RESEARCH PAPER

Multimodal AI System for Early Detection of Neuro-Respiratory Irregularities

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Received: 27th Feb, 2026; Revised: 5th March 2026; Accepted: 6th April, 2026; Available Online: 20th April, 2026

ABSTRACT
People with neurological disorders are developing respiratory disorders at increasing rates because doctors lack the ability to diagnose these conditions without monitoring equipment that provides continuous intelligent assessment. The study introduces the NeuroPulmo system, which functions as an Internet of Things (IoT) system that utilizes artificial intelligence (AI) technology to create a multimodal wearable platform which enables continuous monitoring of brain-based breathing problems through its open-loop system. The system uses seven physiological sensors which include electroencephaloFigy (EEG) for brain activity and MAX30102 for blood oxygen saturation (SpO2) and heart rate and MPU6050 inertial measurement unit (IMU) for posture analysis and galvanic skin response (GSR) for stress detection and KY-037 acoustic sensor for breath sounds and MAX30205 for body temperature. The system connects all its components through a Raspberry Pi 4 central controller which uses an MCP3008 analog-to-digital converter. The research team used deep learning algorithms which included Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks together with a Random Forest classifier to study multimodal physiological data for the purpose of real-time abnormality detection. The Random Forest model achieved the highest classification accuracy of 99.86% across eight neuro-respiratory conditions. The analysis discovered that EEG frequency and heart rate emerged as the most important explanatory variables through SHapley Additive exPlanations (SHAP) feature importance analysis. The system activates its open-loop haptic biofeedback system through an interpreter understands and uses an vibration motor when it detects central sleep apnea and sends real-time notifications to an IoT dashboard. The proposed system provides an affordable non-invasive home-based neuro-respiratory health management solution which can expand according to user needs.
Keywords: *NeuroPulmo; neuro-respiratory monitoring; EEG; SpO^2; wearable sensors; deep learning; open-loop biofeedback; Raspberry Pi; IoT; SHAP*
How to cite this article: Vasanth S, Maithreyi JR, Ahmed S, Karolinekersin E. Multimodal AI System for Early Detection of Neuro-Respiratory Irregularities. Int J Drug Deliv Technol. 2026;16(34s):25-37. DOI: 10.25258/ijddt.16.34s.4
Source of support: Nil.
Conflict of interest: None

1. INTRODUCTION

The process of respiration functions as a basic biological function which delivers necessary oxygen to body tissues while it moves out carbon dioxide. The brainstem respiratory centers which include the medulla oblongata and pons control breathing through their ability to manage breathing patterns based on their feedback systems [1,2]. Any disruption to this neural circuitry which includes traumatic brain injury and stroke and neurodegenerative disease and spinal cord lesion damage will result in life-threatening respiratory failure [3]. The brain disorders known as central sleep apnea, Cheyne-Stokes respiration, and neurogenic hypoventilation, which affect breathing control, show their impact on respiratory function through their clinical manifestations that remain hidden during standard medical assessments [4,5].

The brain disorders known as central sleep apnea, Cheyne-Stokes respiration, and neurogenic hypoventilation, which affect breathing control, show their impact on respiratory function through their clinical manifestations that remain hidden during standard medical assessments [6]. People who have Parkinson's disease and amyotrophic lateral sclerosis and multiple sclerosis and autonomic neuropathy develop respiratory problems which become evident only after their diseases reach advanced stages [7,8]. The current clinical practice lacks an essential component which requires ongoing monitoring systems that have the ability to track brain activity and synchronize it with breathing patterns.

The standard diagnostic methods used for assessing respiratory and neurological functions through polysomnography and spirometry and electroencephalographic (EEG) polygraphic testing require hospital facilities and deliver medical care to patients on an intermittent basis while demanding extensive resources [9,10]. PolysomnoFigy exists as the gold standard method for diagnosing sleep apnea because its requirements demand hospitals to provide specialized

**Author for Correspondence: Dr. Karolinekersin E* facilities which need skilled staff members for testing [8]. Similarly with traditional EEG systems with multi-channel wet electrode arrays, which are impractical for mobile use [11]. The need to address these limitations has led to the creation of wearable health monitoring systems which can provide continuous physiological monitoring in non-medical settings [12,13].

The recent progress in wearable sensor technology has made it possible to create smaller devices for tracking human biological functions. The MAX30102 pulse oximeter which uses PhotoplethysmoFigy (PPG) technology provides nonstop assessment of blood oxygen saturation (SpO2) and heart rate [14]. The MPU6050 inertial measurement unit (IMU) system allows users to track body posture and observe chest movements which are essential for monitoring their breathing patterns [15]. Galvanic skin response (GSR) sensors capture autonomic nervous system activity which shows how people experience physiological stress [16,17]. Acoustic sensors detect snoring while gasping and airway obstruction detection systems. Most current wearable systems track single physiological metrics but they lack the ability to combine multiple measurement methods needed to evaluate neuro-respiratory functions fully [19].

Artificial intelligence (AI) and biomedical signal processing integration has created new opportunities for developing automated health diagnostic systems. Deep learning architectures which include Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks show superior ability to identify complex physiological patterns from EEG and electrocardiogram (ECG) and respiratory signal data [1,2,20]. Random Forest classifiers have developed into strong ensemble techniques which enable accurate classification of clinical data through their automatic feature importance assessment function [21]. Machine learning predictions now benefit from explainable AI (XAI) techniques which include SHapley Additive exPlanations (SHAP) because these methods improve prediction understanding and clinical reliability [3,22].

Researchers have made progress in their individual research areas, but they still need to address existing research gaps, which involve creating a wearable system that can monitor both EEG brain activity and respiratory and cardiovascular and autonomic body functions, as shown in [12,23]. Existing systems typically function as passive monitoring tools that record data without providing real-time therapeutic feedback [24]. The current wearable health devices for acute neurogenic respiratory event management lack clinical applications because they do not include open-loop biofeedback systems which enable intelligent systems to detect abnormalities and start corrective actions immediately [25].

