Intelligent Sensor-Based System for Early Detection of Respiratory Distress

Dr.L. Vasanth[1], Mr.A.V. Vinothkumar[2], Aravindh A[3], Augastiar B[4], Kamalakannan S[5]
[1]M.E., PHD, Associate Professor, Department of Biomedical Engineering, Paavai College of Engineering.
[2]M.E, Assistant Professor [2], Department of Biomedical Engineering, Paavai College of Engineering.
[3,4,5] Student, Department of Biomedical Engineering, Paavai College of Engineering.

***Abstract*—Continuous respiratory monitoring plays a critical role in the early diagnosis and management of respiratory distress, especially in vulnerable patients. This project presents an IoT-based intelligent system that integrates SpO_2, heart rate, and body temperature sensors to collect vital physiological data in real time.**

By employing artificial intelligence— specifically the K-Nearest Neighbors (KNN) algorithm—the system can predict abnormal patterns and alert healthcare providers before critical thresholds are reached. This predictive capability facilitates timely interventions and precise ventilator adjustments, ultimately enhancing patient safety, reducing complications, and improving overall treatment outcomes. The combination of real-time monitoring and AI-driven decision support represents a significant advancement in personalized and responsive respiratory care.

***Index Terms*—IoT-based health monitoring, respiratory distress detection, SpO_2 sensor, heart rate monitoring, temperature sensor, machine learning, K-Nearest Neighbors (KNN), real-time patient monitoring, artificial intelligence in healthcare, early warning system.**

I. INTRODUCTION

Respiratory distress is a life-threatening condition characterized by inadequate oxygen supply to the body, often resulting from underlying issues such as pneumonia, asthma, chronic obstructive pulmonary disease (COPD), or acute respiratory infections like COVID-19. Effective management of this condition requires vigilant monitoring of vital signs, especially oxygen saturation (SpO_2), heart rate, and body temperature, to ensure timely intervention and avoid critical deterioration.

In conventional healthcare settings, patient monitoring is typically performed using standard medical equipment or through manual observations by healthcare professionals. However, such approaches are limited by their dependence on periodic checks rather than continuous data acquisition. This gap can lead to delays in detecting sudden drops in oxygen levels or irregularities in heart rate and temperature, which are crucial indicators of impending respiratory distress. Additionally, traditional systems often lack integration, portability, and predictive intelligence, making them less suitable for dynamic, real-time patient management.

In recent years, the advancement of Internet of Things (IoT) technology and artificial intelligence (AI) has opened up new possibilities for smarter, more responsive healthcare solutions. IoT enables the seamless interconnection of sensors and devices to collect real-time data, while AI provides powerful tools to interpret this data, identify patterns, and make predictions. When these technologies are combined, they offer a revolutionary approach to patient monitoring—one that is not only continuous and automated but also intelligent and proactive.

Our project leverages this synergy by designing an IoT-based intelligent sensor system specifically aimed at the early detection of respiratory distress. The system comprises an array of biomedical sensors that measure SpO_2 levels, heart rate, and body temperature with high accuracy. These sensors are interfaced with a microcontroller (Arduino Nano) that collects and transmits data to a central processing unit for real-time analysis.

To enhance the decision-making process, we employ the K-Nearest Neighbors (KNN) algorithm—an effective and interpretable machine learning model known for its reliability in classification and prediction tasks. The algorithm is trained on historical patient data and is capable of recognizing abnormal patterns in sensor readings, thereby predicting the likelihood of respiratory deterioration even before visible symptoms manifest. This prediction capability allows clinicians to adjust ventilator settings, administer medication, or escalate care in a timely manner.

By integrating IoT and AI technologies, this system bridges the gap between traditional monitoring and modern intelligent healthcare. It provides continuous, remote, and automated surveillance of patient health, empowering medical staff with actionable insights and contributing to faster response times, reduced workload, and improved patient outcomes. Ultimately, the proposed system represents a step forward in the digital transformation of respiratory care, particularly in intensive care units (ICUs), emergency departments, and home healthcare environments.

II. RELATED WORKS

In recent years, the integration of intelligent systems into healthcare monitoring has gained significant momentum, particularly in response to the global COVID-19 pandemic. Various research initiatives have explored the use of sensor technologies, artificial intelligence (AI), and the Internet of Things (IoT) to improve real-time diagnosis, patient tracking, and disease prediction. Yamanoor et al. [1] introduced a low-cost contact thermometry system designed for continuous temperature screening and monitoring during the COVID-19 pandemic. Their work emphasized accessibility and affordability, enabling deployment in resourceconstrained environments. Similarly, Cihan et al. [2] employed a fuzzy rule-based system (FRBS) to accurately predict daily COVID-19 case counts. By integrating fuzzy logic into pandemic modeling, their approach achieved high accuracy ($R^2 = 0.96$), showcasing the effectiveness of soft computing methods in public health surveillance.

