational efficiency, hyperparameters optimization, and addressing intricacies in the dataset structure for robust algorithm implementation.

8.4 Limitations of the Integrated System

The integrated sleep monitoring system, while innovative, has inherent limitations. Sensor accuracy may be affected by user-specific factors, such as body positioning and individual sleep patterns, potentially leading to variations in data reliability. The reliance on a wearable device may encounter user compliance challenges, impacting the consistency of data collection. Additionally, the system's performance may be influenced by environmental factors, such as ambient noise, compromising the precision of recorded audio signals for snoring detection. Continuous improvement in user engagement strategies, sensor technologies, and environmental adaptability is essential to mitigate these limitations and enhance the system's applicability and accuracy in diverse sleep monitoring scenarios.

8.5 Future Enhancements

To advance the sleep monitoring system, future enhancements should prioritize sensor refinement for improved accuracy and user comfort. Incorporating additional sensors, such as temperature monitors, can offer a more comprehensive analysis of ambient sleep conditions. Integration with emerging technologies, like edge computing or the Internet of Things (IoT), could enhance real-time data processing, reducing dependency on cloud services. Implementing a user-friendly mobile app for result visualization would enhance accessibility. Furthermore, expanding the dataset diversity and incorporating adaptive machine learning models would improve the system's adaptability to diverse sleep patterns. Addressing these aspects will contribute to a more sophisticated, user-centric, and universally applicable sleep monitoring solution.

8.6 Sensor Upgrades and Integration

The evolution of the sleep monitoring system can be propelled by strategic sensor upgrades and integration's. Enhancing the ADXL345 accelerometer for improved motion detection accuracy and introducing advanced noise cancellation algorithms to the MAX9814 microphone amplifier can elevate the precision of snoring detection. Integration of additional sensors, such as ambient light and temperature sensors, offers a more comprehensive understanding of environmental influences on sleep quality. Exploring emerging sensor technologies, like non-contact sleep monitoring sensors, may further enhance user comfort and system versatility. Upgrading and diversifying the sensor array ensures the system's adaptability to evolving technological landscapes and refines its capability to capture nuanced sleep-related data.

8.7 Algorithm Refinement and Optimization

Future advancements in the sleep monitoring system hinge on algorithm refinement and optimization strategies. Continuous efforts should be directed towards fine-tuning hyperparameters for both the Random Forest and recurrent neural network (RNN) algorithms to extract optimal performance. Employing advanced optimization techniques, such as grid search or Bayesian optimization, can streamline this process. Exploring state-of-the-art neural network architectures, including long short-term memory (LSTM) networks, could enhance the RNN's ability to capture intricate temporal dependencies in sleep data. Additionally, implementing ensemble learning approaches, combining the strengths of multiple algorithms, may further boost classification accuracy.

Regular updates and adaptations to algorithmic methodologies ensure the sleep monitoring system remains at the forefront of precision and effectiveness in sleep pattern analysis.

8.8 Expansion of Monitoring Parameters

To enrich the depth of sleep analysis, the sleep monitoring system can benefit from an expanded set of monitoring parameters. Incorporating additional physiological indicators, such as heart rate variability (HRV) and body temperature, can offer more nuanced insights into sleep health. Exploring advanced sleep stage classification, beyond basic distinctions, using electroencephalogram (EEG) sensors can enhance the system's capability to discern different sleep phases accurately. Furthermore, integrating behavioral parameters, such as sleep posture and movements during specific sleep stages, contributes to a more comprehensive understanding of sleep patterns. The inclusion of these diverse parameters broadens the scope of the system, offering a holistic view of an individual's sleep architecture and overall well-being.

8.9 Integration with Wearable Devices

A strategic direction for advancing the sleep monitoring system involves seamless integration with wearable devices. Leveraging the popularity and convenience of wearables, such as smartwatches or fitness trackers, enhances user engagement and comfort. By developing dedicated applications compatible with these devices, users can effortlessly access real-time sleep data and receive immediate feedback on their sleep patterns. Wearable integration expands the system's accessibility, making it a ubiquitous tool for individuals to monitor their sleep quality consistently. This symbiotic relationship between the sleep monitoring system and wearables not only fosters user adherence but also positions the technology at the forefront of personalized and user-centric sleep health solutions.