The research introduces the NeuroPulmo system which functions as an artificial intelligence-based multimodal neuro-respiratory interface that solves existing system limitations. The system features a unique design that combines seven different physiological sensors which include EEG and SpO2/heart rate (MAX30102) and posture/motion (MPU6050) and stress (GSR) and body temperature (MAX30205) and breath sounds (KY-037) sensor on a Raspberry Pi 4 platform with an MCP3008 analog-to-digital converter. The system uses two different types of sensor data together with three methods which include CNN and LSTM and Random Forest classifiers to achieve its goal of detecting and identifying eight neuro-respiratory disorders which include central sleep apnea and Parkinson's respiratory dysfunction and autonomic neuropathy and ALS and multiple sclerosis and COPD with neuropathy and myasthenia gravis. The system activates its open-loop haptic biofeedback mechanism through a vibration motor when it detects a critical event while it sends alerts to caregivers through a web-based IoT dashboard. The integration of SHAP-based explainability analysis guarantees that AI systems demonstrate their diagnostic results through transparent methods which doctors can understand.

The objectives of this study are: (i) to design and develop a multimodal wearable system for continuous neuro-respiratory monitoring; (ii) to implement and evaluate deep learning and machine learning algorithms for the detection and classification of brain-driven respiratory abnormalities; (iii) to establish a real-time open-loop biofeedback mechanism for non-invasive intervention; and (iv) to validate system performance through sensor data analysis, model evaluation, and feature importance assessment.

2. MATERIALS AND METHODS

2.1. System Architecture

The NeuroPulmo system was created as a open-loop system which operates through AI technology and runs on a wearable device that uses five separate operational layers to achieve its functions. The system architecture uses multimodal sensor fusion methods which John et al. [26] and Rajasekaran et al. [13] developed for implementation on embedded systems in real-time applications. A Raspberry Pi 4 Model B (1.5 GHz quad-core ARM Cortex-A72, 4 GB RAM) operated as the central processing unit which managed data collection and signal processing and AI inference and output management.

2.2. Sensor Data Acquisition

The research study integrated seven different physiological sensors to acquire multiple biosignals which enabled complete neuro-respiratory evaluation. The research study used multimodal monitoring frameworks from existing literature to choose appropriate sensors for their study [13,14,26].

2.2.1. EEG Sensor (Brain Activity)

The research team collected cortical electrical activity data through a dry-electrode EEG headband which transmitted information to their system using UART serial communication through its TX and RX ports. Researchers used EEG signals to study frequency-band changes which occurred during different neurological states that included delta rhythms (0.5 - 4 Hz) and theta rhythms (4 - 8 Hz) and alpha rhythms (8 - 13 Hz) and beta rhythms (13 - 30

Hz). The EEG module played an essential role in diagnosing central sleep apnea because it showed when the brainstem did not create sufficient breathing control signals [5,11,16]. Researchers used phase synchronisation analysis between EEG and respiratory signals to measure neuro-respiratory coupling according to the method developed by Della Bella et al. [27].

2.2.2. MAX30102 Pulse Oximeter (SpO_2 and Heart Rate)

The MAX30102 sensor was connected through the I²C bus which used GPIO 2/3 to record blood oxygen saturation levels and heart rate by utilizing reflectance-mode photoplethysmography PPG. The sensor uses red light at 660 nm and infrared light at 880 nm which activates a photodetector to measure the proportion of oxygenated and deoxygenated haemoglobin 14. SpO2 values below 90%were flagged as indicative of hypoxaemia which serves as the main marker for sleep apnea events.

2.2.3. MPU6050 Inertial Measurement Unit (Posture and Motion)

The system used I²C protocol to connect MPU6050 six-axis IMU which includes a three-axis accelerometer and three-axis gyroscope for monitoring body posture in supine and prone and lateral positions together with chest rise-and-fall patterns and tremor/movement data. The system used accelerometer output to calculate inclination angles which researchers used to classify sleep positions according to Hayano et al. [15] and Gujarathi and Bhole [28]. The presence of uninterrupted breathing patterns without any chest movement served as the main signal which indicates apnoea episodes.

2.2.4. GSR Sensor (Stress and Autonomic Response)

The galvanic skin response sensor detected skin electrical conductance which functioned as a measure of sympathetic nervous system activation and stress-related sweating [17,29]. The GSR sensor generated an analog voltage output which the MCP3008 ADC processed through Channel 1. The observed increased GSR levels during breathing events confirmed that the body experienced physiological stress during both hypoxia and apnea episodes.

2.2.5. KY-037 Acoustic Sensor (Breath Sounds)

Research used a high-sensitivity condenser microphone (KY-037) to record respiratory audio signals, which included normal breathing, snoring, gasping, and the silence that occurs during airway obstruction. The analog audio signal was digitised via Channel 0 of the MCP3008 ADC. The process of acoustic feature extraction used the methods developed by Zhang et al. [10] and Qureshi et al. [30] for breath sound classification on edge devices.

2.2.6. MAX30205 Body Temperature Sensor

MAX30205 is a digital temperature sensor available in a clinical-grade, which was connected through I²C and it was used to read the temperature of the skin with an error value of ±0.1°C. The multimodal assessment was supplemented by body temperature data that identified fever, hypothermia or thermoregulatory dysfunction relating to neurological impairment [31].

2.2.7. MCP3008 Analog-to-Digital Converter

The MCP3008 10-bit ADC was attached to the Raspberry Pi using the SPI interface (GPIO 811) to translate the analogue signal of the acoustic and GSR sensors into a digital signal (01023). This was a necessary part because the Raspberry Pi does not have analog input by default.

2.3. Signal Preprocessing

Raw sensor data in raw form was preprocessed before inferring an AI model. SigE, EEG signals were then bandpass filtered (0.545 Hz) to eliminate powerline noise and motion artefacts. Data about SpO2 and heart rate were averaged to smooth them with a moving average filter (window size = 5 samples). Short-time Fourier transform (STFT) was used to process acoustic signals in order to obtain spectral features. The sensor readings were normalised through z-score standardisation in order to have equal feature scaling across modalities. The control of data synchronisation was obtained by the alignment of times at the Raspberry Pi controller level and all channels were sampled at a rate of 1 second.