Expanding the scope of intelligent monitoring, Rahman et al. [3] developed an automated facial mask detection system using deep learning within a smart city surveillance framework. The system achieved a classification accuracy of 98.7%, effectively identifying individuals not adhering to mask-wearing protocols in public spaces, and automatically notifying authorities. This application highlighted the potential of computer vision in enforcing public health policies. Additionally, Ankur Utsav et al. [4] proposed an innovative IoTbased patient monitoring system that utilizes thermal scanning and unique QR codes for individual identification. This approach enabled automated tracking of symptomatic individuals and facilitated real-time alerts for suspected infections, thereby reducing manual intervention and enhancing efficiency in pandemic response. Collectively, these studies underscore the transformative potential of combining IoT, sensor technologies, and AI for predictive, automated, and cost-effective healthcare solutions. While each of these systems addresses different aspects of healthcare monitoring, our proposed work extends these ideas into the domain of respiratory distress detection by integrating biomedical sensors and machine learning to enable proactive and intelligent patient care.

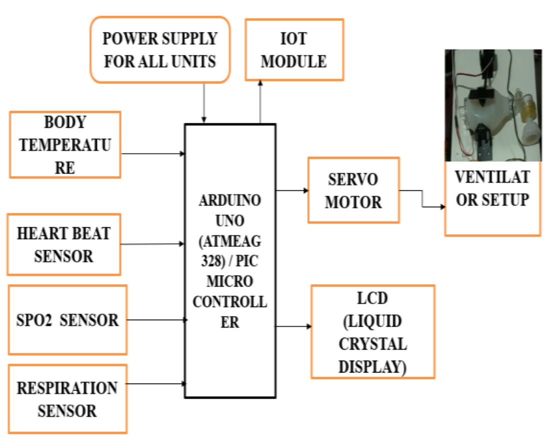
III. PROPOSED MODEL

The proposed system presents an IoTenabled, intelligent health monitoring framework designed specifically for the early detection of respiratory distress in patients. It is built upon a modular hardware and software architecture that integrates biomedical sensors, a microcontrollerbased data acquisition system, and an artificial intelligence (AI) engine for predictive analysis. The core objective of the system is to continuously monitor three critical physiological parameters: oxygen saturation (SpO_2), heart rate, and body temperature—each of which plays a crucial role in evaluating respiratory function. To achieve this, the system utilizes a set of non-invasive sensors including the MAX30100 pulse oximeter and heart rate sensor module, and the LM35 temperature sensor. These sensors are interfaced with an Arduino Nano microcontroller, which acts as the central unit for data collection and preliminary signal processing. The Arduino captures real-time data from the sensors at regular intervals and transmits it to a central processing system (typically a PC or cloud server) via serial or wireless communication protocols.

At the software level, the collected data is preprocessed and fed into a machine learning model—specifically the K-Nearest Neighbors (KNN) algorithm. KNN, a supervised learning technique, is chosen for its simplicity, interpretability, and effectiveness in pattern recognition based on proximity in feature space. Historical datasets comprising labeled values of SpO_2, temperature, and heart rate are used to train the model.

Once trained, the system can classify incoming real-time data and identify deviations that suggest early signs of respiratory distress, such as hypoxemia or tachycardia. When such anomalies are detected, the system immediately generates alerts that can be relayed to healthcare providers for timely medical intervention. Furthermore, the system is designed with scalability and portability in mind, making it suitable for both hospital and home-based patient monitoring scenarios. Its continuous real-time tracking not only enables proactive respiratory care but also supports remote health management—especially critical in pandemic situations or for patients in intensive care units. Overall, the integration of IoT and AI within the proposed model enhances diagnostic accuracy, reduces response time, and significantly improves the standard of care for patients at risk of respiratory complications.