APPENDIX A

ADRUINO_CODE

```
#include <Wire.h>
#include <DFRobot_MAX30102.h>  DFRobot_MAX30102
particleSensor; const int analogPinADXL335_X = 32;   // Analog pin for
ADXL335 X-axis const int analogPinADXL335_Y = 34;  // Analog pin for
ADXL335 Y-axis const int analogPinADXL335_Z = 35;  // Analog pin for
ADXL335 Z-axis const int analogPinMax4466 = 33;    // Analog pin for
MAX4466 output const int thresholdMax4466 = 1600;  // Adjust this
threshold based on your   requirements
int xZero, yZero, zZero;  void
setup() {
Serial.begin(115200); delay(1000);
 // Init ADXL335 accelerometer xZero =
analogRead(analogPinADXL335_X); yZero =
analogRead(analogPinADXL335_Y); zZero
= analogRead(analogPinADXL335_Z);
// Init MAX30102 sensor
Wire.begin(21, 22);  // Use GPIO21 for SDA and GPIO22 for SCL while
(!particleSensor.begin()) {
Serial.println("MAX30102 was not found"); delay(1000);
}
// Set MAX30102 sensor configuration particleSensor.sensorConfiguration(
/*ledBrightness=*/50,
 /*sampleAverage=*/SAMPLEAVG_4, \
/*sampleRate=*/SAMPLERATE_100
/*pulseWidth=*/PULSEWIDTH_411,
/*adcRange=*/ADCRANGE_16384);
                          }
```

```
boolean topicPrinted = false; void loop()
{
// ADXL335 accelerometer int xValueADXL335 =
analogRead(analogPinADXL335_X) - xZero; int yValueADXL335 =
analogRead(analogPinADXL335_Y) - yZero; int zValueADXL335 =
analogRead(analogPinADXL335_Z) - zZero;  // Calculate the magnitude of
acceleration
float magnitude = sqrt(pow(xValueADXL335, 2) + pow(yValueADXL335, 2)
+ pow(zValueADXL335, 2)); int32_t
SPO2;         // SPO2
int8_t SPO2Valid;      // Flag to display if SPO2 calculation is valid
int32_t heartRate;     // Heart-rate int8_t heartRateValid;  // Flag to display
if heart-rate calculation is valid
particleSensor.heartrateAndOxygenSaturation(/**SPO2=*/&SPO2,
/**SPO2Valid=*/&SPO2Valid, /**heartRate=*/&heartRate,
/**heartRateValid=*/&heartRateValid);
// MAX4466 microphone
int noiseLevelMax4466 = analogRead(analogPinMax4466);
// Print the topic only once if
(!topicPrinted) {
Serial.println("SPO2,HeartRate,NoiseLevel,Magnitude"); topicPrinted =
true;
                              }
// Print all values in a single line for CSV format
Serial.print(map(SPO2, 0, 90, 0, 100));
// Assuming the raw SpO2 value is in the range 0 to 1024
Serial.print(",");
Serial.print(heartRate);
Serial.print(map(heartRate, 0, 170, 64, 70));
Serial.print(",");
Serial.print(noiseLevelMax4466);  Serial.print(",");
Serial.println(magnitude);
delay(500);  // Adjust the delay based on your monitoring frequency}
```

RANDOM_FOREST_CODE

```
import pandas as pd
from sklearn.model_selection import train_test_split from
sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier  from
sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
column_names = ['SpO2', 'HeartBeat', 'Noise', 'BodyMotion']   data =
pd.read_csv('sleep_data.csv', names=['Combined'], header=None, skiprows=1)
data[column_names] = data['Combined'].str.split(',', expand=True)
numeric_cols = ['SpO2', 'HeartBeat', 'Noise', 'BodyMotion']
data[numeric_cols] = data[numeric_cols].apply(pd.to_numeric,
errors='coerce')  def categorize_sleep(row):     spo2 = row['SpO2']
heart_beat = row['HeartBeat']     noise
= row['Noise']
   body_motion = row['BodyMotion']     if (90 <= spo2 <= 96) and (65 <=
heart_beat <= 67) and (1700 <= noise <= 1850) and (200 <= body_motion <=
250):         return 'Good'     elif (90 <= spo2 <= 96) and (65 <= heart_beat
<= 67) or
(1700 <= noise <= 1850) or (200 <= body_motion <= 250):         return
'Average'     else:         return 'Bad'   data['SleepQuality'] =
data.apply(categorize_sleep, axis=1)  X = data[['SpO2',
'HeartBeat', 'Noise', 'BodyMotion']]  y =
data['SleepQuality']  label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)
X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, test_size=0.2,
random_state=42)   scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)  X_test_scaled
= scaler.transform(X_test)
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_scaled, y_train)  y_pred =
```

```
rf_model.predict(X_test_scaled)  accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
feature_importance = rf_model.feature_importances_
feature_names = X.columns  plt.figure(figsize=(8,
6))
plt.bar(feature_names,      feature_importance)
plt.xlabel('Features')    plt.ylabel('Importance')
plt.title('Feature Importance (Random Forest)')
plt.xticks(rotation=45)  plt.tight_layout()  plt.show()
from sklearn.metrics import mean_squared_error  import numpy as
np        rmse_rf  =  np.sqrt(mean_squared_error(y_test,   y_pred))
variance_rf
=  np.var(y_pred)     mse_rf  =  mean_squared_error(y_test,
y_pred)  accuracy_rf
=  accuracy     print("Root  Mean  Square  Error  (RMSE)  for  Random
Forest:", rmse_rf)
print("Variance for Random Forest:", variance_rf)  print("Mean Square Error
(MSE) for Random Forest:", mse_rf)  print("Accuracy for
Random Forest:", accuracy_rf)  from sklearn.metrics import f1_score
#  Calculate  F1  score       f1_rf  =  f1_score(y_test,  y_pred,
average='weighted')  print("F1
Score:", f1_rf)
```

