IoT - DRIVEN SLEEP APNEA DETECTION

Capstone Project Report

MID-SEMESTER EVALUATION

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ABSTRACT

Sleep apnea is an underdiagnosed but prevalent sleep disorder that is associated with repeated breathing pauses, decreased oxygen levels, cardiovascular stress, and poor quality sleep. Traditional diagnostic tools like polysomnography are effective but costly, invasive, and not scalable for real-time tracking. This work shows the design and development of a wearable wristband prototype with non-invasive detection and monitoring of sleep apnea symptoms by employing SpO_2, Heart Rate Variability (HRV), and Electrocardiogram (ECG) signals. The system combines biomedical sensors such as the MAX30102 for blood oxygen saturation and heart rate monitoring, and the MAX30003 for continuous ECG measurement. An ESP32 microcontroller is used for wireless transmission, preprocessing, and sensor data acquisition. On the cloud, an AI/ML model inspects the received physiological data to detect patterns suggesting apnea episodes. The system also includes dual alerting mechanisms: a local buzzer to give the user haptic feedback and a mobile app for caregiver alerts. This method presents a non-invasive, low-cost, and pervasive monitoring solution that facilitates early detection, enhances patient safety, and aids in more effective sleep apnea management.

DECLARATION

We hereby declare that the design principles and working prototype model of the project entitled IoT-Driven Sleep Apnea Detection is an authentic record of our work carried out in the Computer Science and Engineering Department, TIET, Patiala, under the guidance of Dr. Rohit Ahuja and Dr. Amit Mishra during the 6th semester (2025).

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They always wanted the best for us, and we admire their determination and sacrifice.

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API	Application Programming Interface
HRV	Heart Rate Variability
SPO2	Peripheral Capillary Oxygen Saturation
ECG	Electrocardiogram
RR	Respiratory Rate
IoT	Internet of Things
GUI	Graphical User Interface
ML	Machine Learning
AI	Artificial Intelligence
WBS	Work Breakdown Structure
SRS	Software Requirements Specification
HR	Heart Rate

INTRODUCTION

1.1 Project Overview

This capstone project is intended to create an intelligent IoT-based wristband capable of real-time detection and monitoring of sleep apnea. Sleep apnea is a widespread but severe condition in which breathing is interrupted and starts repeatedly during sleep. These interruptions not only disturb sleep but also pose a risk of heart disease, diabetes, and concentration or memory issues.

The gold standard for sleep apnea diagnosis is polysomnography (PSG). While effective, it involves an overnight sleep clinic visit with bulky, high-cost equipment. This makes it inconvenient, costly, and inaccessible to many individuals, resulting in a huge number of undiagnosed and untreated cases globally.

Our solution is a small, wearable, and non-surgical wristband with several biosensors to track, in real time, critical health indicators like heart rate, oxygen saturation (SpO_2), respiratory patterns, and brain waves. AI processing will interpret all this information in real time to identify episodes of apnea and quantify their severity.

The objective is to deliver an affordable, easy-to-use device that enables individuals to monitor their sleep health on an ongoing basis in the home, and provide physicians with precise data to deliver enhanced care. Through this, the project closes the gap between clinical-quality diagnosis and general availability, providing a feasible solution to the worldwide problem of undiagnosed sleep apnea.

1.2 Need Analysis

Sleep apnea is now an emerging worldwide health issue. Literature indicates that nearly one billion individuals can be affected, but the majority are not yet diagnosed. In India alone, more than a million new patients are diagnosed annually. This enormous diagnostic gap arises due to the difficulties and limitations of current clinical tools.

Polysomnography (PSG), the present gold standard, works well but is about as practical for bulk diagnosis as it gets. It involves costly equipment, skilled technicians, and a night spent in a sleep lab. In India, a single test can range from ₹5,000 to ₹20,000, making it unaffordable for most patients. To further compound the problem, the artificial setting of a sleep lab environment can influence the way a person sleeps, sometimes producing biased results.

Certain consumer devices, the Withings Sleep Analyzer or Go2Sleep, attempt to bridge this void. But these mostly measure a single parameter—i.e., SpO_2 or heart rate variability. Such a narrow approach predisposes them to false alarms and diminishes their clinical utility. These limitations reveal the imperative for a more cost-effective, precise, and multi-sensor solution that patients can rely on and physicians can trust.

1.3 Research Gaps

This project is a deliberate effort to address several critical gaps in the current research landscape of sleep apnea detection. By identifying these gaps, the project solidifies its contribution and establishes its novelty within the field.

- **Single-signal over-reliance:** The majority of consumer wearables monitor a single physiological metric, e.g., SpO_2 or breathing audio. Although helpful, this renders them extremely susceptible to noise, movement artifacts, and ambient interference, often reducing their diagnostic performance [1].
- **Cloud dependency:** Most IoT-based healthcare systems transmit information to outside cloud servers for processing. Convenient though this is, it poses data privacy issues, introduces latency in processing, and restricts the generation of secure, real-time feedback [2].
- **Weak multi-sensor AI integration:** Even though research has been done on signals such as ECG, respiration, and SpO_2 separately, few wearable systems integrate a number of biosignals with sophisticated AI algorithms. Without integration, high accuracy and robustness are difficult to gain in real-world applications [3].
- **Issues with research integrity:** There have been retractions of some IoT healthcare studies that were unclear in their scope, had missing datasets, or failed peer review. This serves to emphasize the need to confirm transparency, reproducibility, and credibility in subsequent work [4].

- **Small testing populations:** Most AI-based sleep apnea models are tested on small, homogeneous populations. It makes them less capable of being reliable across a wide range of different populations with diverse demographics and medical histories [5].

By directly confronting these challenges, this project aims to provide a system that is not merely technically sound but also transparent, reproducible, and clinically useful—ultimately making safe sleep apnea monitoring more ubiquitous.

1.4 Problem Definition and Scope

Problem Definition

The main challenge is developing a system that is non-invasive, cost-effective, and very accurate for early detection and ongoing monitoring of sleep apnea. Although polysomnography (PSG) is the gold standard, it tends to be inaccessible to the majority of patients due to its high expense, technical complexity, and requirement for specialized clinical equipment [6]. In contrast, consumer wearables, although cheaper, lack reliability because they usually rely on a single measurement (e.g., SpO_2 or HRV). This single-measure strategy renders them susceptible to false alarms and non-clinical usage [1].

What is needed immediately, thus, is an affordable solution that matches the precision of medical-grade systems while retaining the ease of use and accessibility of contemporary wearable technology.

Scope of the Project

This project moves beyond mere detection and strives to develop clinically viable, smart, and scalable IoT-enabled wristband capable of revolutionizing the monitoring and management of sleep apnea globally. Its range encompasses:

- **Multi-sensor hardware design:** A light wristband combining ECG, SpO_2, HRV, and respiration sensors that must be comfortable enough for long-term wear.
- **AI-driven analysis:** Sophisticated algorithms that fuse several biosignals to identify and grade apnea events in real-time with high sensitivity.
- **Hybrid edge + cloud platform:** Intelligence on the device for instant response, supplemented by cloud-based platforms for secure long-term storage, sophisticated analytics, and physician portals.

- **Mobile app ecosystem:** Simple and intuitive app to enable real-time visualization, customized health monitoring, and immediate alerts.
- **Clinical-grade monitoring:** Characteristics that comply with telemedicine platforms, including compatibility for personal use and integration with hospitals, diagnostic centers, and home healthcare networks.
- **Immediate intervention mechanisms:** In-built vibration or buzzer alerts to wake the patient lightly in cases of long apnea episodes, precluding life-threatening situations.

This broad scope guarantees that the project will not just lead to an operational prototype but also build the basis for a scalable healthcare innovation. With successive iterations, it can go for full-scale deployment, regulatory clearance, and clinical acceptance—closing the divide between medical precision and real-world usability.

1.5 Assumptions and Constraints

S.NO.	ASSUMPTIONS
1.	It is assumed that users properly wear and use the wristband consistently, providing adequate skin contact to all sensors. Inadequate placement or loose wear is likely to produce biased readings or spotty data. Users are also assumed to adhere to general device usage practices, including charging prior to sleep, sensor calibration as indicated, and cleaning the device.
2.	It is assumed that the implanted biosensors (ECG, SpO_2, HRV, and respiration) are properly functioning under standard environmental conditions like normal room temperature, humidity, and sleep movements. Although the system is capable of removing low-level noise or motion artifacts, drastic conditions like excessive sweating, high humidity, or large, rapid movement will impact measurement reliability.
3.	The machine learning models employed for apnea detection are assumed to generalize fairly well over heterogeneous populations. These models are also trained on publicly accessible databases like MIT-BIH Sleep Apnea. These databases are believed to contain enough variability in age, gender, body shape, and sleep habits to enable the models to function well for the majority of users.
4.	It is assumed that users are using a smartphone with support for Bluetooth Low Energy and an internet connection for data synchronization and cloud communication. Users are expected to know the basic use of smartphones like app installation and usage. Intermittent or limited internet connectivity can hold up cloud syncing or physician access but is not expected to be an obstacle for local monitoring.
5.	The wristband is assumed to be worn mainly in normal home or clinical settings. Severe environmental conditions, including highly high or low temperatures, high vibration, or immersion in liquids, can impact sensor operation or device longevity. The design presumes such extreme conditions will not be encountered by the user.
6.	It is assumed that users will react appropriately to in-device vibration or buzzer notifications initiated during extended apnea episodes. These notifications are provided for safety and timely intervention. Users are anticipated to comprehend the reason behind these notifications and respond accordingly, making the intervention successful.
7.	It is assumed that the battery and device firmware are operating at their best, permitting round-the-clock overnight monitoring. Users should charge the device based on recommended routines and not run a number of high-power applications at the same time if there is a coupled smartphone for data processing.
8.	It is assumed that users agree to safe storage and transmission of health information. The system uses encrypted BLE and cloud protocols to ensure safety of sensitive physiologic data. Users are supposed to use secure passwords and adhere to privacy guidelines to preserve data integrity.
9.	It is assumed that the wristband is used with BLE and standard Wi-Fi-supported smartphones or tablets. Conformance issues with older devices or non-standard equipment are presumed to be minimal. The system presumes a normal level of device performance that is adequate to support the mobile application and get real-time notifications.
10.	Users are expected to keep the wristband as directed, such as cleaning it regularly, updating firmware, and re-calibrating sensors from time to time. Proper care guarantees the device remains a stable source for extended use physiological monitoring.