Block Diagram



IV REQUIREMENTS

Hardware Requirements

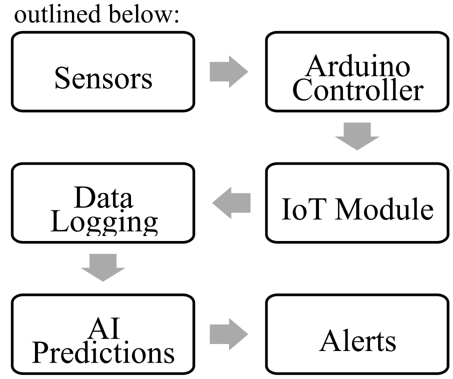
The hardware setup for this project consists primarily of biomedical sensors, a microcontroller, and communication modules. The MAX30100 sensor module is used to measure blood oxygen saturation (SpO_2) and heart rate, leveraging photoplethysmography technology for accurate and non-invasive readings. For temperature measurement, the LM35 temperature sensor is employed due to its linear output and high precision. These sensors are connected to an Arduino Nano microcontroller, which functions as the central processing unit for data acquisition, preprocessing, and transmission. To enable wireless communication and remote monitoring, an IoT communication module such as the ESP8266 Wi-Fi module is integrated, allowing real-time data transfer to a central PC or cloud platform. A regulated 5V power supply provides stable power to the entire system. Optionally, an LCD display can be connected to the Arduino to provide immediate local visualization of sensor data. For systems interfacing directly with ventilator hardware, a relay driver circuit may be included to control mechanical components.

Software Requirements

The software stack involves both embedded programming and data analytics components. The Arduino IDE is utilized to write and upload embedded C programs to the Arduino Nano, handling sensor interfacing and data communication. On the data processing side, Python 3.x serves as the primary programming language, supported by scientific computing libraries such as NumPy for efficient numerical operations and Pandas for data manipulation and organization. The machine learning model is implemented using Scikit-learn, which provides a streamlined framework for training and deploying the K-Nearest Neighbors (KNN) algorithm on the collected sensor data. To facilitate communication between the Arduino and the Python environment, serial communication libraries such as PySerial are employed. The development environment is compatible with major operating systems, including Windows, Linux, and macOS, ensuring flexibility and accessibility for developers and clinicians alike.

V. WORKFLOW DIAGRAM

The proposed system follows a structured and modular workflow to ensure real-time monitoring, intelligent analysis, and timely alert generation. The entire process can be described in six sequential stages, as outlined below:



1. Sensors:
The system begins with the deployment of biomedical sensors that continuously capture the patient's physiological parameters. The MAX30100 sensor is used to measure oxygen saturation (SpO_2) and heart rate, while the LM35 sensor records body temperature. These sensors are noninvasive, low-power, and suitable for continuous operation, making them ideal for both clinical and home environments.

2.Arduino Controller:
The sensor outputs are interfaced with an Arduino Nano microcontroller, which serves as the primary data acquisition unit. The Arduino is programmed to read analog and digital signals from the sensors at defined intervals. It performs basic preprocessing, such as signal smoothing and filtering, before forwarding the data to the next stage. This microcontroller ensures seamless integration and real-time data flow within the system.
3.IoT Module:
The processed data from the Arduino is transmitted to a central processing unit via an IoT communication module, such as a Wi-Fi or Bluetooth transceiver (e.g., ESP8266). This module enables wireless transmission, allowing for remote monitoring and data access. The IoT capability ensures that healthcare providers can observe patient vitals from a distance, enhancing safety and reducing physical contact—particularly crucial during infectious outbreaks like COVID-19.
4.Data Logging:
Once the data reaches the central server or PC, it is logged and stored in a structured format for further analysis. This data logging module ensures a chronological record of all patient readings, which is essential for tracking health trends over time, auditing system performance, and training machine learning models with realworld data.
5.AI Prediction:
The heart of the system lies in its AI prediction engine. Real-time data is fed into a K-Nearest Neighbors (KNN) model that has been trained on historical patient datasets. By comparing current readings with past labeled data, the algorithm determines if the patient's vitals indicate potential respiratory distress. The KNN model effectively identifies patterns such as declining SpO_2 levels, increased heart rate, or abnormal temperature spikes, which could signal the onset of respiratory complications.

6. Alerts:
When the AI model detects anomalies or patterns associated with respiratory risk, it triggers an alert system. Notifications can be sent via a graphical user interface (GUI), mobile app, or directly to medical personnel through SMS or email. These alerts enable rapid clinical response, allowing timely adjustments in ventilator settings or other medical interventions.

This workflow ensures end-to-end automation—from sensing to prediction and alerting—thereby providing a robust framework for intelligent, real-time respiratory health monitoring. The system's modularity also allows for easy upgrades or integration with hospital information systems and electronic medical records (EMRs).

VI TRAINING AND IMPLEMENTATION

The training and implementation phase of the proposed respiratory distress detection system involves the seamless integration of hardware components for data acquisition and software tools for data analysis, prediction, and alert generation. The system is engineered to ensure real-time functionality, accuracy in prediction, and scalability for various healthcare environments.
6.1 Sensors Used
The system employs two key biomedical sensors for capturing physiological data:
MAX30100 Pulse Oximeter and Heart Rate Sensor: This sensor integrates two light-emitting diodes (LEDs)—one red and one infrared—along with a photodetector to measure SpO_2 and heart rate. It operates on the principle of photoplethysmography, where changes in light absorption correspond to the volume of oxygenated blood. It provides high precision and low noise measurements, making it ideal for clinical applications.

