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IoT BASED SLEEP APNEA MONITORING SYSTEM USING MACHINE LEARNING

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Abstract :Millions battle a hidden enemy during sleep: apnea, where breathing repeatedly pauses, disrupting slumber and leading to a cascade of health woes. From chronic fatigue and brain fog to increased heart disease risk, sleep apnea silently casts a long shadow. Early detection and management are crucial, but traditional diagnosis hinges on costly sleep labs, creating a significant accessibility gap. This project dares to bridge that gap, exploring a promising path forward: an ESP32-powered system equipped with respiratory and heart rate sensors. Imagine a system silently monitoring your sleep in the comfort of your home, gathering vital data as you slumber. We envision a future where affordable, user-friendly monitoring empowers individuals to take charge of their sleep health.How does this work? Think of the sensors as vigilant sentinels, tracking your breathing patterns and heart rate variability – key indicators of sleep apnea events. Subtle changes are captured and analyzed, potentially revealing the telltale signs of disrupted sleep. The collected data is securely stored in the cloud, accessible for further analysis or professional review.However, caution is paramount. This prototype is not a substitute for professional diagnosis. Rigorous research and clinical validation are essential to assess its accuracy and real-world effectiveness. Responsible development demands transparency and ethical considerations.Looking ahead, we envision constant refinement. Adding sensors like oximeters could paint a more comprehensive picture of sleep physiology. Machine learning algorithms could enhance the system's ability to differentiate between sleep apnea and other disturbances, improving its accuracy.Ultimately, rigorous clinical trials hold the key. Only through meticulous evaluation can we solidify its potential as a valuable tool in the fight against sleep apnea. This journey, filled with both promise and responsibility, has the power to empower individuals to manage their sleep health and seek timely intervention. Imagine a future where technology stands as a guardian of sleep, silently monitoring and alerting, paving the way for a healthier and more vibrant life for millions. This future beckons, but ethical considerations and responsible development remain the guiding principles of this crucial journey.

Keywords-Sleep apnea,ESP32-powered system,Respiratory and heart rate sensors,Machine learning algorithms,Cloud storage

I. INTRODUCTION

Sleep apnea stands as a significant medical condition with intricate connections to both the respiratory system and neurological functions during sleep. It manifests primarily in two forms: obstructive sleep apnea (OSA) and central sleep apnea (CSA), with complex sleep apnea representing a rare combination of both. OSA arises from the relaxation of muscles in the upper airway, resulting in a partial or complete blockage of airflow. This obstruction leads to breathing difficulties and, in severe cases, can pose serious health risks such as strokes, hypertension, cardiac abnormalities, and even depression.On the other hand, CSA involves disruptions in the brain's signaling mechanisms responsible for controlling breathing during sleep. Unlike OSA, where the issue lies primarily in physical obstructions, CSA occurs due to the brain's failure to send appropriate signals to the respiratory muscles, causing intermittent pauses in breathing. While less common than OSA, CSA can also lead to severe complications, particularly when associated with conditions like heart failure or stroke.Despite advancements in medical research, sleep apnea remains significantly underdiagnosed, with millions worldwide affected by its adverse effects. Several risk factors contribute to its prevalence, including obesity, alcohol consumption, smoking, genetic predisposition, and certain medical conditions such as hypertension and type-2 diaFurthermore, individuals with Parkinson's disease or those who have suffered strokes are particularly susceptible to developing central sleep apnea.Recognizing the symptoms of sleep apnea is crucial for timely intervention. These symptom include loud snoring, daytime fatigue, weakness, and difficulties in concentration.Moreover, the consequences of untreated sleep apnea can be dire, with increased risks of heart attacks, strokes, and even premature death. The impact extends beyond individual health, as sleep apnea has been linked to an elevated risk of accidents, with significant implications for public safety.Addressing sleep apnea requires a multifaceted approach encompassing awareness, education, and medical intervention By increasing awareness and promoting research efforts, we can enhance diagnosis rates and ensure that individuals receive appropriate treatment to mitigate the associated health risk