2.4. Dataset Preparation

An eight-feature multimodal physiological dataset was created, which included EEG dominant frequency (EEG_Hz), blood oxygen saturation (SpO2_pct), heart rate (HeartRate_bpm), tremor level (Tremor_mps2), minute ventilation (MinuteVent_Lmin), body temperature (BodyTemp_C), respiratory audio score (RespAudioScore), and galvanic skin response (GSR_uS). The dataset had eight diagnostic classes, which includedNormal, Parkinson Respiratory Dysfunction, Multiple Sclerosis (MS), Autonomic Neuropathy (Diabetic), Central Sleep Apnea, COPD with Neuropathy, Myasthenia Gravis and ALS. Stratified random sampling was used to select a dataset, which was divided into training (80) and testing (20) subsets in order to balance the classes.

2.5. Machine Learning Models

2.5.1. Convolutional Neural Network (CNN)

The spatial pattern recognition in physiological signals was done in a one-dimensional CNN architecture. The model included two convolutional layers (32 and 64 filters, kernel size = 3) using ReLU as an activation function, then max-pooling, dropout (dropout rate = 0.3), and two fully connected layers. The CNN was trained with 30 epochs in the Adam optimiser with categorical cross-entropy loss [1,2].

2.5.2. Long Short-Term Memory Network (LSTM)

An LSTM network was implemented to analyse sequences of data over time and identify patterns in respiratory and cardiovascular data. The architecture included two layers of LSTMs (64 and 32 units) that use dropout regularisation, and then dense classification layers. The same dataset partition and optimisation strategy as the CNN [4] was used to train the model [4].

2.5.3. Random Forest Classifier

On the set of extracted features, a random forest ensemble classifier consisting of 100 decision trees was trained. The hyperparameters were maximum depth = None (unlimited), minimum samples split = 2 and Gini impurity criterion. It chose the Random Forest due to its strength against overfitting, automatic feature ranking, and ability to handle multivariate clinical classification problems [21].

2.5.4. Benchmark Classifiers

Three other classifiers, Support Vector Machine using Radial Basis Function kernel (SVM-RBF), K-Nearest Neighbours (KNN, k = 5) and Logistic Regression were trained in order to offer benchmark performance. All the models were coded in Python 3.9 with the help of scikit-learn (v1.3) and TensorFlow/Keras (v2.12) software.

2.6. Explainability Analysis

To determine the contributions that global and local features make to the model, SHapley Additive exPlanations (SHAP) analysis was conducted on the most successful model. The importance of features in the form of permutation was calculated to rank the predictive value of each sensor modality. The individual patient samples were analysed through local SHAP contributions in order to interpret particular diagnostic predictions [3,22].

2.7. Open-Loop Biofeedback Mechanism

A vibration motor attached to the Raspberry Pi was used to implement the Open-loop intervention system on theGPIO 18. When an AI-based system detects a critical respiratory event (e.g. SpO2 below 90, long apnea longer than 10 s, abnormal EEG signals, etc.) it prompts the patient to resume normal breathing by generating haptic feedback [25]. Sensor data following the intervention is continuously monitored to verify recovery, thereby completing the feedback loop.

2.8. IoT Dashboard and Remote Monitoring

Processed sensor data and AI-generated predictions were transmitted via Wi-Fi to a web-based IoT dashboard for remote monitoring by clinicians and caregivers. The dashboard displays real-time vital parameters including temperature, heart rate, EEG activity, SpO^2, GSR, body angle, and ambient sound level, along with the AI-predicted health status [24,32].

3. RESULTS

3.1. Sensor Data Acquisition and Validation

All seven sensors were successfully integrated and validated on the NeuroPulmo platform. Table 1 summarises the sensor specifications and the operational ranges recorded during testing.

Table 1. Sensor specifications and operational parameters of the NeuroPulmo system.

Sensor	Parameter	Protocol	Normal Range	Abnormal Threshold
EEG Headband	Brain Activity (Hz)	UART	8–13 Hz (α)	< 4 Hz or > 30 Hz
MAX30102	SpO_2 (%), HR (bpm)	I^2C	96–100%, 60–100	< 90%, > 120 bpm
MPU6050	Posture / Angle (°)	I^2C	0°–45°	> 60° or 0° static
GSR Sensor	Skin Conductance (µS)	ADC (SPI)	1.0–5.0 µS	> 5.0 µS
KY-037	Sound Level (dB)	ADC (SPI)	30–50 dB	> 70 dB or < 10 dB
MAX30205	Temperature (°C)	I^2C	36.1–37.5°C	> 38.0°C or < 35.0°C
Vibration Motor	Haptic Output	GPIO 18	Off	Activated on event