RNN_ALGORITHM _CODE

```
import pandas as pd
from sklearn.model_selection import train_test_split  from
sklearn.preprocessing import StandardScaler, LabelEncoder  from
sklearn.metrics import accuracy_score  from keras.models import
Sequential  from keras.layers import Dense, LSTM  import
numpy as np  import matplotlib.pyplot as plt
column_names = ['SpO2', 'HeartBeat', 'Noise', 'BodyMotion']  data =
pd.read_csv('sleep_data.csv', names=['Combined'], header=None, skiprows=1)
data[column_names] = data['Combined'].str.split(',', expand=True)
numeric_cols = ['SpO2', 'HeartBeat', 'Noise', 'BodyMotion']  data[numeric_cols]
= data[numeric_cols].apply(pd.to_numeric, errors='coerce') def
categorize_sleep(row): spo2 = row['SpO2'] heart_beat = row['HeartBeat']
noise = row['Noise'] body_motion = row['BodyMotion'] if (90 <= spo2 <=
96) and (65 <= heart_beat <= 67) and (1700 <= noise <= 1850) and (200 <=
body_motion <= 250):
    return 'Good' elif (90 <= spo2 <= 96) and (65 <= heart_beat <= 67) or
(1700 <= noise <= 1850) or (200 <= body_motion <= 250): return
'Average' else: return 'Bad' data['SleepQuality'] =
data.apply(categorize_sleep, axis=1)  X = data[['SpO2',
'HeartBeat', 'Noise', 'BodyMotion']]  y =
data['SleepQuality']
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)
X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, test_size=0.2,
random_state=42)  scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
X_train_lstm = X_train_scaled.reshape(X_train_scaled.shape[0], 1,
X_train_scaled.shape[1])
X_test_lstm = X_test_scaled.reshape(X_test_scaled.shape[0], 1,
X_test_scaled.shape[1])  model
= Sequential()
```

```
model.add(LSTM(64,input_shape=(X_train_lstm.shape[1],
X_train_lstm.shape[2]))) model.add(Dense(3, activation='softmax')) # Output
layer for 3 classes
model.compile(loss='sparse_categorical_crossentropy', optimizer='adam',
metrics=['accuracy'])
history = model.fit(X_train_lstm, y_train, epochs=10, batch_size=32,
validation_data=(X_test_lstm, y_test), verbose=0) _, accuracy =
model.evaluate(X_test_lstm, y_test) print("Accuracy:", accuracy)
plt.figure(figsize=(10, 6)) plt.plot(history.history['accuracy'],
label='Training Accuracy') plt.plot(history.history['val_accuracy'],
label='Validation Accuracy') plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy (RNN)')
plt.legend() plt.grid(True) plt.tight_layout()
plt.show()
```