Ultimately, prioritizing sleep health is essential for improving overall well-being and quality of life, minimizing the detrimental effects of sleep apnea on individuals and society as a wholeIn addition to the physical health implications, sleep apnea also takes a toll on mental well-being and cognitive function. The fragmented sleep patterns characteristic of sleep apnea often result in daytime sleepiness and fatigue, impacting productivity, mood stability, and overall quality of life. Individuals with untreated sleep apnea may struggle with memory problems, difficulty concentrating, and impaired judgment, affecting their performance at work, school, and in personal relationships.Furthermore, the economic burden associated with untreated sleep apnea cannot be understated. The costs incurred from medical treatments, hospitalizations, and lost productivity due to absenteeism or decreased performance in the workplace contribute to substantial healthcare expenditures and societal costs. Addressing sleep apnea through early detection and effective management can alleviate this financial strain while improving individual health outcomes and productivity levels.Moreover, raising awareness about sleep apnea is essential for dispelling misconceptions and reducing stigma surrounding the condition. By fostering open discussions and encouraging individuals to seek medical evaluation if they suspect they may have sleep apnea, we can promote early diagnosis and intervention. This proactive approach not only improves individual health but also contributes to public health initiatives aimed at reducing the overall burden of sleep-related disorders on healthcare systems worldwide.Ultimately, addressing sleep apnea requires a collaborative effort involving healthcare professionals, policymakers, advocacy groups, and the general public. By prioritizing research, education, and access to effective treatments, we can work towards a future where sleep apnea is promptly diagnosed, effectively managed, and its associated health risks minimized, leading to healthier and more productive lives for individuals affected by this common yet often overlooked condition.In this study, our aim is to comprehensively to detect the sleep apnea by using the sensor for measuring the heart beat and respiratory rate and activate the CPAP mechanism.

The task at hand involves crafting a comprehensive solution to address the multifaceted challenges associated with monitoring individuals suffering from sleep apnea. Our aim is to develop a system that not only ensures accurate detection of apnea events but also prioritizes user-friendliness, robust data analysis, timely alerts, long-term monitoring capabilities, and stringent privacy and security measures. The proposed solution will be anchored in cutting-edge technology, leveraging the power of Artificial Intelligence (AI) and the Internet of Things (IoT) to create a monitoring system that seamlessly integrates into the lives of individuals with sleep apnea. Through continuous and unobtrusive monitoring of their sleep patterns and respiratory activities, our system aims to provide invaluable insights and support for managing this condition effectively.

Key to the success of this endeavor is the utilization of advanced AI algorithms, meticulously designed to accurately detect and analyze sleep apnea events. By employing sophisticated machine learning techniques, we can not only identify these events with precision but also tailor interventions and treatment options to suit each individual's needs, thereby enhancing the efficacy of their care.

Furthermore, we will explore avenues for integration with other smart home devices or wearables, thereby creating a holistic sleep health ecosystem. By harnessing the interconnectedness of these technologies, we can provide users with a comprehensive understanding of their sleep health and facilitate proactive measures to improve it.

Moreover, our system will delve into the realm of advanced sleep quality analysis, employing AI-driven insights to offer personalized sleep coaching. Through tailored recommendations and actionable insights, we aim to empower users to make informed decisions regarding their sleep habits, ultimately leading to better overall health and well-being.

In summary, our endeavor seeks to revolutionize the monitoring and management of sleep apnea by combining AI, IoT, and smart home technologies into a cohesive and user-centric solution. Through relentless innovation and a steadfast commitment to excellence, we endeavor to redefine the standards of care in sleep health management.