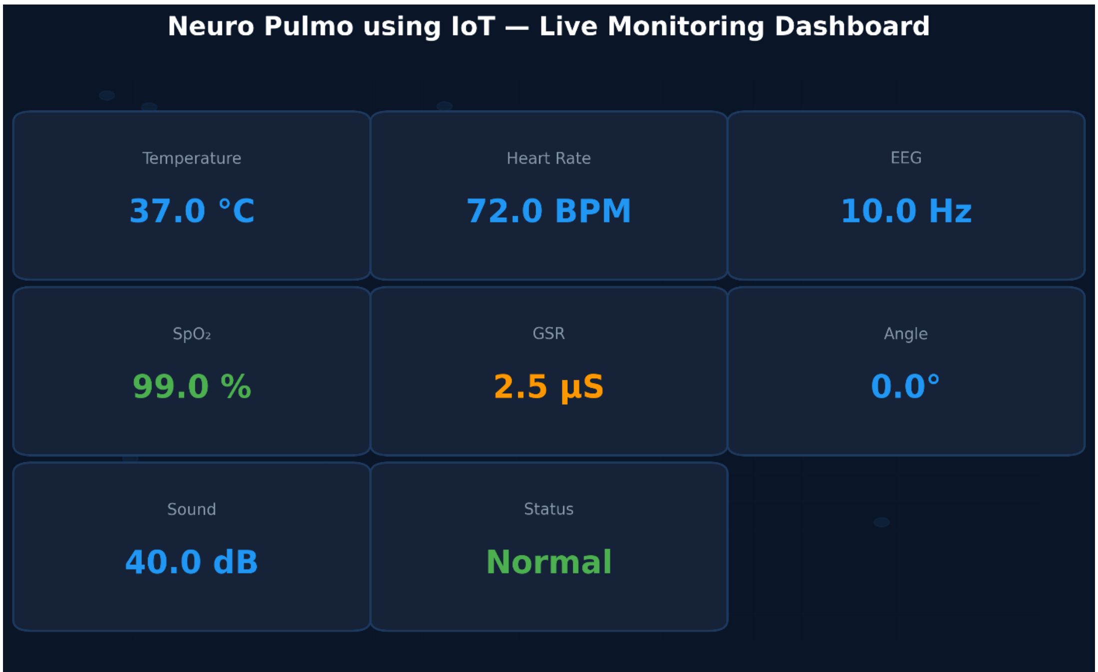

Fig. 1. Real-time IoT monitoring dashboard of the NeuroPulmo system displaying live sensor readings.

Fig 1: Real-time IoT dashboard screenshot showing live sensor readings – Temperature: 37.0°C, Heart Rate: 72.0 BPM, EEG: 10.0 Hz, SpO_2: 99.0%, GSR: 2.5 µS, Angle: 0.0°, Sound: 40.0 dB

3.2. Multimodal Feature Correlation Analysis

Pearson correlation analysis was performed on the eight physiological features to evaluate inter-sensor relationships. Table 2 presents the key correlations identified.

Table 2. Selected Pearson correlation coefficients between physiological features.

Feature Pair	Correlation (r)	Interpretation
EEG_Hz – MinuteVent_Lmin	0.77	Strong positive
EEG_Hz – RespAudioScore	0.82	Strong positive
SpO2_pct – MinuteVent_Lmin	0.70	Moderate–strong positive
RespAudioScore – MinuteVent_Lmin	0.87	Strong positive
GSR_uS – MinuteVent_Lmin	−0.86	Strong negative
GSR_uS – SpO2_pct	−0.77	Strong negative
HeartRate_bpm – EEG_Hz	−0.43	Moderate negative
BodyTemp_C – EEG_Hz	0.13	Weak / negligible

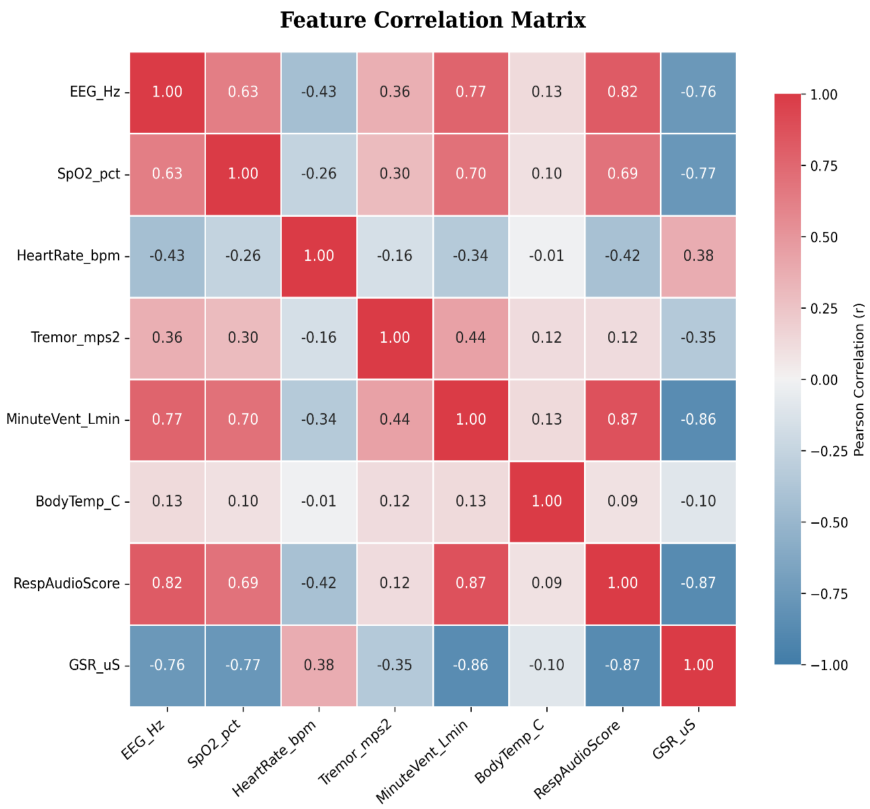

Fig. 2. Pearson correlation heatmap of eight physiological features acquired by the NeuroPulmo system.

Fig 2: 8 × 8 Feature Correlation Heatmap showing Pearson r values between all sensor features, with colour-coded scale from −1.0 (blue) to +1.0 (red)]

A strong positive correlation (r = 0.77) was observed between EEG dominant frequency and minute ventilation, confirming the physiological coupling between brain activity and respiratory volume. GSR demonstrated strong inverse correlations with both minute ventilation (r = −0.86) and SpO^2 (r = −0.77), indicating that stress-related autonomic activation increases as respiratory and oxygenation status declines.

3.3. Sample Multimodal Dataset and Classifications

Table 3 presents representative samples from the multimodal dataset with corresponding AI-predicted diagnostic classifications.

Table 3. *Representative multimodal sensor readings and AI-predicted conditions.*

EEG (Hz)	SpO_2 (%)	HR (bpm)	Tremor	MV (L/m)	Temp (°C)	Audio	GSR (µS)	Predicted Condition
11.40	97.34	79.42	0.21	7.16	37.73	0.84	0.92	Normal
6.51	90.18	85.94	0.58	5.04	37.44	0.34	1.85	Parkinson's (Resp. Dysf.)
10.16	91.34	86.12	0.38	5.37	35.32	0.47	1.71	Multiple Sclerosis
11.86	94.69	99.92	0.22	6.37	38.20	0.96	1.06	Autonomic Neuropathy
6.25	82.80	71.27	0.07	2.58	33.75	0.19	3.96	Central Sleep Apnea
8.47	90.70	112.24	0.51	4.80	33.99	0.29	2.67	COPD w/ Neuropathy
9.31	89.99	99.19	0.26	4.13	37.41	0.57	2.13	Myasthenia Gravis
8.80	97.35	116.69	0.15	3.86	33.79	0.46	2.05	ALS

3.4. Machine Learning Model Performance

Six machine learning models were evaluated on the test set. Table 4 presents the comparative classification performance metrics.