APPENDIX B

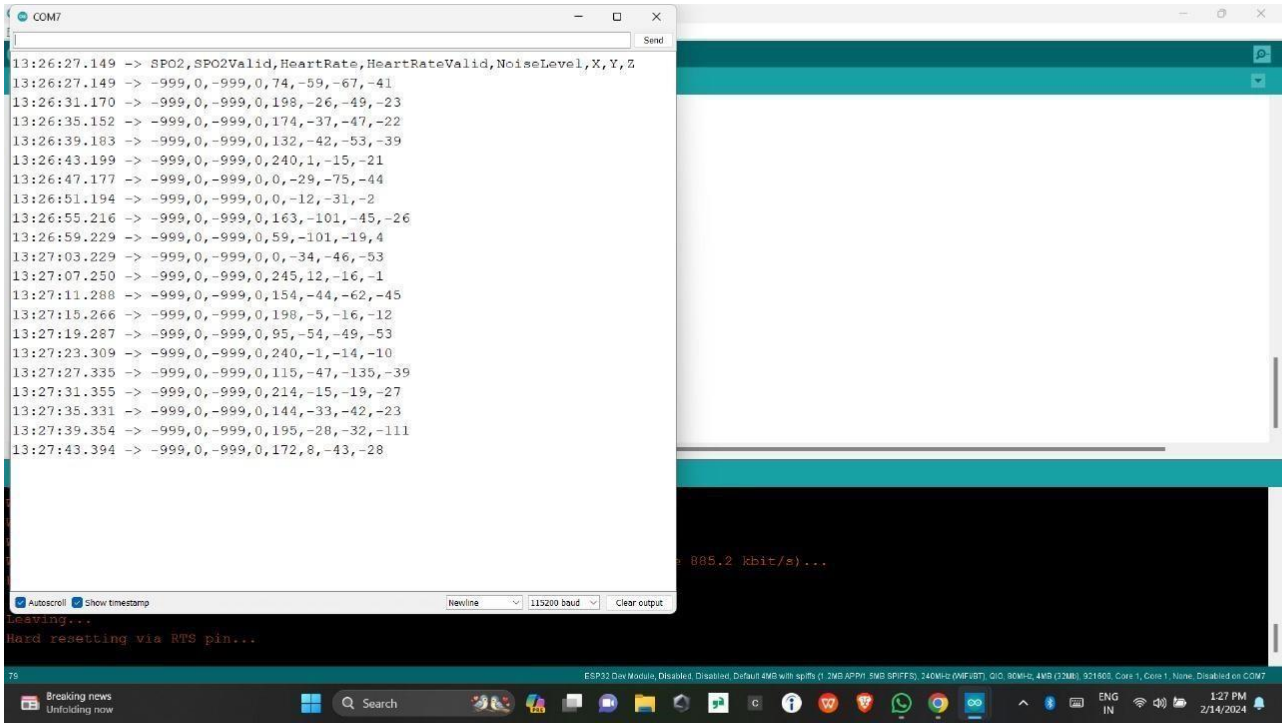


Fig B.1 Hardware data Output

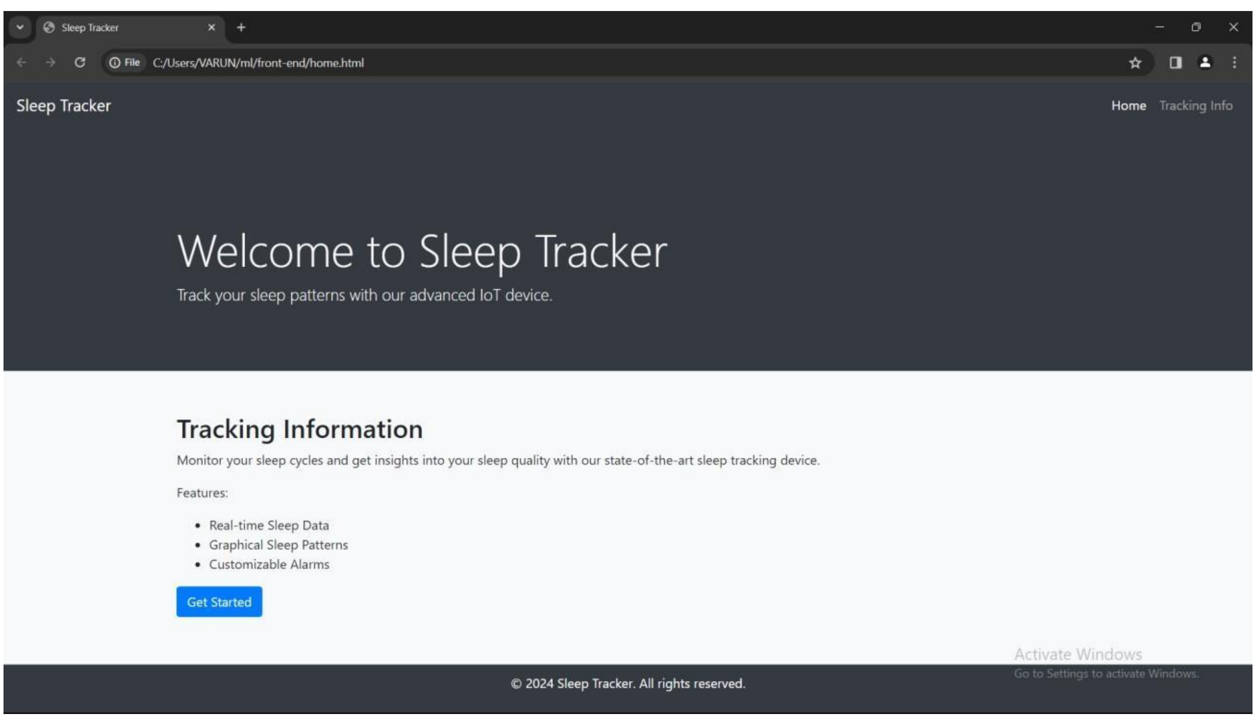


Fig B.2 Web portal

References

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