Table 1: Assumptions

S.NO.	Constraints
1.	While the wristband is outfitted with quality biosensors, there can be compromises in measurement accuracy through user movement, improper or loose wearing, or external environmental conditions. Excessive sweat, high humidity, or very hot or cold temperatures can cause readings to be distorted and may result in false apnea event detection.
2.	Continuous overnight monitoring demands efficient power management. The wristband's battery life is limited, and extended use beyond its design capacity without recharging may lead to interruptions in monitoring. Users are constrained by the need to maintain adequate charge levels to ensure reliable operation.
3.	Real-time data synchronization and remote monitoring depend on BLE and internet connectivity. Limited, sporadic, or fragile network access can introduce delays for data transfer to cloud servers, mobile apps, or physician dashboards. Offline functionality is feasible, but long-term analytics might be limited until connectivity resumes.
4.	AI models are trained on benchmark datasets that, while varied, are not representative of all possible user populations or physiological variation. Users with unusual sleep patterns, medical conditions, or extreme BMI values can have lower detection accuracy.
5.	The equipment is mainly suited for clinical or domestic use. Prolonged exposure to harsh environmental conditions like high vibration, liquid immersion, or high dust might corrupt the hardware or data quality. The system is not built to withstand harsh outdoor or industrial settings.
6.	Success of on-wrist vibration or buzzer notifications relies on user reaction. Alert-disabling users, notification-ignoring users, and users operating in loud settings might not be able to realize the full benefit of immediate intervention.
7.	The wristband is dependent on phone or tablet pairing that has minimum hardware and software requirements. Legacy hardware, non-standard BLE peripherals, or unsupported operating systems can restrict functionality or make some features not work at all.
8.	Although the system employs encryption and secure cloud protocols, there are intrinsic risks of data breaches or unauthorized access. Users and administrators need to adhere to privacy guidelines to maintain ongoing security for sensitive health information.
9.	Reliability for long periods is based on good care, firmware revisions, and periodic sensor recalibration. Failure to maintain or abusive treatment of the device can degrade performance, decrease accuracy, or shorten device life.

Table 2: Constraints

1.6 Standards

To be both clinically valid and technically sound, this project follows set medical and engineering standards. These standards form the basis of creating a system that not only functions but is also trustworthy for practical application in healthcare.

- **Medical Standards**
    - The system adheres to American Academy of Sleep Medicine (AASM) standards for sleep apnea detection and classification. According to AASM:
    - Apnea is ≥90% reduction in airflow for ≥10 seconds.
    - Hypopnea is ≥30% reduction in airflow for ≥10 seconds, with either ≥3% reduction in oxygen saturation or an arousal [8].
    - Severity is measured by the Apnea-Hypopnea Index (AHI), which approximates the number of apnea and hypopnea per hour of sleep.
    - By adhering to these definitions, the system ensures its outputs are clinically relevant and equivalent with existing diagnostic standards like polysomnography (PSG).
- **IoT & Communication Standards**
    - Security and data transfer are most critical in wearable medical devices. To counteract this, the project incorporates the following standards:
    - Bluetooth Low Energy (BLE): Ensures energy-conserving, real-time communication between the mobile app and wristband without depleting the battery overnight.
    - Wi-Fi (if available): For the transfer of sleep data to the cloud for long-term archiving, analysis, and access by doctors.
    - Security Protocols: Patient data will be protected using SSL (Secure Sockets Layer) and AES (Advanced Encryption Standard) which will ensure unauthorized data accessibility while keeping patient information confidential.

- **Data Standards**
    - For scalability and interoperability, the system adheres to globally accepted healthcare data structures:
    - HL7 (Health Level Seven): Provides a normalized platform for exchanging healthcare information across different platforms.
    - FHIR (Fast Healthcare Interoperability Resources): A modern standard that provides seamless interoperability with electronic health records (EHRs), telemedicine platforms, and hospital systems.

These choices make sure the wristband is not simply a standalone proof of concept but also a system that can easily be integrated into the larger digital health platform, and that provides clinical adoptability at scale.

1.7 Approved Objectives

The approved objectives of this capstone project are:

- **Develop a Multi-Sensor Wearable Wristband:** Create a comfortable, non-intrusive wristband that integrates ECG, SpO_2, HRV, and respiration sensors for continuous overnight monitoring.
- **Implement AI-Driven Multi-Sensor Fusion:** Design advanced ML/DL algorithms to combine biosignals, ensuring accurate, real-time detection of apnea events with minimal false alarms.
- **Design a Secure Edge–Cloud Hybrid Monitoring System:** Perform immediate analysis on-device while enabling encrypted cloud storage, longitudinal analytics, and physician dashboards for remote care.
- **Develop a Mobile Application Interface:** Provide users with real-time insights, personalized reports, and timely alerts through an intuitive smartphone app.
- **Integrate Immediate Intervention Mechanisms:** Include vibration or buzzer alerts to gently wake patients during prolonged apnea events, ensuring safety during critical episodes.

1.8 Methodology

The approach is a multi-cycle, multi-phase process that assures technical feasibility, clinical precision, and scalability:

- **Research & Feasibility Analysis**
  - Conduct literature surveys on detection of sleep apnea, wearable health monitoring, and IoT architectures.
  - Specify requirements for hardware, biosensors, algorithms, and data flow models.

- **Hardware Development**
  - Design a wristband with ECG, SpO_2, HRV, and respiration sensors integrated within.
  - Emphasize comfort, long service life, and low power consumption to facilitate nighttime and extended wearability.

- **Firmware & Software Integration**
  - Design embedded firmware for ongoing biosignal acquisition and preprocessing (e.g., noise filtering, segmentation).
  - Facilitate secure BLE data transmission to smartphones for real-time monitoring.
- **AI Model Training & Multi-Sensor Fusion**
  - Train deep learning algorithms (CNNs, LSTMs, and hybrid models) with benchmark datasets like PhysioNet Apnea-ECG and MIT-BIH Sleep Apnea.
  - Implement multi-sensor fusion techniques to increase detection precision and reduce false alarms.
- **System Integration**
  - Integrate the wristband, firmware, mobile app, and cloud platform into a single system.
  - Apply edge-based inference for real-time intervention and cloud analytics for long-term monitoring.
- **Testing & Validation**
  - Demonstrate user performance against gold-standard polysomnography (PSG) datasets.
  - Perform controlled user testing to evaluate accuracy, usability, and reliability.

- **Real-World Deployment**
  - Roll out in home and hospital settings for longer trials.
  - Test system performance across demographics and environmental factors.
- **Feedback & Iterative Refinement**
  - Collect feedback from users and clinicians.
  - Streamline sensor calibration, AI algorithms, and app user experience for best-in-class performance.

- **Scalability Optimization**
  - Revamp hardware for cost-effectiveness and manufacturability.
  - Ensure compatibility with medical standards like HL7 and FHIR.

- **Clinical & Regulatory Pathway Preparation**
  - Validate system performance for clinical trials and regulatory filings.
  - Prepare the device for adoption by healthcare professionals.

1.9 Project Outcomes and Deliverables

The project seeks to provide an end-to-end ecosystem that balances clinical accuracy with consumer convenience:

- **Prototype Wristband Device:** Wearable ergonomic device combining ECG, SpO_2, HRV, and respiration sensors.
- **AI-Based Detection Engine:** Deep learning-based multi-sensor model able to detect apnea and hypopnea events accurately.
- **Immediate Intervention Mechanism:** Built-in buzzer or vibration alert on the device to wake users during extended apnea periods.
- **Mobile Application:** Real-time graphics, historical patterns, and alerts for users.
- **Cloud-Based Monitoring Dashboard:** Secure portal for doctors to remotely monitor and analyze patient data.
- **Scalability Roadmap:** Documentation, validation studies, and routes towards clinical deployment and healthcare integration.

These deliverables place the project not only as a working prototype but as a scalable healthcare solution with real-world potential for impact.