II. METHODS AND MATERIALS

These crucial components form the backbone of our sleep apnea monitoring project. Each component plays a distinct role in enabling accurate data collection and analysis, contributing to a perfect assessment of detecting the sleep apnea.

a.ESP32 -ESP32 is an affordable System on Chip (SoC) Microcontroller developed by Espressif Systems, renowned for their ESP8266 SoC. It represents an advancement over the ESP8266, featuring single-core and dual-core options of Tensilica's 32-bit Xtensa LX6 Microprocessor with built-in Wi-Fi and Bluetooth connectivity..

b.Heart beat sensor- Heartbeat sensors provide digital output indicating heartbeats when a finger is placed on them. Concurrently, the LED blinks with each heartbeat. Respiratory sensors, worn as a sensitive girth sensor with a durable elastic band and adjustable webbing belt, detect chest or abdominal expansion/contraction, and output the respiratory waveform.

d.CPAP Mechanism-CPAP operates by delivering a continuous positive airway pressure through a mask, effectively maintaining airway openness. This aids in preventing breathing issues, elevates lung oxygen levels, and expels excess carbon dioxide from the lungs.

The advent of a portable monitoring device for sleep apnea patients marks a significant advancement in sleep disorder treatment. This innovative solution enables continuous monitoring during sleep, detecting and tracking breathing patterns while also being equipped to respond in emergencies. By activating a CPAP mechanism and leveraging IoT technology for data transmission, it ensures timely intervention and care coordination with caregivers and hospitals. Utilizing advanced sensors such as heart rate and breathing sensors, this system provides a comprehensive assessment of sleep patterns, facilitating tailored interventions and real-time alerts for improved sleep quality and overall health. This integrated solution prioritizes personalized care, aiming to revolutionize sleep apnea management and promote better well-being through restful nights..

Demodulated signal:

This involves extracting the modulating signal from a carrier wave ,the mixer processing part likely involves mixing different signals together, perhaps to isolate specific frequency bands or to enhance certain features.

2.1 Active analysis

2.1.1 Feature extraction

Feature extraction in sleep apnea monitoring involves identifying and extracting relevant information or patterns from the raw data collected during the monitoring process. In the context of machine learning, these features serve as input variables for algorithms to learn and make predictions.

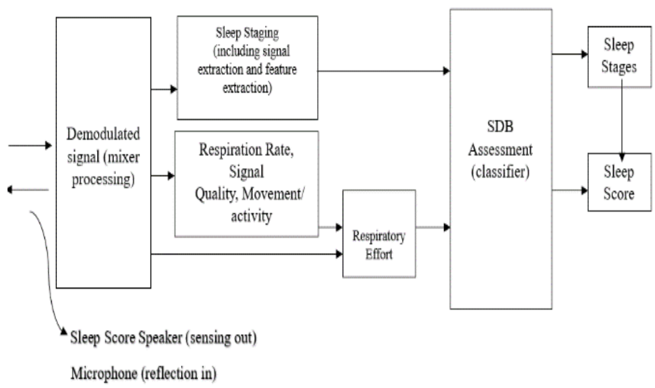

Fig.1 Active analysis of input signal

Some common features might include:

2.1.1.1Respiratory Rate: Analyzing the frequency of breathing patterns can be crucial in detecting abnormalities.

2.1.1.2Heart Rate Variability: Variations in the time intervals between heartbeats can provide insights into the autonomic nervous system and overall cardiovascular health.

2.1.1.3 Snoring Intensity: Analyzing the intensity and frequency of snoring sounds can be a useful feature, as snoring is a common symptom of sleep apnea.

2.1.1.4 Respiratory effort: Monitoring respiratory effort in sleep apnea using machine learning and IoT (Internet of Things)involves collecting data on the respiratory

2.1.1.5 Signal Preprocessing: The raw respiratory signals often require preprocessing to remove noiseand artifacts. Filtering techniques can be applied to isolate the relevant information and enhance the quality of the data.

2.1.1.6 Feature Extraction: Extract features from the preprocessed signals.Features could include parameters like respiratory rate and heart rate .Machine Learning Model: Training a machine learning model using the extracted features.

This model could be designed to classify normal breathing patterns and detect anomalies associated with sleep apnea.

2.1.1.7 Data Transmission with IoT: The processed data is then transmitted to a central system or cloud platform using IoT technologies. This enables real-time monitoring and analysis.

Real-Time Monitoring and Alerts: Deploy the system for real-time monitoring. The IoT connectivity allows continuous data transmission and, if abnormalities are detected, alerts or notifications can be sent to healthcare providers or individuals.