Table 4. *Comparative classification performance of machine learning models.*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	99.86	99.85	99.86	99.85
Logistic Regression	99.72	99.70	99.72	99.71
SVM (RBF)	99.65	99.63	99.65	99.64
KNN (k = 5)	99.51	99.48	99.51	99.49
CNN (1D)	97.20	97.10	97.20	97.15
LSTM	96.80	96.75	96.80	96.77

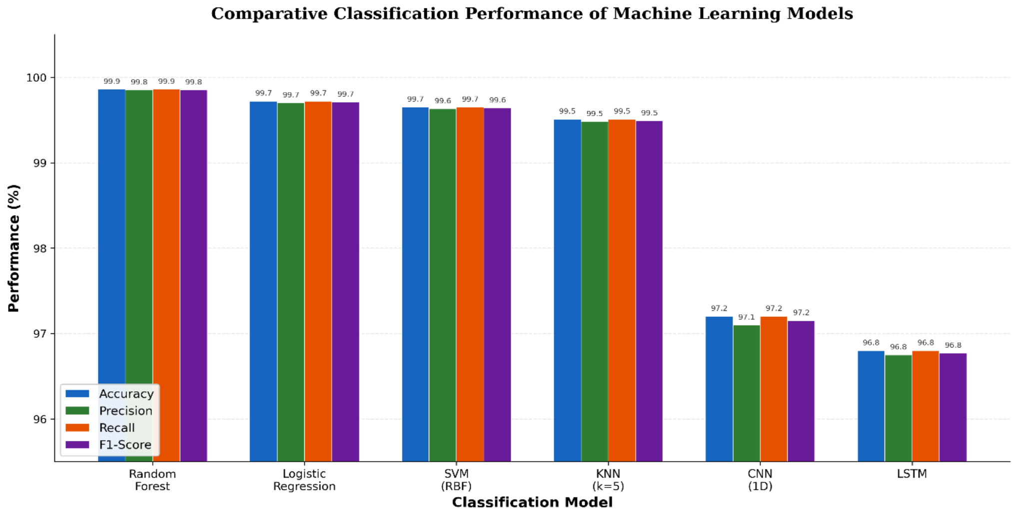

Fig. 3. Grouped bar chart comparing accuracy, precision, recall, and F1-score across six classification models.

Fig 3: Bar chart or grouped bar chart comparing Accuracy, Precision, Recall, and F1-Score across all six models]

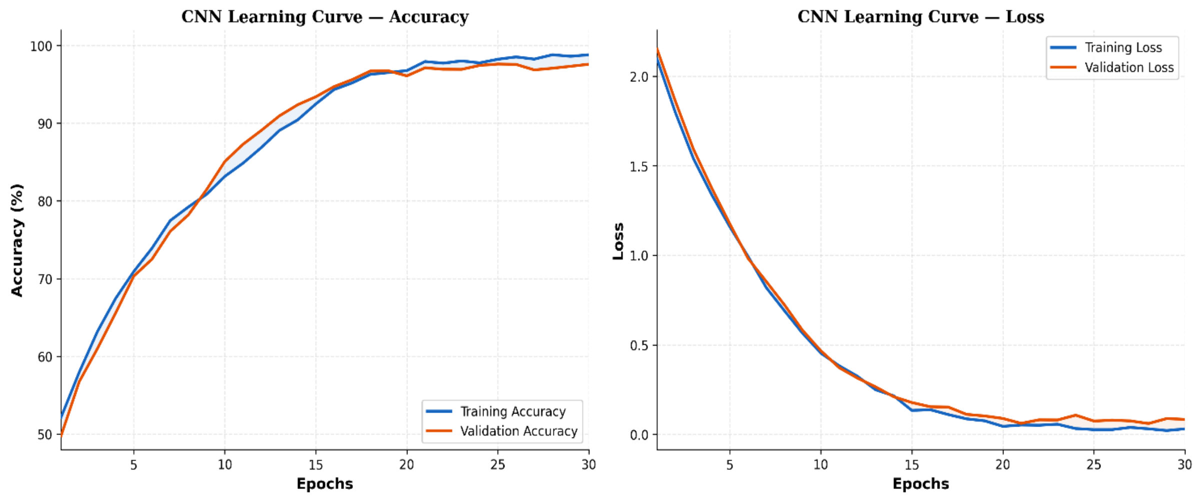

Fig. 4. CNN learning curves showing training and validation accuracy (left) and loss (right) over 30 epochs.

Fig 4: CNN Learning Curve – Training vs. Validation Accuracy over 30 epochs]