1.10 Novelty of Work

The innovation in this project is integrating clinical-grade accuracy, real-time intelligence, and active intervention in one wearable device:

- Multi-Sensor Fusion: Contrary to the majority of commercial products that depend on one signal (e.g., SpO_2), this device combines ECG, HRV, respiration, and SpO_2 for greater diagnostic accuracy.
- Edge-Based Real-Time Intervention: Integrated AI enables real-time apnea event detection, sending immediate buzzer or vibration alerts to further improve safety.
- Scalable Health Integration: Built with HL7 and FHIR interoperability, allowing easy integration into telemedicine and hospital systems.

- Transparent and Reproducible Research: Focuses on strict dataset validation, open method reporting, and clinical relevance, mitigating reproducibility issues observed in some IoT research.
- Conjoining Consumer and Clinical Spaces: Sitting between costly PSG testing and consumer-level wearables, providing cheap, scalable, and clinically sound monitoring—a space mostly untapped by existing solutions.

2. REQUIREMENT ANALYSIS

2.1 Literature Survey

2.1.1 Theory Associated With the Problem Area

Sleep apnea is a chronic sleep disorder where breathing is halted and resumed repeatedly during sleep. They are produced due to airway obstruction, also known as obstructive sleep apnea (OSA), or due to neural respiratory drive failure, also known as central sleep apnea (CSA). They impose an enormous burden on the cardiovascular and nervous systems with added risk for hypertension, arrhythmias, and cognitive impairment.

The most critical physiological parameters to be measured for the diagnosis of sleep apnea are:

- **Heart Rate Variability (HRV):** Reflects the activity of the autonomic nervous system, which is disrupted with apneic activity.
- **Oxygen Saturation (SpO_2):** Drops with apnea as a result of impaired airflow and consequent hypoxemia.
- **Electrocardiogram (ECG):** Records arrhythmic changes and heart rate variability with respect to sleep disordered breathing.

With the use of wearable sensors and machine learning algorithms, these signals can be kept tracked in a non-invasive fashion so as to detect real-time apnea events. This method can thus decrease dependence on costly, hospital-based polysomnography (PSG).

2.1.2 Existing Systems and Solutions

- **Conventional PSG:** Polysomnography is still the clinical gold standard, recording EEG, ECG, SpO_2, breathing, and chest movement all together. Although very reliable, PSG is invasive, necessitates an overnight stay in a sleep laboratory, and is costly, which restricts its suitability for mass screening. [8]
- **Consumer Wearables:** Products like the Withings Sleep Analyzer and Go2Sleep monitor SpO_2 and HRV but tend to use a single parameter. Single-sensor reliance has the potential to generate false positives and decreases the reliability of diagnoses in real-world scenarios. [1]

- **Research Prototypes:** Certain experimental systems incorporate sensors such as MAX30003 (ECG, HRV) and MAX30102 (SpO_2, pulse) into wristbands or chest straps. These prototypes usually accompany mobile apps for visualization of data and cloud storage. Yet, the majority of them do not include real-time multi-sensor AI integration, explainable decision-making, and regulatory compliance for clinical use. [3]
- **IoT Cloud Models:** Multiple frameworks transfer data to cloud platforms for processing by AI. Though useful for analysis, cloud reliance brings in latency, privacy threats, and demands stable internet connectivity, inhibiting real-time intervention. [2]

The missing link among current solutions is the combination of multiple sensors' data with advanced, explainable AI at the edge for prompt detection and trustworthy, actionable insights for users and clinicians alike.

2.1.3 Research Findings for Existing Literature

S. No.	Roll Number	Name	Paper Title	Tools/ Technology	Findings	Citation
1	102217058	Armaan Saini	Sleep Apnea Detection with Wearable Sensors	MAX30102, HRV analysis	Demonstrated feasibility of wearable oximetry for apnea detection.	[1]
2			Wearable IoT for Remote Health	BLE, Cloud (AWS)	Emphasized privacy & latency challenges in IoT health.	[2]
3	102203180	Baneet Singh Sachdeva	Multi-Sensor Fusion for Sleep Apnea	CNN, LSTM models	Improved accuracy with ECG + SpO_2 fusion.	[3]
4	102203208	Babandeep Kaur	Retraction Study on IoT Health	IoT Monitoring Prototype	Highlighted research reproducibility issues.	[4]
5			Ambulatory Sleep Apnea Screening	Ambulatory PSG	Found portable monitoring feasible but less precise than PSG.	[5]
6	102217071	Ramitdeep Kaur	Obstructive Sleep Apnea as a Risk Factor for Stroke and Death	Not specified	Confirmed sleep apnea as a significant, independent risk factor for stroke and death.	[6]
7			PhysioBank, PhysioToolkit, and PhysioNet	Not specified	Established a public-access database of physiological signals to support research on sleep apnea, among other conditions.	[7]
8	102203242	Mehakdeep Kaur	International Classification of Sleep Disorders	Not specified	Provided a definitive clinical framework for classifying and diagnosing various sleep disorders, including sleep apnea.	[8]

Table 3: Research Findings

2.1.4 Problem Identified

Despite improvements in sleep apnea detection, current systems have several limitations:

- **Intrusiveness and Cost:** Traditional Polysomnography (PSG) requires overnight monitoring in a clinic. This process is expensive, inconvenient, and not available for many patients.
- **Limited Real-Time Monitoring:** Many wearable solutions do not allow for continuous, real-time analysis of multi-parameter physiological data. This limits early detection.
- **Data Integration Challenges:** Existing devices often struggle to combine HRV, SpO_2, ECG, respiratory rate, and motion data at the same time for accurate diagnosis.
- **Lack of Explainability:** AI-based sleep apnea detection systems often operate as black boxes. This makes it hard for clinicians to understand or trust the model's predictions.
- **Scalability Issues:** Many systems cannot efficiently manage multiple users or large datasets. This restricts their use in home monitoring or larger clinical settings.

The proposed system tackles these issues by using wearable sensors, AI deep learning models and cloud storage (Firebase). It aims to enable affordable, non-invasive, real-time, and understandable sleep apnea monitoring.

2.1.5 Survey of Tools and Technologies Used

To build a clinically sound and scalable IoT-based sleep apnea monitoring system, the following technologies and tools are utilized:

- **Programming**: Python is the primary programming language for signal processing, backend development, and AI model deployment, offering flexibility and robust library support.
- **AI Frameworks:** Pytorch are utilized to create, train, and fine-tune different models(CNN, CNN+GRU, SimCL-Contrastive Learning) that are capable of processing complicated, multi-sensor physiological data.
- **Data Processing:** Tools such as NumPy and Pandas are employed to process ECG, SpO_2, HRV, and motion signals such that clean, structured input can be supplied to AI models.

- **Deployment Frameworks:** Streamlit or React is utilized to develop user-friendly dashboards for real-time visualization, and Firebase provides secure cloud storage in addition to real-time analysis.
- **Hardware Elements:**
    - MAX30003 for accurate ECG and HRV recording.
    - MAX30102 for continuous SpO_2 and pulse oximetry tracking.

Through the combination of these tools, the project gives a solid technical foundation to a wearable system with real-time, multi-sensor monitoring, AI interpretation, and actionable insights. Through the integration of all these elements, the difference between clinical-grade sleep apnea diagnostic quality and consumer-grade wearables is eliminated, offering a viable, scalable solution for home use and clinical application.

2.2 Software Requirement Specification

2.2.1 Introduction

2.2.1.1 Purpose

The proposed system is an AI-driven diagnostic and monitoring solution for sleep apnea. It aims to provide high accuracy, scalability, and clarity. This enables early detection and ongoing monitoring of sleep apnea events. By using wearable, non-invasive sensor technology and machine learning models, the system helps medical professionals act quickly. This ensures timely intervention and better patient care.

2.2.1.2 Intended Audience and Reading Suggestions

1. **Intended Audience:**

- **Medical Professionals and Sleep Specialists:** To evaluate the system's role in diagnosing and monitoring sleep apnea, supporting clinical decision-making, and enabling integration into healthcare workflows.
- **Researchers and Academicians:** To study the combination of wearable biosensors (HRV, SpO_2, ECG) with AI and machine learning methods, and explore explainability techniques used in detecting sleep disorders.

- **AI and Machine Learning Practitioners:** To improve applications of deep learning and hybrid models in healthcare diagnostics, especially for processing physiological signals.
- **Healthcare Technology Developers and Innovators:** To assist in designing portable, affordable, and scalable health-monitoring devices for home use and clinical settings.
- **Policy Makers and Healthcare Administrators:** To investigate non-invasive, affordable diagnostic solutions for potential use in public health initiatives and remote healthcare programs.

2. **Reading Suggestions:**

- **For Non-Technical Readers (Medical Professionals & Policy Makers):** Focus on sections like Problem Definition, Solution Statement, Novelty of Work, and Project Outcomes to understand the system's purpose, benefits, and applications.
- **For Technical Readers (Researchers & AI Practitioners):** Examine sections such as Methodology, Tools and Technologies Used, Signal Processing Pipeline, and Model Development for insights into the technical innovations and challenges involved.
- **For Cross-Functional Teams (Developers & Innovators):** Review Hardware Integration, Communication Frameworks, and Scalability Considerations to understand how wearable devices work with computational systems.
- **For Complete Understanding:** Start with the Literature Survey and Related Work for background knowledge, then move on to Proposed Approach and Outcomes to see how this system builds on existing research while addressing important gaps.