LM35 Temperature Sensor: The LM35 is a widely used analog temperature sensor that offers linear output directly proportional to temperature in degrees Celsius. With a sensitivity of 10 mV/°C and minimal self-heating, it enables continuous and accurate body temperature monitoring, which is crucial for identifying fever—a common symptom of respiratory distress.

Controller Unit

The Arduino Nano microcontroller serves as the system's data acquisition and transmission hub. It reads analog and digital signals from the connected sensors, processes the signals to reduce noise, and sends the processed data to the central system through a serial or IoT communication interface. Its small form factor, low power consumption, and USB programmability make it ideal for wearable or compact medical device implementations.

AI Model and Training

To enable predictive capability, the system incorporates a K-Nearest Neighbors (KNN) algorithm—a supervised machine learning technique known for its simplicity and robustness in classification tasks. The training dataset consists of labeled sensor data representing various patient conditions, including normal respiratory patterns and early signs of distress. Features extracted from the sensor inputs (e.g., SpO_2 percentage, heart rate beats per minute, and temperature values) are used to form the input vector for the model.

During training, the KNN algorithm stores historical data in a multidimensional feature space. When new data is received, the model calculates the Euclidean distance between the new input and the stored samples, then classifies it based on the majority label among the k-nearest data points. This allows the system to predict potential health anomalies in real time, offering early alerts before the onset of severe symptoms.

Software Stack

The implementation is supported by the following software tools:

Arduino IDE: Used to develop and upload embedded C programs to the Arduino Nano, enabling real-time sensor communication and serial data transmission.

Python: Acts as the primary programming environment for data processing and machine learning tasks.

NumPy: Provides efficient handling of numerical data and matrix operations required for realtime signal processing and model computation.

Pandas: Used for structured data storage, preprocessing, and exploratory analysis of the collected sensor data.

Scikit-learn: A powerful machine learning library in Python, used to implement and train the KNN classifier. It provides functions for model training, evaluation, and prediction based on real-time inputs.

6.5 Implementation Summary

The entire system—from data collection to prediction and alert—is designed for endto-end automation. The Arduino board reads physiological data and transmits it to a Python-based application on a PC or cloud server. This application handles logging, visualization, and predictive analysis through the trained KNN model. When thresholds indicating potential respiratory distress are crossed, alerts are triggered to prompt timely clinical response.

This integrated setup ensures that patients under observation receive proactive care, minimizing delays in diagnosis and improving clinical outcomes. The modular nature of the system also supports future enhancements, including cloud connectivity, mobile integration, and additional machine learning techniques

VII. RESULTS AND ANALYSIS

The developed system successfully demonstrated its ability to predict early signs of respiratory distress with a high degree of accuracy. By continuously monitoring vital parameters such as SpO_2, heart rate, and body temperature, the system was able to detect abnormal patterns using the K-Nearest Neighbors (KNN) algorithm. The AI model responded effectively to variations in input data and classified patient conditions accurately in real time.

Real-time visualization of sensor data through plotted graphs provided clear insights into the patient's health trends. These visual outputs made it easier for observers to track sudden drops in oxygen levels, temperature spikes, or irregular heartbeats. The system also generated alerts automatically when predefined thresholds were exceeded, ensuring timely notifications.

The use of the KNN algorithm significantly improved the system's responsiveness and reliability in identifying early-stage respiratory issues. In comparison to traditional manual methods, the AIenhanced monitoring system provided quicker and more consistent feedback, supporting timely ventilator adjustments and clinical interventions.

Overall, the results indicate that the proposed system is effective for continuous respiratory health monitoring and can assist healthcare providers in delivering proactive, data-driven care.

VIII. CONCLUSION

This project successfully demonstrates how the integration of Internet of Things (IoT) technologies with artificial intelligence (AI) can create an efficient, cost-effective, and scalable system for the early detection of respiratory distress. By continuously monitoring vital signs such as oxygen saturation, heart rate, and temperature, and applying a machine learning-based predictive model (K-Nearest Neighbors), the system enables timely identification of potential respiratory complications.

The real-time monitoring and AI-driven alerts provide healthcare professionals with valuable insights that enhance clinical decision-making, leading to faster interventions and improved patient outcomes. Furthermore, the modular design and wireless communication capabilities make this system adaptable to various healthcare environments, including hospitals, home care, and remote patient monitoring.

Overall, this approach highlights the potential of combining IoT and AI to transform traditional healthcare monitoring into a proactive and personalized care model, which is particularly crucial for managing respiratory diseases and improving patient safety.

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