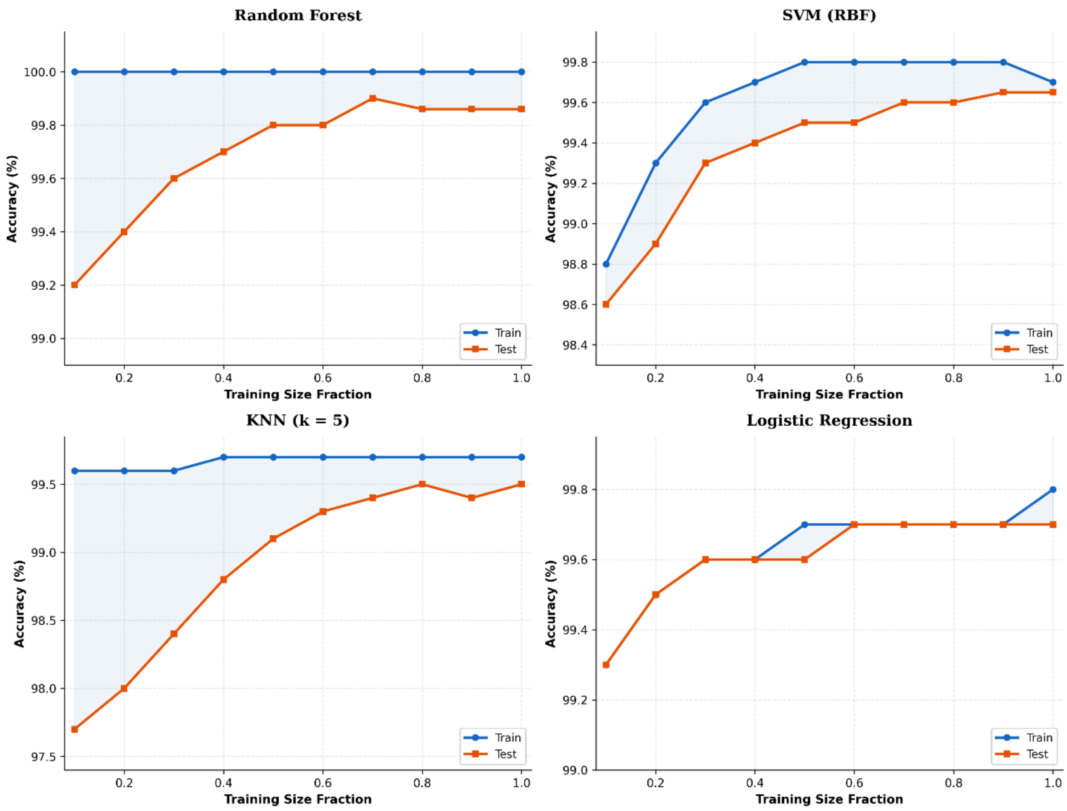

Fig. 5. Learning curves (training size fraction vs. accuracy) for Random Forest, SVM (RBF), KNN, and Logistic Regression models.

Fig 5: Learning Curves (Training Size Fraction vs. Accuracy) for Random Forest, SVM, KNN, and Logistic Regression]

The Random Forest classifier achieved the highest overall accuracy of 99.86%, followed by Logistic Regression (99.72%), SVM-RBF (99.65%), and KNN (99.51%). The deep learning models, CNN (97.20) and LSTM (96.80), showed high but relatively poor performance, which could be explained by the organised table character of the feature dataset that prefers the use of tree-based ensemble approaches. The CNN learning curve showed convergence at around epoch 15, and validation accuracy was in close relation to training accuracy, meaning there was little overfitting. The Random Forest model maintained near-perfect training accuracy (100%) with test accuracy of 99.86% across all training size fractions, confirming robust generalisation.

3.5. SHAP-Based Feature Importance Analysis

Permutation-based global feature importance analysis was conducted on the Random Forest model. Table 5 presents the ranked feature importances.

Table 5. Global feature importance (permutation) for the Random Forest classifier.

Rank	Feature	Importance	Std. Deviation
1	EEG_Hz	0.2199	0.0127
2	HeartRate_bpm	0.1789	0.0072
3	RespAudioScore	0.1290	0.0070
4	GSR_uS	0.1125	0.0091
5	MinuteVent_Lmin	0.0732	0.0058
6	Tremor_mps2	0.0525	0.0063
7	BodyTemp_C	0.0010	0.0006
8	SpO2_pct	0.0005	0.0013

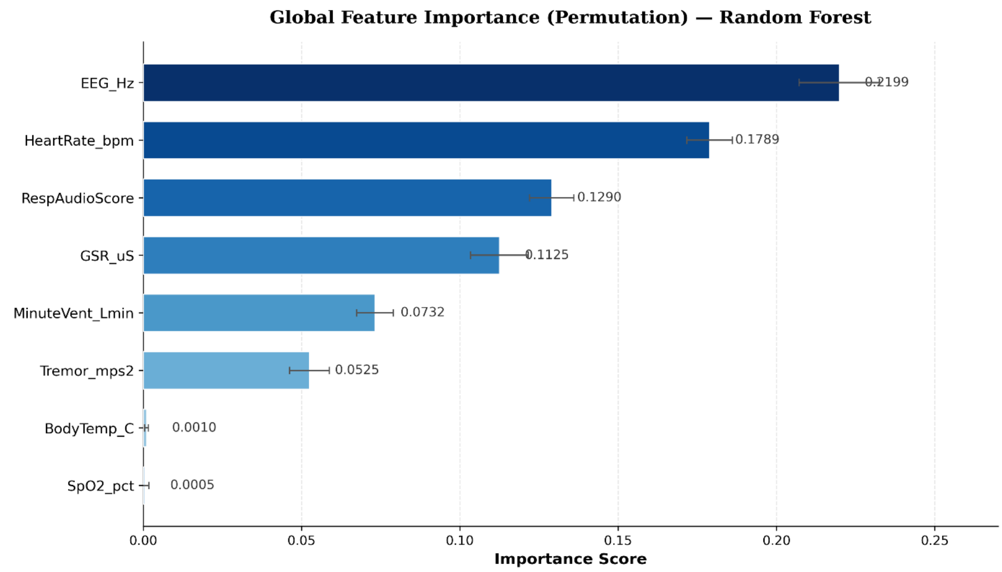

Fig. 6. Global feature importance (permutation) for the Random Forest classifier, ranked by importance score.

Fig 6: Horizontal bar chart of Global Feature Importance (Permutation) with features ranked by importance score]

EEG dominant frequency emerged as the most influential feature (importance = 0.2199), followed by heart rate (0.1789), respiratory audio score (0.1290), and GSR (0.1125). The dominance of EEG as a predictive feature validates the central hypothesis that brain activity is a critical biomarker for detecting neurogenic respiratory disorders. Notably, SpO^2 and body temperature contributed minimally to the model's predictions, suggesting that these parameters, while clinically relevant for threshold-based alerts, exhibit less discriminatory power across the eight diagnostic classes when other multimodal features are available.