2.2.1.3 Project Scope

This project aims to develop a non-invasive, affordable, and scalable system for detecting and monitoring sleep apnea. It uses a wearable wristband with multiple biosensors, including HRV, SpO_2, and ECG, for continuous overnight data collection. A hybrid deep learning model processes the collected signals, ensuring high accuracy and timely identification of apnea events.

The system includes explainability features, like attention-based interpretability, to give clear insights into how decisions are made. This approach helps build trust and acceptance in clinical settings. Its portable and energy-efficient design makes it ideal for home monitoring, clinical use, and environments with limited resources.

This project tackles issues with existing methods, such as the high cost and invasiveness of polysomnography, the unclear nature of black-box AI models, and the scalability limits of traditional diagnostic tools. This allows for earlier detection, continuous monitoring, and tailored treatment planning.

The goal is to develop a system that is affordable, portable, and accessible, improving patient outcomes while supporting the broader vision of AI in healthcare—delivering meaningful, human-centered innovation.

2.2.2 Overall Description

2.2.2.1 Product Perspective

The proposed diagnostic system is a wearable wristband that combines multiple sensors and machine learning to detect and monitor sleep apnea. It has biosensors like HRV, SpO_2, ECG, respiratory rate, and motion sensors that connect to a microcontroller. This setup allows for real-time collection of physiological data during sleep. The data is analyzed using a hybrid deep learning model, which can identify patterns linked to apnea events.

This system provides a non-invasive and cost-effective option compared to traditional methods like polysomnography, which tend to be expensive and invasive, and usually only work in specialized clinics. To build trust and gain acceptance in clinical settings, the model includes features that explain its predictions.

The device is designed to be portable, energy-efficient, and easy to use. It can be easily set up in homes, clinical settings, and areas with limited resources. By enabling early detection, continuous monitoring, and scalability, the system aims to improve diagnostic accuracy, aid in timely interventions, and support personalized treatment plans for patients with sleep apnea.

2.2.2.2 Product Features

- **Non-Invasive Diagnosis System:**
    - Uses a wearable wristband with biosensors (HRV, SpO_2, and ECG) to gather sleep-related data.

- Removes the need for invasive or costly diagnostic procedures, offering a comfortable and patient-friendly option.

- **Hybrid Machine Learning Model:**
  - Uses deep learning and ensemble models to detect sleep apnea events by analyzing multi-sensor data.
  - Provides high accuracy and reliability in classification and assessing apnea severity.
- **Model Interpretability and Transparency:**
  - Includes interpretability techniques to show important features that contribute to apnea detection.
- **Portable and Cost-Effective Design:**
  - Developed on a low-power microcontroller platform (ESP32), the wristband is lightweight, energy-efficient, and affordable.
  - Made for use in various environments, including home monitoring and healthcare settings with limited resources.
- **Scalable and Real-Time Monitoring:**
  - Supports real-time data collection and analysis, giving apnea event predictions in seconds.
  - Can handle multiple users and datasets, allowing integration into both clinical workflows and personal health management systems.

2.2.3 External Interface Requirements

2.2.3.1 User Interfaces

- **Wearable Sensor Interface:**
  - **Description**: A lightweight wristband that has several biosensors. These include HRV, SpO_2, and ECG sensors.
  - **Purpose**: To monitor physiological signals and sleep-related activity throughout the night. This helps in detecting apnea events without being invasive.
  - **Interaction**: The patient wears the wristband while sleeping. The sensors collect and send data automatically, ensuring comfort and ease of use.

- **Monitoring and Prediction Results Interface (Mobile App / GUI):**
  - **Description**: A simple mobile or desktop application that shows real-time monitoring of physiological signals, detects apnea events, and visualizes data through graphs, trend charts, and severity scores.
  - **Purpose**: To present apnea predictions along with clear visualizations. This helps clinicians analyze how often events occur, their severity, and long-term trends in sleep health. Patients can also use it to check their own sleep quality.
  - **Interaction**: Clinicians can look at diagnostic results and historical records to make medical decisions. Patients can see predictions, receive alerts, and track their progress over time.

2.2.3.2 Hardware Interfaces

- **Multi-Sensor Wristband Interface**
  - **Description:** A wearable wristband embedded with biosensors, including HRV (Heart Rate Variability), SpO_2, and ECG electrodes.
  - **Purpose:** Continuously collects physiological and movement-related data during sleep for apnea detection and monitoring.
  - **Interaction:** Sensors directly interface with the microcontroller for synchronized data acquisition, requiring minimal user setup.

- **Microcontroller Interface (ESP32)**
  - **Description:** A lightweight microcontroller that integrates signals from all onboard sensors.
  - **Purpose:** Facilitates real-time data acquisition and preprocessing before transmitting to the computational system.
  - **Interaction:** Operates automatically with basic initialization; designed for low power consumption to enable overnight monitoring.

- **Data Transmission Interface**
  - **Description:** Communication channel between the wristband microcontroller and the computational/processing unit, using Wi-Fi.
  - **Purpose:** Ensures reliable and energy-efficient transfer of sensor data for real-time monitoring and analysis.
  - **Interaction:** Runs seamlessly in the background, allowing uninterrupted data flow without requiring user intervention.
- **Computational System Interface**
  - **Description:** A system (local smartphone app or cloud server with sufficient computational resources) to process incoming physiological data.
  - **Purpose:** Performs advanced tasks such as signal preprocessing, feature extraction, apnea event detection, and real-time alerts.
  - **Interaction:** Operates without direct user involvement, aside from initial pairing or configuration; requires compatibility with the wearable device.

2.2.3.3 Software Interfaces

- **Data Preprocessing Tools**
  - **Description**: Uses Python libraries like NumPy, Pandas, and Scikit-learn for cleaning, manipulating, and preprocessing sensor readings.
  - **Purpose**: Prepares raw physiological data from MAX30003 and MAX30102 sensors, including HRV, SpO_2, ECG, and motion, for input into machine learning models.

  - **Interaction:** Works in the backend, performing tasks such as feature extraction, normalization, signal filtering, and managing missing or noisy data.
- **Machine Learning Frameworks**
  - **Description:**TensorFlow/Keras: Designs and trains deep learning models to detect sleep apnea events from time-series sensor data.
  - **Purpose:** Implements and optimizes the 1D CNN model for accurate detection and classification of apnea events.
  - **Interaction:** Integrated into the backend pipeline for both training and real-time inference.

- **Explainability Tools**
    - **Description**: SHAP (SHapley Additive exPlanations) interprets model predictions.
    - **Purpose**: Offers clear insights by visualizing feature importance, helping clinicians and researchers understand the reasoning behind each prediction.
    - **Interaction:** Displayed on the frontend dashboard to aid decision-making and build trust in AI predictions.

- **Data Storage and Retrieval**
    - **Description:** Uses Firebase Firestore / Realtime Database to store patient sensor data and diagnostic results.
    - **Purpose**: Keeps historical records for trend analysis, long-term monitoring, and clinical review.
    - **Interaction:** Clinicians and researchers can retrieve, analyze, and compare past patient data through the dashboard interface.
- **Deployment Platforms**
    - **Description:** Hosted on platforms like Firebase Hosting, Streamlit Cloud, AWS, or Google Cloud.
    - **Purpose:** Ensures the application is scalable, accessible, and functional for real-time monitoring.
    - **Interaction:** Users access the application via web browsers or mobile devices, with minimal setup and smooth integration.

2.2.4 Other Non-functional Requirements

2.2.4.1 Performance Requirements

- **Accuracy and Precision**
    - The system must detect sleep apnea events with at least 90% accuracy using multi-sensor data: HRV, SpO_2, breathing rate, ECG, and body movement.
    - We should optimize precision and recall values to reduce false alarms and missed detections. This will help ensure reliable monitoring.

- **Real-Time Processing**
    - The device must process physiological signals and provide event detection or predictions within 5 seconds of data collection. The total delay, including sensor data collection, wireless transmission, and model inference, should be minimal to support real-time monitoring.
- **Scalability**
    - The system should be scalable for use with multiple patients. It should integrate with larger clinical databases and research platforms.The design should allow for future additions of new biosensors or updated machine learning models without major changes to the structure.
- **Robustness**
    - The detection algorithm must work well across different patient groups, sleep positions, and various environmental conditions, such as bedroom temperature, noise, or movement artifacts.The system should effectively manage signal noise and artifacts, like those caused by body movements, without reducing performance.
- **Resource Efficiency**
    - The wearable device and backend application must be designed to run on mid-tier hardware, such as microcontrollers or smartphones with limited processing power or GPUs with 4GB memory for cloud inference.The design must prioritize energy efficiency to enable long-term, overnight monitoring without needing to recharge frequently.

2.2.4.2 Safety Requirements

- **Non-Invasive Operation:** The wearable system, which includes sensors and a wristband, must be lightweight, skin-friendly, and comfortable for overnight use. It should not cause any harm or discomfort to the patient.
- **Data Integrity:** The physiological signals collected, such as SpO_2, ECG, and HRV, must be reliable. They should have minimal noise and error to avoid diagnostic inaccuracies that could affect medical decisions.

- **Compliance with Medical Standards:** The system must meet established medical device regulations and patient data protection standards, like ISO 13485, HIPAA, and GDPR. This ensures safety and trust.
- **Fail-Safe Mechanisms:** If there is a sensor malfunction, electrode detachment, or data transmission failure, the system must alert the user quickly. It should also ensure that patient safety is not at risk.