Feedback Loop: Continuous monitoring allows for a feedback loop where the machine learning model can be updated and improved over time based on new data and insights.

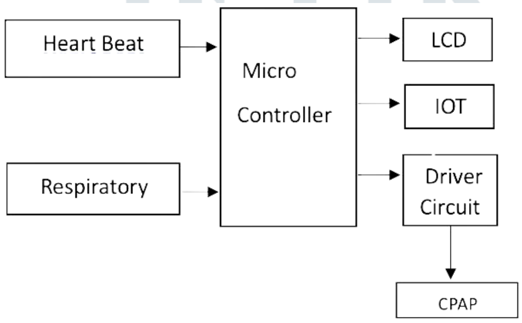

Fig.2 Hardware Module of the sleep Apnea

2.1.2 Detection system

Sleep apnea, a pervasive sleep disorder, disrupts the restorative process of sleep, impacting the health and quality of life of millions of individuals. Characterized by intermittent interruptions in breathing during sleep, it demands early detection and management. To address this imperative need, we present an innovative approach for the detection of sleep apnea, employing advanced heart rate and respiratory sensors**.**

2.1.2.1Data Acquisition:

The heart rate sensor continuously records the heart rate by detecting changes in blood flow, typically through light absorption or reflection. The breathing sensor records the chest and abdominal movements or airflow patterns associated with respiration**.**It refers to the process of collecting, measuring, and digitizing various types of data from the physical world for analysis, storage, and further processing.

2.1.2.2Data Synchronization:

The data from both sensors need to be synchronized to ensure that heart rate and breathing patterns are recorded concurrently. Data synchronization can occur between various systems, databases, devices, or applications and serves several purposes. The primary goal of data synchronization is to ensure that all copies of the data are consistent and accurate. Data synchronization helps to detect and resolve conflicts that arise from concurrent updates, ensuring that no data is lost or overwritten unintentionally.

2.1.2.3Data Analysis :

The system can generate reports or visualizations showing periods of normal breathing, apnea events, and corresponding changes in heart rate. This data may be stored for later analysis. It is a process of collecting, processing, and interpreting data generated from electronic devices, circuits, or systems. It plays a crucial role in various aspects of electronics, from quality control and performance optimization to troubleshooting and research. Raw data collected from electronic systems often contain noise, outliers, and other artifacts. Pre-processing involves cleaning and preparing the data for analysis. Pre-processing may include filtering, smoothing, data reduction, and calibration to ensure the data is in a suitable form for analysis

2.1.2 Long-Term Monitoring:

Long-term monitoring refers to the continuous or extended observation and data collection over an extended period. In various fields, long-term monitoring is crucial for gaining a comprehensive understanding of trends, changes, or patterns that occur over time. When applied to sleep apnea and the use of heart rate and respiratory sensors, long-term monitoring is particularly valuable . The system may continuously monitor the individual over an extended period, such as overnight or for multiple nights, to collect sufficient data for a comprehensive analysis of sleep patterns.

2.1.3 IoT Module

Building an IoT module for sleep apnea monitoring involves integrating sensors, Bluetooth, and WiFi modules to collect and transmit data. Sensor Integration Use respiratory effort sensors (e.g., chest and abdominal movement sensors) to capture relevant data.

Position the sensors on the user's body to ensure accurate measurement of respiratory signals and heart rate.

2.1.4 Bluetooth Module:

Integrate a Bluetooth module to enable wireless communication between the sensors and a local device (e.g., a microcontroller or a small processing unit).The Bluetooth module facilitates real-time data transmission from the sensors to the local device

Outline of the process:

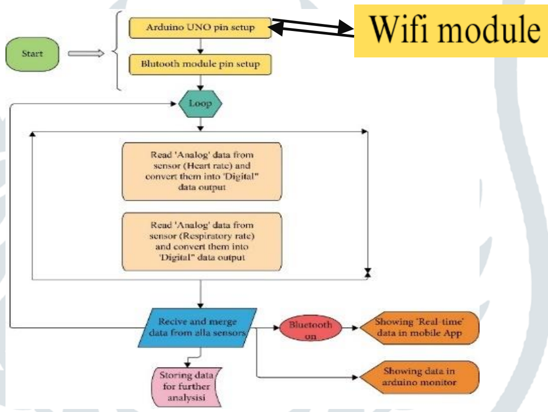

Fig .3 Workflow of the IOT module

2.1.5 WiFi Module:

Integrate a WiFi module to enable communication between the local processing unit and cloud platform.WiFi connectivity allows for remote monitoring and data storage on a centralized server.