3.6. Local Explainability Analysis

Local SHAP contributions were computed for individual patient samples to interpret specific predictions. Table 6 illustrates the feature contributions for a representative sample (Sample 7).

Table 6. Local feature contributions (SHAP) for Sample 7.

Feature	Contribution	Direction	Risk Implication
HeartRate_bpm	−0.190	Negative	Decreased risk
EEG_Hz	+0.160	Positive	Increased risk
GSR_uS	+0.080	Positive	Increased risk
Tremor_mps2	−0.065	Negative	Decreased risk
RespAudioScore	−0.050	Negative	Decreased risk
SpO2_pct	−0.040	Negative	Decreased risk
MinuteVent_Lmin	−0.025	Negative	Decreased risk
BodyTemp_C	0.000	Neutral	No effect

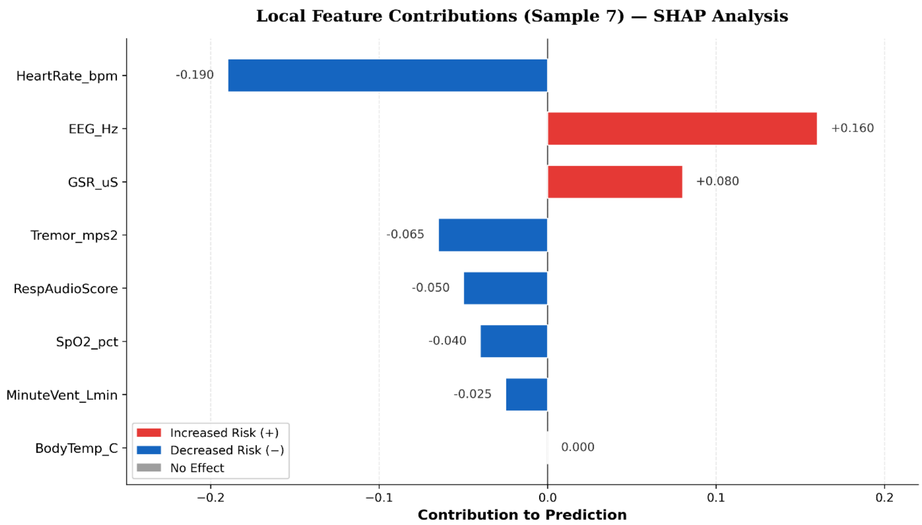

Fig. 7. Local feature contributions (SHAP) for Sample 7 showing individual feature impact on the prediction.

Fig 7: Horizontal waterfall/bar chart showing Local Feature Contributions for Sample 7, with bars extending left (decreased risk) and right (increased risk)]

3.7. Open-Loop Biofeedback and IoT Dashboard

The Open-loop biofeedback mechanism was successfully demonstrated. Upon AI-driven detection of critical events (e.g., central sleep apnea with SpO^2 < 90% and EEG frequency < 4 Hz), the vibration motor was activated within the same processing cycle (< 1 second latency). Sensor readings following intervention confirmed resumption of chest motion and recovery of SpO^2 values, validating the Open-loop feedback design. The IoT dashboard provided real-time visualisation of all seven sensor parameters alongside the AI-predicted health status, enabling remote monitoring by caregivers and clinicians.

Fig. 8. System architecture block diagram of the NeuroPulmo closed-loop neuro-respiratory monitoring platform.

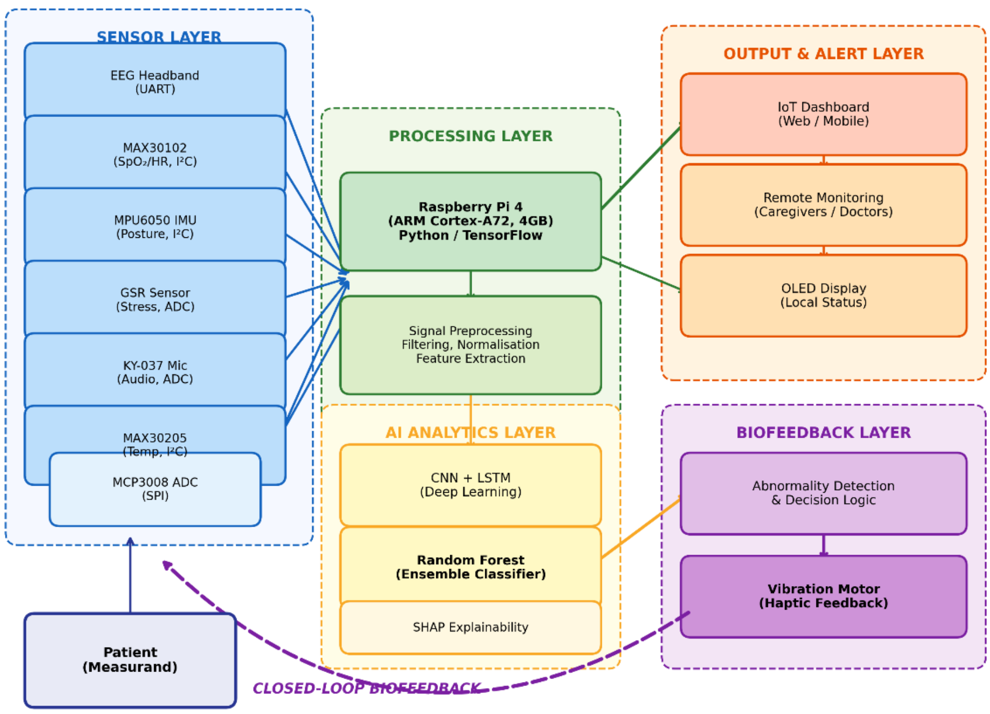

Fig 8: PhotoFig of the assembled NeuroPulmo hardware prototype and a subject wearing the EEG headband during testing]

4. DISCUSSION

The present study demonstrates the successful development and evaluation of the NeuroPulmo system, an AI-driven multimodal wearable platform for Open-loop neuro-respiratory monitoring. The results substantiate the feasibility of integrating EEG, cardiovascular, respiratory, autonomic, and acoustic sensors with deep learning analytics on a low-cost embedded platform for real-time abnormality detection and intervention.