2.2.4.3 Security Requirements

- **Data Privacy and Confidentiality:**
    - All patient data must be encrypted during transmission and storage to prevent unauthorized access or breaches.
    - Use of secure protocols such as HTTPS for web-based interfaces.
- **Authentication and Authorization:**
    - Access to the system must be restricted through secure login mechanisms, ensuring that only authorized users, such as clinicians, can access sensitive information.
- **Resilience to Cyber Threats:**
    - Implement firewalls, intrusion detection systems, and secure coding practices to protect against cyberattacks like data breaches or malware.
- **Data Integrity Checks:**
    - Use checksum validation and error-detection techniques to ensure transmitted data is not tampered with or corrupted.
- **Regular Updates:**
    - The system must be regularly updated with the latest security patches.

2.3 Cost Analysis

The total cost for the Sleep Apnea Detection Wristband will include both hardware and software components, along with maintenance costs.

The hardware cost is about INR 7300. This includes essential biomedical sensors such as the MAX30003 ECG sensor (₹3500), the MAX30102 SpO_2 sensor (₹330), the ESP32 microcontroller, and the wristband housing (₹1500). There may be extra expenses from 3D printing and prototyping (approximately ₹2000) for refining the enclosure. The sensors in the system must be precise and dependable because apnea detection depends on capturing accurate changes in oxygen saturation and heart rhythm.

We also expect maintenance costs, especially for calibrating ECG patches and sensors to maintain accuracy. Regular electrode replacement and device servicing may add to ongoing expenses. Another significant area of cost is software development. This includes embedded programming for the ESP32, signal pre-processing pipelines (digital filtering, peak detection, and motion artifact removal), and machine learning models for apnea classification. Complex algorithms, including possible deep learning models, require computing resources, which can increase costs.

Additionally, the system may feature a mobile application for real-time visualization of SpO_2, ECG, and HRV metrics, along with Apnea-Hypopnea Index (AHI) summaries. Developing this application adds more cost due to the need for cross-platform support, UI/UX design, and integration with healthcare workflows.

For cloud-based storage and analysis, services like AWS or Google Cloud could be used for remote monitoring. However, this infrastructure introduces ongoing costs for secure storage, computing power, and meeting healthcare data privacy regulations.

Overall, the total cost must find a balance between being affordable and ensuring high accuracy, reliability, and scalability. This will help the system remain effective for patients and viable for use in both clinical and home monitoring settings.

2.4 Risk Analysis

Like any medical-grade wearable device, the Sleep Apnea Detection Wristband faces several risks during its development, use, and clinical application. Identifying these risks early and outlining ways to manage them is crucial to make sure the system is reliable and safe for patients.

- **Sensor Noise and Motion Artifacts**
    - One of the biggest challenges in wearable health devices is signal noise. Physiological signals like SpO_2, ECG, and HRV are very sensitive to body movements, the quality of skin-electrode contact, and environmental interference. A restless sleeper, for instance, may introduce artifacts that lower the system's ability to detect apnea events accurately.

    - Mitigation: To tackle this issue, the system will use strong digital filtering methods along with adaptive signal cleaning algorithms. Additionally, using high-quality, medical-grade electrode patches and regularly calibrating sensors can help reduce noise and provide more consistent readings.

- **Data Privacy and Security**
    - The wristband collects sensitive patient health data that must always be protected. A data breach, whether on the mobile app or in cloud storage, could have serious legal, ethical, and financial consequences.
    - Mitigation: End-to-end encryption, secure authentication methods, and anonymizing patient identifiers will be central to the system's design.
- **Algorithm Reliability**
    - Machine learning models can be powerful, but they are not free from overfitting or underfitting. A model trained on limited or biased datasets may perform well in testing but fail with new patients, resulting in missed apnea events (false negatives) or unnecessary alarms (false positives).

    - Mitigation: The answer is to use diverse and representative datasets, apply cross-validation techniques, and avoid overly complex models that may not generalize well. Extensive clinical validation will be essential before moving toward commercial use.

- **User Compliance and Adoption**
    - For long-term success, the wristband must not only function well but also be acceptable to users. Patients might find it uncomfortable to wear overnight, and healthcare professionals may initially be reluctant to use it instead of traditional polysomnography in clinics.
    - Mitigation: The design will focus on comfort, using lightweight materials and skin-friendly electrodes to encourage regular use. On the clinical side, clear validation studies and user-friendly reports will help build confidence among healthcare providers.

- **Operational and Hardware Risks**
  - Like any electronic device, the system can experience operational failures. Sensor problems, loose electrode patches, or battery issues during overnight studies could interfere with monitoring and affect results.
  - Mitigation: To lessen these risks, the device will include fault-tolerant firmware, real-time error detection, and low-battery alerts. Using durable materials and carefully testing hardware components will also enhance the system's reliability.

3. METHODOLOGY ADOPTED

3.1 Investigative Techniques

S.No.	Investigate Projects Techniques	Investigate Techniques description	Investigate Projects examples
1.	**Descriptive**	The project involves observing and recording biomedical signals (SpO_2, ECG, HRV) to analyse physiological changes during sleep. These signals are catalogued and processed to study patterns related to sleep apnea.	Signal acquisition and preprocessing of ECG and spo2 data; HRV metrics computation.
2.	**Comparative**	The project compares normal sleep signal patterns with apnea-affected patterns by analyzing differences in oxygen saturation levels, heart rate variability, and ECG-derived respiration.	Comparison of normal vs. apnea episodes based on SpO_2 desaturation, HRV fluctuations, and cardiac response.
3.	**Experimental**	The project designs and tests hypotheses by implementing algorithms to detect apnea events using biomedical signal features. It uses control datasets and validation techniques to evaluate detection accuracy.	Machine learning–based apnea event classification, rule-based detection models, testing sensitivity and specificity of the device.

Table 4: Investigative Techniques

3.2 Proposed Solution

The solution of the proposed project relies on the detection and monitoring of sleep apnea symptoms on the basis of physiological information recorded from **SpO_2, ECG, and HRV** sensors embedded in a wearable wristband. It is supported by the fact that sleep apnea episodes are reflected through oxygen desaturation, abnormal heart rate variability, and characteristic ECG patterns. Such a concept can generate an effective and reliable observation of breathing irregularities without the need for bulky clinical equipment.

Such a solution integrates tools including:

- Actual hardware for live sensing.
- Data acquisition.
- Pre-treatment.
- Feature extraction and analysis.

Core Components

Sensors' Data Acquisition:

- **SpO_2**: Captured using a dual-wavelength photoplethysmography (PPG) sensor (e.g., MAX30102), measuring red and infrared light absorption at the wrist to estimate blood oxygen levels.
- **ECG**: A single-lead ECG front-end (e.g., MAX30003) captures electrical signals of the heart in real time through integrated electrodes.
- **HRV**: Derived from ECG R-R intervals to track autonomic nervous system fluctuations.
- The sensors are connected to a low-power microcontroller (e.g., nRF52840) with Bluetooth Low Energy (BLE) for real-time data transfer.

Data Pre-processing and Feature Extraction:

- Raw sensor data is filtered to remove noise and motion artifacts using digital filters.
- From ECG signals, R-peaks are detected and cleaned to compute R-R intervals.
- From PPG signals, AC/DC ratios are calculated to estimate SpO_2 levels.
- HRV features are extracted, including time-domain metrics (SDNN, RMSSD) and frequency-domain metrics (LF, HF, LF/HF ratio).

Algorithmic Analysis:

- Extracted features are fed into a rule-based detection algorithm, which flags potential apnea events based on:
  - A drop in SpO_2 of ≥3% lasting at least 10 seconds.
  - Suppression in ECG-derived respiration or abnormal HRV patterns.

    - Characteristic cardiac responses such as bradycardia followed by rebound tachycardia.
- Accuracy, sensitivity, and specificity would be used as performance metrics to validate the detection model.

Visualization and Interpretation:

- Results are transmitted to a mobile application via BLE for real-time visualization.
- Graphical plots display SpO_2 trends, HRV variations, and apnea-likely events throughout the night.
- The mobile platform provides a clinically meaningful measure of apnea severity.

This entire solution can easily be scaled up and deployed in real-world implementations where patients can be continuously monitored remotely through portable wearable devices. It improves early detection, supports long-term monitoring, and offers a low-cost alternative to conventional polysomnography for sleep apnea screening.

3.3 Work Breakdown Structure (WBS)

A work breakdown structure breaks the entire process into steps to deliver the final system for the Sleep Apnea Detection Wristband.

- **Phase 1: Requirement Analysis**
    - Identify project scope and objectives focused on real-time detection of sleep apnea.
    - Collect requirements for hardware (SpO_2, ECG, HRV sensors)and software algorithms.
    - Review literature on current wearable devices and clinical polysomnography methods.
    - Develop performance metrics for validation, including accuracy, sensitivity and specificity.

- **Phase 2: Hardware Setup and Integration**
    - Purchase the SpO_2 sensor (MAX30102), ECG front-end (MAX30003), and a ESP32.
    - Establish connections via I^2C/SPI and integrate a BLE module for wireless communication.
    - Write basic embedded code for data collection using libraries for PPG and ECG.
    - Validate hardware with test subjects to confirm proper logging of physiological data.