2.1.6 Cloud Platform

Send the preprocessed data to a cloud-based platform for further analysis and storage.Train and deploy machine learning models on the cloud for more robust and scalable monitoring.

2.1.7 User Interface

Develop a user interface (e.g., a mobile app or a web portal) to provide real-time feedback to users and healthcare providers. Display alerts or notifications for potential sleep apnea episodes.

2.2 PASSIVE ANALYSIS:

Passive analysis for an IoT-based sleep apnea system involves using machine learning algorithms like Support Vector Machines (SVM) and Logistic Regression to analyze data collected from various sensors such as heart rate, sleep quality, sleep score, etc. Here's how you can approach it:

2.2.1.Data Collection: Utilize IoT devices equipped with sensors to collect data on heart rate, sleep quality, sleep score, etc., from individuals over a period of time.

2.2.2.Data Preprocessing: Prepare the collected data for analysis by performing necessary preprocessing steps such as handling missing values, normalization, and feature engineering. Features could include statistical measures derived from heart rate variability, sleep cycle patterns, etc.

2.2.3. Feature Selection: Identify the most relevant features that are highly correlated with sleep apnea. This can be done through techniques like correlation analysis or using domain knowledge.

2.2.4 Model Selection: Choose appropriate machine learning models for the analysis. SVM and Logistic Regression are popular choices for binary classification tasks like detecting sleep apnea.

2.2.5 Model Training: Split the preprocessed data into training and testing sets. Train the SVM and Logistic Regression models on the training data.

2.2.6 Model Evaluation: Evaluate the trained models using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC score on the testing data.

2.2.7 Hyperparameter Tuning: Fine-tune the hyperparameters of the models to improve performance. Techniques like grid search or random search can be employed for this purpose.

2.2.8 Model Interpretation: Interpret the trained models to understand which features contribute the most to the prediction of sleep apnea. This can help in gaining insights into the underlying relationships between the features and the target variable.

2.2.9 Deployment: Deploy the trained models into the IoT-based sleep apnea system to perform real-time analysis of sleep data and provide passive monitoring for potential sleep apnea.

2.2.10 Continuous Monitoring and Maintenance: Continuously monitor the performance of the deployed models and update them as necessary to adapt to changes in data patterns or to improve performance over time.

By following these steps, you can develop an effective passive analysis system for detecting sleep apnea using machine learning algorithms and IoT-based sensors.

III. MACHINE LEARNING ALGORITHM

The following are the algorithm used in this study:

3.1SUPPORT VECTOR MACHINE (SVM):

Support Vector Machine (SVM) is a supervised machine learning algorithm primarily used for classification tasks, although it can also handle regression problems. It operates by plotting each data point as a coordinate in an n-dimensional space, where n represents the number of features. The goal is to find a hyper-plane that effectively separates the two classes. Support Vectors are the coordinates of pivotal data points that define this hyper-plane. SVM can create a linear hyper-plane between classes easily, but for non-linear problems, the kernel trick comes into play. This technique transforms the input space into a higher-dimensional one, making non-separable problems separable. Through complex data transformations, SVM determines the optimal approach for classifying data based on specified labels or outputs.