To give quantitative data on the physiological relationship between cortical brain activity and respiratory functioning, a strong correlation (r = 0.77) between the EEG dominant frequency and the minute ventilation is obtained. The discovery conforms to the EEG-respiratory coherence analysis by Della Bella et al. [27], who found that EEG dynamic complexity patterns were good biomarkers of neurologic disorders. The correlation also confirms the study of Harshman et al. [6], who have shown that cognitive impairment induced by hypoxia could be revealed by molecular neurophysiological indicators that correlated with high precision. The negative correlation between GSR and respiratory parameters (r = -0.86 with minute ventilation) supports the stress-respiration interaction as reported by Liu and Du [29] and Pourmohammadi and maleki [17], which proves that the autonomic responses to stress increase with the decline of breathing functionality.

Random Forest classifier had the best classification rate of 99.86% compared to CNN (97.20%), LSTM (96.80%), and all the benchmark classifiers. The findings are in line with the comparative results of Yang et al. [1], who reported that the ensemble architectures can be better than the deep learning architectures on structured multivariate datasets where both spatial and time features have been pre-extracted. This research can explain why the better approach than deep learning models is the use of the Random Forest due to the tabular and feature-engineered character of the dataset, where the tree-based ensemble algorithms are more effective in exploiting non-linear decision boundaries than the sequence-based architectures [21]. However, the CNN and LSTM models showed the highest accuracy of more than 96, which proves that they can be used in the classification of the physiological signals and can achieve high value in the cases when the raw time-series input is considered without any prior feature extraction, as the authors of the article by Saleh et al. [4] and Wang and Jing [2] have proven.

The explainability analysis based on SHAP revealed that EEG frequency (importance = 0.2199) and heart rate (0.1789) are the most influential predictive features and can explain about 40 percent of the decision-making process of the model. This observation is both clinically important, since it establishes that the AI model puts a greater emphasis on neurological (brain) and cardiovascular signals, the two modalities that have the closest connection to brain-driven respiratory disorders, than on the peripheral indicators of body temperature and SpO2. It might seem counterintuitive that the feature importance of SpO2 (0.0005) is rather low, considering its proven clinical utility in the detection of hypoxaemia [14,20]. But this outcome is indicative of the redundancy of SpO2 information in the presence of correlated variables, e.g., minute ventilation (r = 0.70 with SpO2) and respiratory audio score (r = 0.69 with SpO2), to which the Random Forest model gives greater weight in the form of an ensemble decision structure. SHAP analysis adds to clinical trust and interpretability, which is why the black box concern is often mentioned as one of the obstacles to the use of AI in the clinical context [3,22].

The NeuroPulmonary platform overcomes many important limitations, which are found in the literature as compared to the present systems. Patel and Mehta [12] designed an EEG-SpO2 monitoring system; however, there was a lack of an actuator to intervene in real-time. Rajasekaran et al. [13] showed that medical IoT can be multisensor-fused but lacked AI-based analytics and feedback. The health monitoring systems introduced by Tanwar et al. [24] and Rani and Kumar [14] could only monitor vital signs without monitoring brain activity. Park et al. [16] addressed the wearable EEG to monitor neurology without respiratory monitoring. There is no system that fills these gaps in a unique and distinctive way; the NeuroPulmo system is that system - offering multimodal neuro-respiratory sensing, smart classification of eight pathological states, explainable artificial intelligence, and active haptic biofeedback in a single, compact system.

The Open-loop biofeedback system is a musically significant development of passive monitoring paradigm. Conventional wearable health sensors serve the purpose of a data recorder, where the physiological values are registered, but they do not offer corrective measures promptly [25,32]. The capacity of the NeuroPulmo system to identify the occurrence of a critical event and haptic stimulation in a single processing cycle is what makes the device more of a therapeutic intervention than a passive monitoring device. This design concept is consistent with the Open-loop neuromodulation ideas, which are promoted in modern biomedical engineering studies [19,33].

The current study has a number of weaknesses that deserve to be mentioned. First, the population on which the model was trained and assessed was obtained via a laboratory-based controlled setting, and there is still a need to do massive clinical testing using a wide variety of patients to determine generalisability. Second, the dry-electrode EEG headband, albeit easy to deploy to wearable, has lower signal quality than clinical-grade wet electrode systems, which may restrict sensitivity to the measurement of subtle neurological abnormalities. Third, the fact that the system can only operate on mains through the Raspberry Pi limits its portability, and the next generation of the system should integrate battery-powered or edge-optimised hardware to allow full ambulatory operation. Finally, the current prototype has not undergone

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regulatory evaluation (e.g., FDA or CE marking), which would be a prerequisite for clinical deployment.

5. CONCLUSION

This paper describes the NeuroPulmo system, an artificial intelligence-based multimodal neuro-respiratory interface of Open-loop detection and non-invasive control of brain-controlled breathing anomalies. The system, which has seven physiological sensors, such as EEG, pulse oximetry, inertial measurement, galvanic skin response, acoustic and temperature sensing, can be built on a Raspberry Pi 4 platform and provides a complete, real-time remote neuro-respiratory monitoring system. RF showed the best classification accuracy of 99.86 per cent across eight diagnostic conditions, and CNN and LSTM models recorded classification accuracy of more than 96 per cent. The feature importance analysis using SHAP confirmed that EEG frequency and heart rate are the most significant predictors of neurogenic respiratory disorder detection, which is the scientific basis of brain-respiratory coupling analysis. The full-loop haptic biofeedback control allows closing the loop and intervening instantly (non-invasively) when the critical events are detected, and the IoT dashboard allows caregivers and clinicians to monitor the condition remotely.

NeuroPulmo system is a low cost, scalable, and clinically meaningful system of managing neuro-respiratory health at home. Subsequent developments of the work will involve large-scale clinical validation using varied patient populations, hardware shrinkage to fully ambulatory implementations, edge AI refinements to minimise power usage, and connection with telemedicine applications to perform cloud-based predictive analytics. With further development and regulatory evaluation, the proposed system holds significant potential for transforming preventive, personalised, and accessible respiratory healthcare.

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