- **Phase 3: Data Acquisition and Pre-processing**
    - Acquire raw SpO_2 (red & IR absorption), ECG waveforms, and R-R intervals for HRV.
    - Pre-process signals with digital filters to remove noise, motion artifacts, and outliers.
    - Extract key metrics: SpO_2 levels, ECG R-peaks, and HRV features.
    - .Verify data quality and stability across multiple recording sessions.

- **Phase 4: Algorithm Development and Analysis**
    - Implement rule-based detection for apnea events.
    - Explore ML classification methods for apnea detection.
    - Validate models using metrics like accuracy, precision, recall, sensitivity, specificity etc.
    - Optimize the system for real-time performance and low power use on wearable hardware.

- **Phase 5: Testing and Validation of System**
    - Run simulations on recorded data sets and test live recordings.
    - Compare results with standard clinical sleep apnea diagnostic criteria.
    - Document test cases, record outcomes and adjust algorithms based on performance.
- **Phase 6: Visualization and Result Interpretation**

- Display real-time SpO_2, HRV, and apnea event markers on a mobile app.
- Provide a summary analysis with nightly AHI scores and event logs.
- Compare results with clinical tools and suggest potential improvements.

- **Phase 7: Documentation and Presentation**
  - Compile the project report, including system design, workflow diagrams and results.
  - Prepare a presentation that highlights project objectives, approach and outcomes
  - Discuss future scalability, such as continuous remote monitoring for patients at home.

The WBS helps address the project step by step from hardware setup to data interpretation. It ensures a structured path toward the successful development and testing of the wristband.

3.4 Tools and Technologies Used

Our project brings together a mix of hardware and software to capture body signals, process them, and detect sleep apnea in a way that's both accurate and affordable.

- **Hardware**
  - **MAX30102 Pulse Oximeter (SpO_2 + Heart Rate):** This small sensor measures blood oxygen levels and heart rate by shining light through the skin. It's lightweight, energy-efficient, and ideal for wearables.
  - **MAX30003 ECG Module:** This chip records single-lead ECG signals with high precision. It's designed for low-power devices and can detect heart rhythm variations, which are important for analyzing breathing patterns.
  - **ESP32 / nRF52840 Microcontroller:** Think of this as the project's "brain." It collects data from the sensors and sends it to a phone or cloud system over Bluetooth. It's low-cost, reliable, and widely used in wearable devices.
  -

- **Software**
  - **Embedded Programming (Arduino IDE / PlatformIO):**
    We made the use of these platforms to program the microcontroller and talk to the sensors. Libraries like Wire.h and sensor-specific drivers make communication easier. Filters are also added to remove noise from the signals.
  - **Python for Analysis:**
    - After the data is collected, Python helps us make sense of it:
    - *NumPy & Pandas* organize and process the raw numbers.
    - *SciPy* applies signal processing techniques to clean and refine the data.
    - *Matplotlib & Seaborn* let us visualize patterns like dips in oxygen or irregular heartbeats.
    - *Scikit-learn* powers the machine learning models that can flag potential apnea events.

  - **Mobile App (Flutter / React Native):**
    A user-friendly app displays the results in real-time. Patients (or doctors) can view graphs of oxygen levels, heart rate, and apnea events directly on their phones. The app connects wirelessly via Bluetooth.

- **Technology Workflow**

  Here's how everything fits together:

  - **Collect Data:** The sensors pick up SpO_2, ECG, and HRV signals.
  - **Clean the Data:** Filters remove noise so only useful information remains.
  - **Extract Features:** Key patterns like oxygen dips, HRV fluctuations, and ECG changes are pulled out.
  - **Detect Apnea:** Machine learning or rule-based logic identifies when an apnea event might have occurred.
  - **Show Results:** The mobile app displays easy-to-read charts and summaries.

By combining affordable hardware with smart software, this system can make sleep apnea detection more accessible outside of hospital labs—whether for personal health tracking or clinical monitoring.

4. DESIGN SPECIFICATIONS

4.1. System Architecture

The overall system architecture of the proposed IoT-driven Sleep Apnea detection project is shown in Figure 4.1.

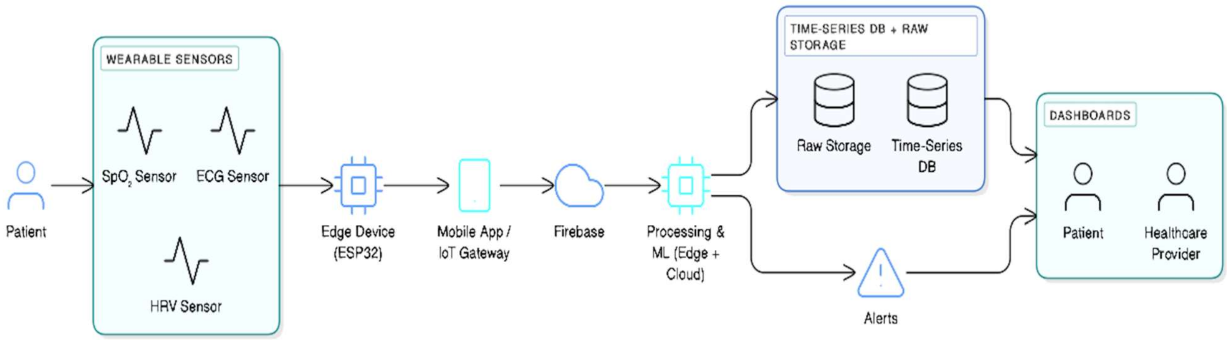

Figure 4.1: System Architecture diagram

This System Architecture diagram illustrates the system architecture of the proposed IoT-based Sleep Apnea.. The system architecture starts with SpO_2 and airflow sensors, which are wearable and gather the physiological data of the patient. It is then transferred through an edge device (ESP32) to a mobile application, which serves as an IoT gateway. The gateway exports data to a cloud-based platform in which preprocessing, storage, and machine learning algorithms identify apnea events. The results are represented using dashboards for patients and caregivers with alert notifications for critical cases.

4.2. Design Level Diagrams

The State Chart diagram of the proposed IoT-driven Sleep Apnea detection project is shown in Figure 4.2.

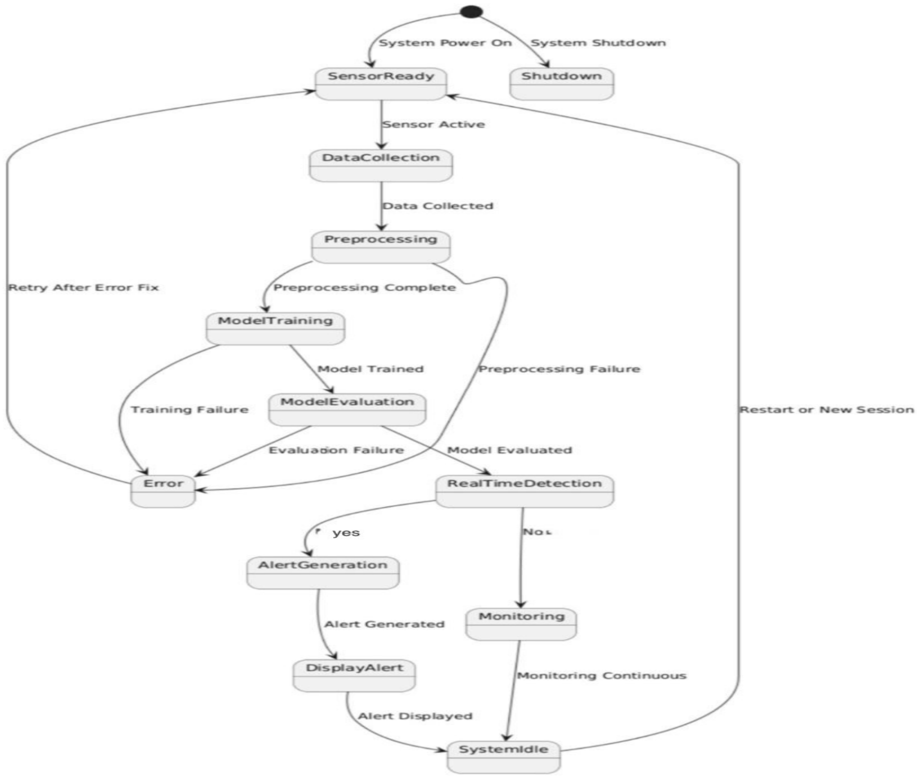

Figure 4.2: State Chart diagram

Figure 4.2: The State Chart diagram represents the way the Sleep Apnea Detection System operates as it goes through various phases while in use. When the machine is turned on, the sensors go on standby and begin to take readings including oxygen saturation levels and breathing patterns. After data is gathered, it undergoes a preprocessing phase where noise is filtered out, and the signals cleaned. If anything goes wrong here, the system goes into an error state and continues to wait until the problem gets resolved and it retries.

The data, after preprocessing successfully, is then sent to the AI/ML model to train and evaluate. In case the model doesn't train or evaluate successfully, the system goes to an error state again. But if all goes well, the system goes into real-time detection mode, where it continuously monitors the patient for apnea. If an apnea event is identified, the system produces and shows an alarm so that both the patient and healthcare provider will be aware. If no abnormal occurrence is discovered, the system just keeps monitoring in the background.