3.2LOGISTIC REGRESSION FUNCTION:

Logistic regression serves as a statistical technique tailored for binary classification, where the target variable presents two potential outcomes. Widely applied in various machine learning tasks like spam filtering, medical prognosis, and credit risk assessment, logistic regression operates through the logit function to constrain the dependent variable within the range of 0 to 1, regardless of independent variable values. Additionally, logistic regression accommodates the modeling of relationships among multiple independent variables and a single dependent variable.

$$f(x) = \frac{1}{1 + e^{-x}} \quad (1)$$

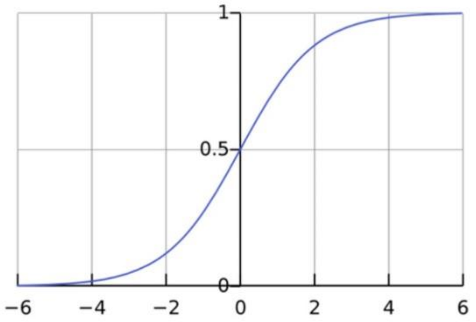

Fig 4. Logistic regression graph

3.2.1.Model Representation:

Logistic regression models the probability that a given input belongs to a particular category. It's represented by the logistic function (also known as the sigmoid function), which maps any real-valued number into a range between 0 and 1.

3.2.2 Sigmoid Function:

The sigmoid function is defined as:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

Where z is a linear combination of input features and their corresponding weights.

3.2.3 Linear Combination:

Logistic regression assumes a linear relationship between the input features and the log-odds of the output. Mathematically, it can be represented as:

$$z = b_0 + b_1x_1 + b_2x_2 + \ldots + b_nx_n \tag{3}$$

Where $b_0, b_1, b_2, \ldots, b_n$ are the coefficients (weights) associated with each feature, and $x_1, x_2, \ldots, x_n$ are the input features.

3.2.4 Training Process:

The model is trained using a method like maximum likelihood estimation. The objective is to find the optimal values for the coefficients that maximize the likelihood of observing the given data under the assumed model.

This is typically achieved through iterative optimization algorithms like gradient descent or more advanced methods like Newton's method.

3.2.5Prediction:

Once the model is trained, it can be used to predict the probability that a new instance belongs to a particular class.

The predicted probability is then compared to a threshold (usually 0.5), and the instance is classified as belonging to the class with the highest probability.

3.2.6 Evaluation:

The performance of the logistic regression model is typically evaluated using metrics like accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC), depending on the specific requirements of the problem.

Logistic regression is popular due to its simplicity, interpretability, and efficiency. However, it assumes a linear relationship between the features and the log-odds of the output, which may not always hold true in practice.

3.3 ADVANTAGE:

Logistic regression, SVM, and LSTM (Long Short-Term Memory) are all machine learning algorithms used for different purposes. Here are some advantages of logistic regression and SVM over LSTM:

3.3.1 Interpretability:

Logistic regression and SVM models are more interpretable compared to LSTM. In logistic regression, the coefficients associated with each feature provide insights into the importance and direction of their impact on the outcome. Similarly, SVM identifies support vectors, which are data points crucial for determining the decision boundary, providing some interpretability.

3.3.2 Computationally Efficient:

Logistic regression and SVM are often more computationally efficient compared to LSTM, especially for simpler classification tasks with fewer features or smaller datasets. They have lower training and prediction times, making them suitable for real-time or resource-constrained applications.

3.3.3 Less Data Requirement:

Logistic regression and SVM typically require less data for training compared to LSTM. While LSTM, being a deep learning model, often requires a large amount of data to learn complex temporal dependencies effectively, logistic regression and SVM can perform reasonably well with smaller datasets.

3.3.4 No Sequential Data Dependency:

Logistic regression and SVM do not rely on the sequential nature of data. They treat each input feature independently, which can be advantageous for tasks where the order of input features is not significant or when dealing with non-temporal data.

3.3.5 linear Separability:

SVM, especially with appropriate kernel functions, can handle non-linear relationships between features more effectively than logistic regression. It can find complex decision boundaries in the feature space, making it suitable for tasks with non-linear separable classes.

However, it's important to note that the advantages of logistic regression and SVM come with limitations. For example, they may not perform well on tasks with complex temporal dependencies or sequential data, where LSTM excels. LSTM is particularly useful for tasks like natural language processing, time series prediction, and sequence generation, where understanding long-range dependencies is crucial.

In summary, while logistic regression and SVM offer interpretability, efficiency, and simplicity, LSTM provides superior performance in handling sequential data and capturing long-term dependencies. The choice between these algorithms depends on the specific requirements and characteristics of the data and the task at hand.

In the provided code, logistic regression and SVM (Support Vector Machine) are utilized for the task of classifying sleep disorders based on certain predictor variables. Here's a breakdown of how logistic regression and SVM are used:

3.3.6 Data Preprocessing:

The code starts by importing necessary libraries and loading the dataset from a CSV file (dataset.csv). It performs basic data exploration by displaying the head of the dataset, summary statistics, and checking for missing values.

3.3.7 Data Transformation:

The target variable, "Sleep Disorder," is mapped to numerical values using a dictionary (mapping).Missing values in the "Sleep Disorder" column are filled with zeros.Categorical variables like "Gender" are encoded into numerical values for modeling purposes.The dataset is split into predictors (predictors) and the target variable (target).Further, the dataset is divided into training and testing sets using train_test_split from scikit-learn.

3.3.8 Logistic Regression:

Logistic regression is instantiated using LogisticRegression() from scikit-learn.The logistic regression model (lr) is trained on the training data using the fit method.Predictions are made on the test data using the predict method.The accuracy of the logistic regression model is computed using accuracy_score from scikit-learn and printed.An SVM classifier is instantiated using svm.SVC(kernel='linear') from scikit-learn with a linear kernel.The SVM model (sv) is trained on the training data using the fit method.Predictions are made on the test data using the predict method.The accuracy of the SVM model is computed using accuracy_score from scikit-learn and printed

3.3.9Data Normalization:

Data normalization is performed using MinMaxScaler from scikit-learn to scale the predictor variables to a specific range.

3.4 LSTM Model:

A sequential LSTM model is defined using Keras.The model is compiled with an Adam optimizer and binary cross-entropy loss. The model is trained on the training data (X_train_reshaped and Y_train) for a specified number of epochs and batch size.

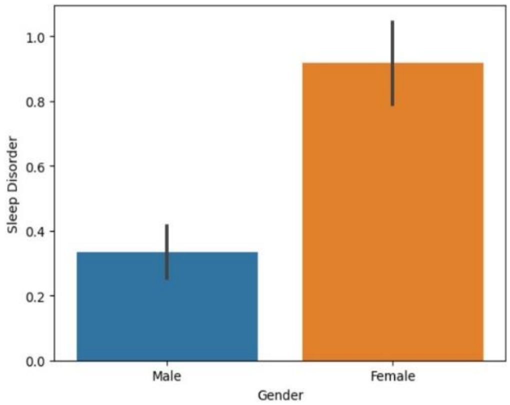

Fig 5.Sleep disorder Comparsion Chart.

Early stopping is applied to prevent overfitting.

Training and validation loss and accuracy are plotted.

3.4.1 Model Serialization:

The SVM model is serialized using the pickle module and saved to a file named model.pkl.

The serialized model is then loaded back into memory for inference using pickle.load.

3.4.2 Model Inference:

A sample data point (data) is provided for making predictions using the SVM model (sv).

Predictions are also made using the deserialized SVM model (loaded_model), demonstrating how to use the saved model for inference.

This code demonstrates how logistic regression and SVM can be implemented using scikit-learn for classification tasks and how to serialize and deserialize trained models for future use.

IV. MONITORING MECHANISM SIMULATION

The main controller for collecting and processing data.ESP32 Used for data communication with the AI software and for Wi-Fi capabilities.16x2 LCD Display to provide real-time data feedback. Heart Rate Sensor to monitor the patient's heart rate. Respiratory Sensor to monitor the patient's breathing patterns.AI software is responsible for analyzing the data and detecting sleep more apnea events. The heart rate sensor and respiratory sensor are attached to the patient. These sensors continuously measure and send data to the Arduino Uno for processing . Data Processing with Arduino Uno the Arduino Uno collects the data from the sensors. It processes this data, including heart rate and respiratory rate, and potentially other relevant metrics like oxygen saturation. The processed data is then sent to the ESP32 for further transmission. Data Transmission with ESP32.The ESP32 is used for Wi-Fi communication to send data from the Arduino Uno to the AI software for analysis. The ESP32 establishes a connection with the AI software through a local network or the internet. The AI software receives the data from the ESP32.The software uses machine learning models or AI algorithms to analyze the data in real-time.It looks for patterns associated with sleep apnea events, such as irregular heart rate, un usual breathing patterns, or drops in oxygen saturation. If a