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The Use Case diagram of the proposed IoT - driven Sleep Apnea detection project is shown in Figure 4.3.

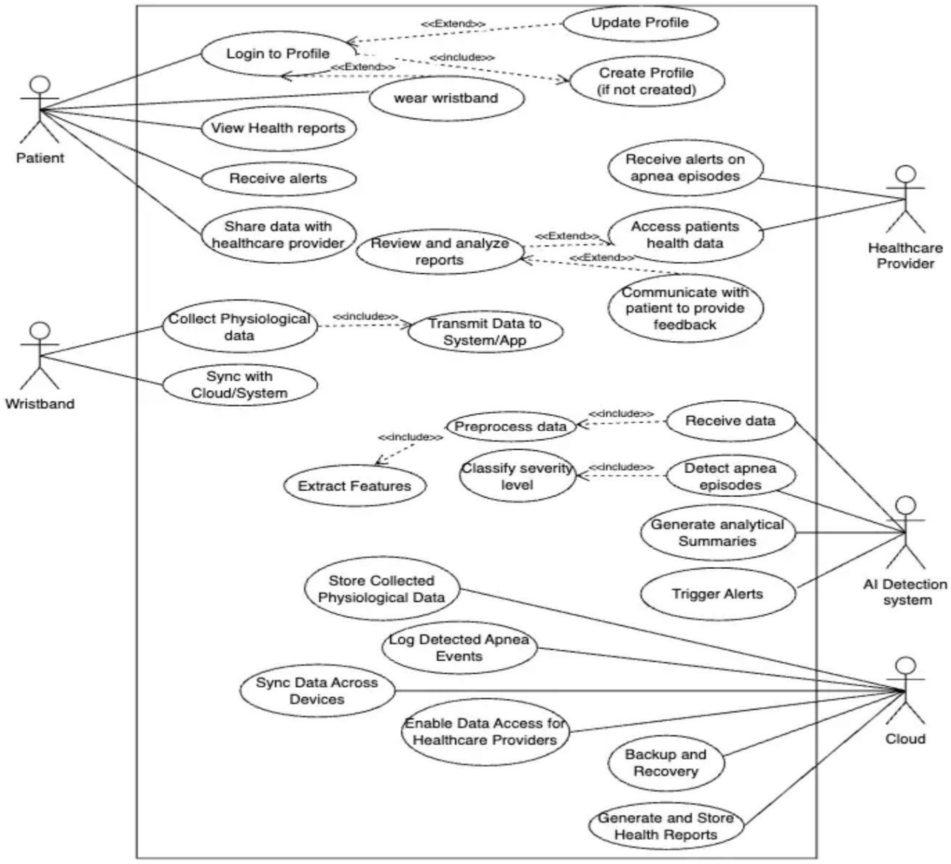

Figure 4.3: Use Case diagram

Figure 4.3: The use case diagram illustrates the interaction between various actors and the system. The primary actors include the Patient, Wristband, Healthcare Provider, AI Detection System, and Cloud Server. The Patient uses the system by setting a profile, wearing a wristband, login, uploading data, viewing reports, and receiving alerts. The Wristband gathers physiological data like oxygen saturation and heart rate variability, and sends this information to the system for processing. The AI Detection System captures and preprocesses data, extracts features, and identifies apnea episodes through ML algorithms. The Cloud module (firebase) stores physiological data, has backups, synchronizes across devices, and provides data access to healthcare professionals. Lastly, the Healthcare Provider checks analytical summaries, keeps track of patients' health status, is alerted for apnea events, and offers medical advice.

The state transitions of the system are shown in Figure 4.4.

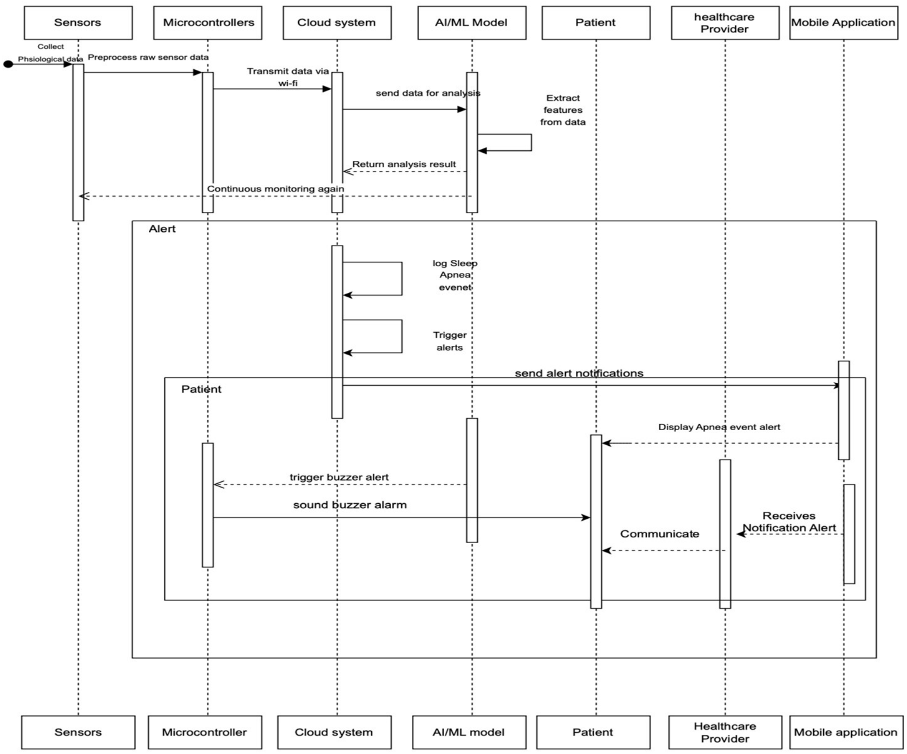

Figure 4.4: Sequence diagram

Figure 4.4: Sequence diagram diagram demonstrates the overall sequence of the proposed Sleep Apnea Monitoring System that illustrates the dynamic collaboration between sensors, processing units, and end users. The process starts with wearable sensors that capture physiological signals like SpO2, ECG and HRV.. These raw signals are transferred to the ESP32 microcontroller, preprocessed by it before sending it to the cloud system through Wi-Fi. The cloud system sends the data to the AI/ML model, which processes the features, inspects the data, and classifies apnea events. The outcome is sent back to the cloud and recorded as detected events.

If the irregular breathing patterns are detected, the AI/ML model activates an alert mechanism. Alerts are returned to the patient via the mobile application, which can send a buzzer alarm on the wearable device for instant awareness. At the same time, an alarm is sent to the doctor, who may see the apnea event information and talk with the patient for medical guidance or follow-up. This process facilitates early detection of apnea events, and improved communication between the patient, system, and doctor.

4.3. User Interface Diagrams

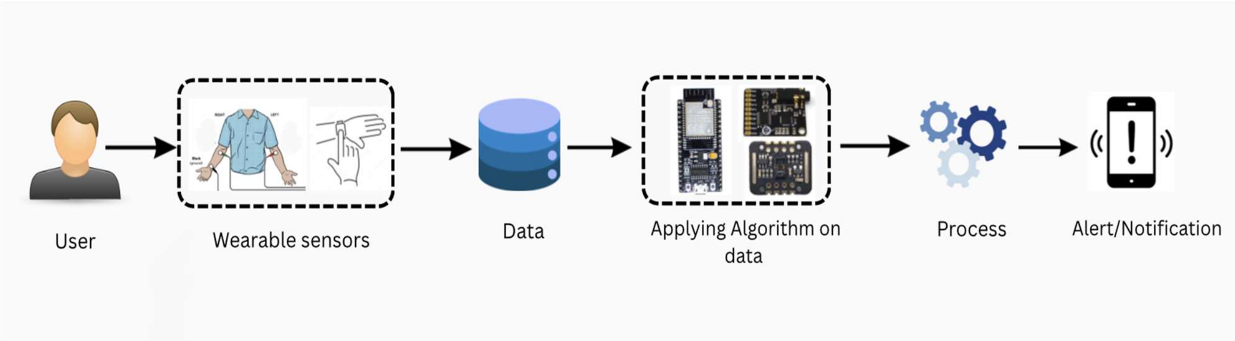

Figure 4.5: Interface Connections

4.4 Snapshots of Working Prototype

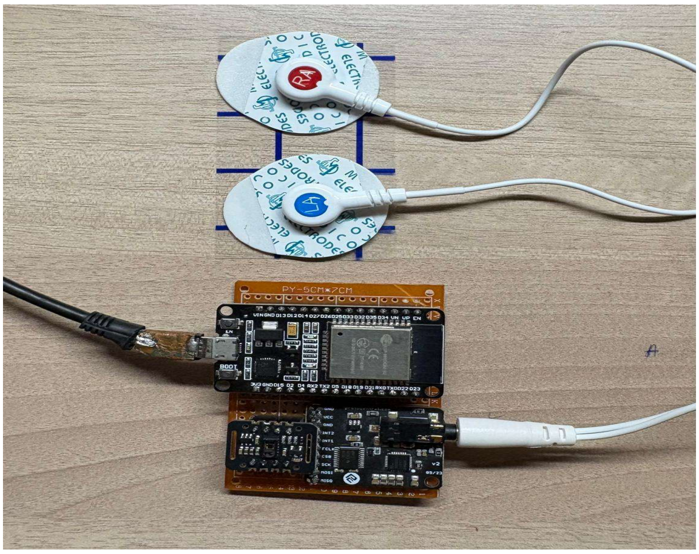

Figure 4.6: Individual components used in the hardware system and testing.