Fig 6. Prototype

potential sleep apnea event is detected, the software triggers an alert. When the AI software detects a sleep apnea event, it sends an alert message back to the ESP32.The ESP32 displays relevant information on the 16x2 LCD display, such as "Sleep Apnea Detected" and the time of the event. The system can also log the detected events, date, and time for future reference or analysis. The ESP32 can send the event data to a remote server for long-term storage or to healthcare professionals for review. The LCD display provides real-time feedback to the user, allowing them to be aware of their condition. The system can be designed to have buttons or touch interfaces for user interaction. Regular maintenance of the system is essential to ensure accuracy. Sensors should be calibrated and checked for proper functionality. Data collected over time can be useful for tracking sleep patterns and the effectiveness of any treatment.The provided code implements logistic regression, SVM (Support Vector Machine), and LSTM (Long Short-Term Memory) algorithms for a sleep disorder classification task.

V.DISCUSSION:

Logistic regression and SVM achieve accuracy scores on the testing set, demonstrating the effectiveness of these traditional machine learning algorithms for binary classification tasks. The LSTM model, although notdirectly comparable in terms of

	Person ID	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Blood Pressure	Heart Rate	Daily Steps	Sleep Disorder
0	1	Male	27	Software Engineer	6.1	6	42	6	Overweight	126/83	77	4200	NaN
1	2	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75	10000	NaN
2	3	Male	28	Doctor	6.2	6	60	8	Normal	125/80	75	10000	NaN
3	4	Male	28	Sales Representative	5.9	4	30	8	Obese	140/90	85	3000	Sleep Apnea
4	5	Male	28	Sales Representative	5.9	4	30	8	Obese	140/90	85	3000	Sleep Apnea

Fig 7.DataSet

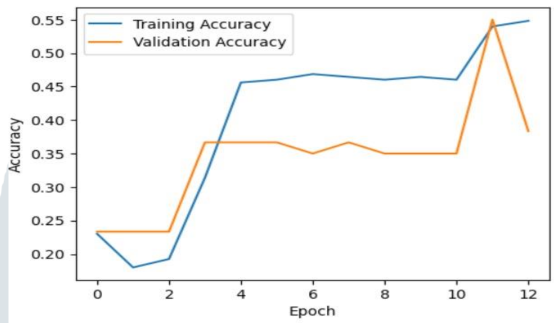

Fig 8.Training and Validation graph

accuracy due to the nature of its architecture and training process, provides insights into the performance of deep learning models for sequence data.The choice between these algorithms depends on various factors such as the size and nature of the dataset, computational resources, interpretability requirements, and the specific goals of the project.Future work may involve fine-tuning hyperparameters.exploring different architectures for LSTM, or experimenting with other deep learning models to further improve performance.

VI. CONCLUSION

Real-time patient monitoring enables prompt intervention in unforeseen circumstances. The proposed method offers a dependable approach to monitoring and preventing sleep apnea. The developed device surpasses existing systems in terms of affordability, comfort, and convenience, benefiting both patients and healthcare professionals. Patients can effortlessly integrate this device into their home environment, resulting in a more comfortable, user-friendly, cost-effective, and sustainable respiratory monitoring solution for healthcare purposes. The integration of artificial intelligence (AI) into a portable monitoring system for individuals with sleep apnea represents a notable advancement in sleep disorder management

VII. FUTURE SCOPE

The future scope for the monitoring of sleep apnea using heart rate and respiratory sensors. The development of more comfortable and unobtrusive wearable sensors will encourage long-term use and data collection. Miniaturized sensors integrated into everyday clothing or accessories may become more prevalent. Advanced data analytics could provide deeper insights into sleep patterns, sleep architecture, and the relationship between sleep apnea and other health conditions

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