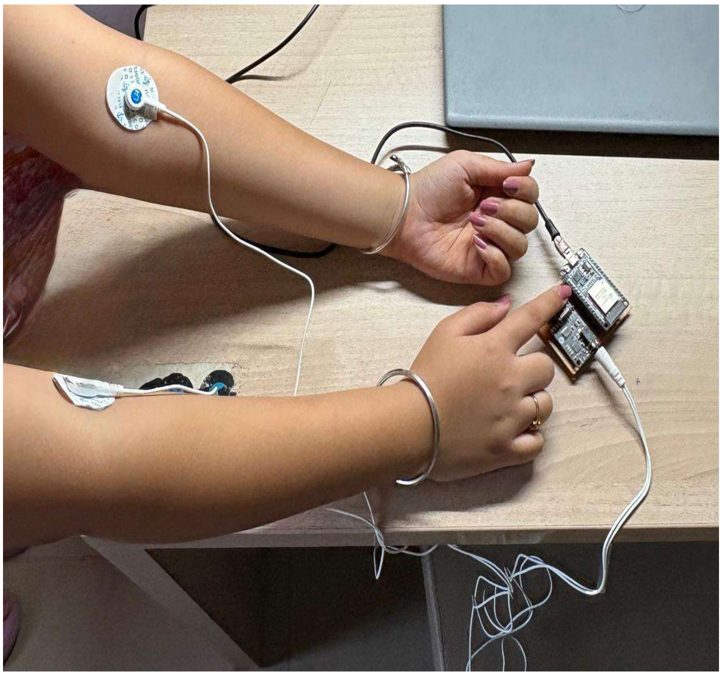

Figure 4.7: Hardware system being attached to subject’s arm

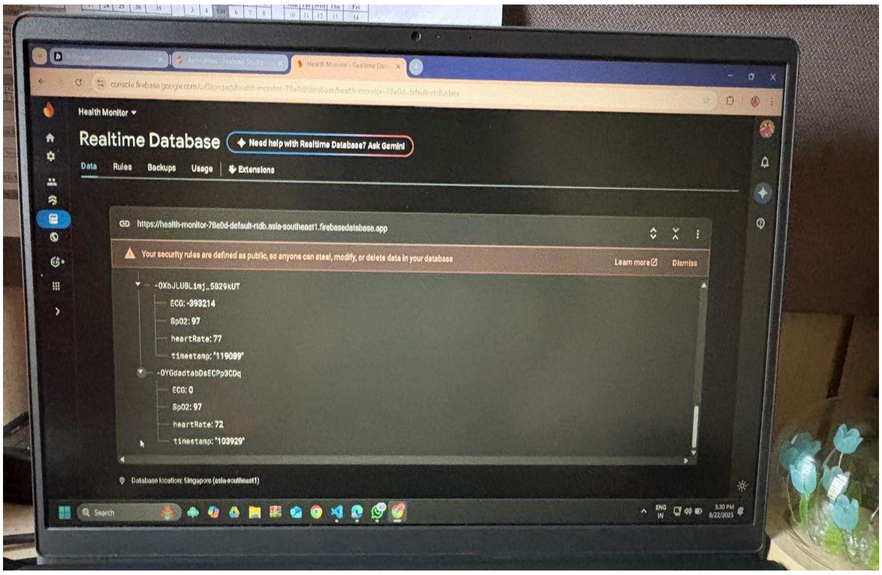

Figure 4.8: Results generated after taking readings from the sensors.

Step-by-Step Discussion:

- **Hardware Assembly:**
  - ESP32 connected with MAX30102 (SpO_2/HR) and MAX30003 (ECG).
  - ECG electrode patches placed on the arm; a finger rested on the SpO_2 sensor.
- **Signal Acquisition**
  - Real-time physiological signals were captured from the sensors.
  - ECG (R-R intervals) and SpO_2 readings were successfully collected.
- **Data Transmission**
  - Biosignals were sent wirelessly from the ESP32 to the cloud.
  - Firebase was selected as the cloud database for data storage.
- **Cloud Integration**
  - Live data (SpO_2 and ECG) is displayed on Firebase in a structured format.
  - This confirms that the communication pipeline is working.
- **Current Progress**
  - Hardware has been tested and is working.
  - Data is successfully reaching Firebase.
  - The model has not been integrated for apnea detection yet.
- **Next Step**
  - Use the stored Firebase data to train and test the apnea detection model.
  - Integrate the processed results into a mobile or PC visualization app.

5. Conclusions and Future Scope

5.1 Work Accomplished

The main aim of this project was to build a wearable wristband that can detect early signs of sleep apnea by tracking key physiological signals such as SpO_2, ECG, and HRV.

To achieve this, the hardware setup was successfully completed by integrating the MAX30102 sensor for SpO_2 and heart rate, the MAX30003 module for ECG, and the ESP32 microcontroller. Embedded code was written to capture and transmit biosignals in real time, ensuring smooth communication between the sensors and the processing unit.

A proper data acquisition pipeline was created to filter out noise and extract meaningful information such as oxygen desaturation levels, R-R intervals, and HRV metrics. Basic algorithms were also implemented to detect possible apnea events, primarily by observing drops in SpO_2 and irregularities in ECG/HRV patterns.

In addition, the groundwork for a mobile application was laid out. This app is designed to visualize live signals and provide summaries, making the data easy to interpret for users.

Overall, the project successfully met its approved objectives and established a strong base for developing a reliable, scalable wristband that can continuously monitor sleep apnea in real time.

5.2 Conclusions

The project demonstrates the feasibility of developing a cost-effective, portable wristband for sleep apnea detection. By combining SpO_2, ECG, and HRV analysis, the device offers a non-invasive solution that can complement or, in some cases, provide an alternative to traditional polysomnography.
The results confirm that the system is capable of:

- Capturing high-quality physiological signals.
- Processing and filtering biosignals for accuracy.
- Providing event-based detection of possible apnea episodes.

This establishes the wristband as a promising step toward accessible, real-time sleep health monitoring.

5.3 Environmental Benefits

- **Environmental Benefits:**
  The wristband encourages sustainable healthcare by cutting down the need for bulky, power-hungry hospital machines. Its low-power design reduces energy use and material requirements, while its compact form factor creates less electronic waste compared to traditional diagnostic equipment.
- **Economic Benefits:**
  Conventional sleep studies are both expensive and time-consuming, often requiring overnight stays in specialized labs. In contrast, this wearable provides a cost-effective alternative that makes apnea screening more affordable and accessible, while also saving time for both patients and healthcare providers.
- **Social Benefits:**
  Sleep Apnea often goes undiagnosed due to limited awareness and restricted access to sleep clinics. By enabling people to monitor their health from the comfort of home, this wristband promotes early detection and timely medical intervention. In the long run, it not only improves health outcomes but also enhances overall quality of life for individuals and communities.

5.4 Future Work Plan

Although the current prototype successfully meets its initial objectives, there is significant potential to enhance and expand the system to make it more robust, accurate, and user-friendly. The following directions are planned for future development:

- **Advanced Algorithms:** While the present system uses rule-based logic for detecting apnea events, the next step is to incorporate advanced machine learning and deep learning models. These will help capture subtle signal variations, reduce false alarms, and improve the overall accuracy of apnea classification. By training models on larger datasets, the wristband can evolve into a highly reliable diagnostic tool.
- **Mobile Application Development:** A dedicated mobile application is planned to provide users with an interactive, user-friendly experience. The app will feature real-time plots of biosignals, personalized dashboards displaying AHI scores, and sleep quality summaries.

Additionally, it could include notifications, lifestyle recommendations, and integration with digital health platforms, making the device more than just a diagnostic tool — but also a companion for long-term wellness.

- **Cloud Integration and Remote Monitoring:** To enable continuous and secure healthcare support, future versions of the system will integrate with cloud platforms. This will allow safe storage of patient data for long-term tracking, remote monitoring by doctors, and potential integration with hospital management systems. Such a feature will bridge the gap between home monitoring and clinical intervention.
- **Miniaturization and Wearability:** Current hardware components, though compact, can be further optimized for comfort and aesthetics. Future efforts will focus on miniaturizing the circuit design, improving battery efficiency, and creating a lightweight, ergonomic wristband. These improvements will make the device more suitable for overnight studies and long-term use without discomfort.
- **Clinical Validation and Trials:** To move from prototype to a clinically viable product, large-scale validation studies are essential. Trials will be conducted with diverse patient groups to compare device performance against gold-standard polysomnography. These studies will help refine detection algorithms, establish credibility, and build trust among healthcare professionals.

In summary, the future work plan is aimed at transforming this project from an experimental prototype into a reliable, scalable healthcare solution. With advancements in algorithms, mobile integration, miniaturization, and clinical validation, the wristband has the potential to be adopted widely in both hospitals and for at-home monitoring, which is helpful in contributing to early diagnosis, better patient care, and improved quality of life.

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