ORIGINAL ARTICLE

An Integrated Wearable Nasal Humidity Sensor with Deep AI for Continuous Respiratory Assessment

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ABSTRACT

Introduction: In physiological assessment, analyzing variations in breathing patterns under different conditions: normal breathing, deep breathing, physical exertion, and recover is crucial. This study focuses on leveraging deep learning algorithms to identify and interpret these variations, providing valuable insights into an individual's physiological state. An integrated wearable nasal based flexible humidity sensor that captures the variations from right and left nostrils, with deep-AI model to monitor the respiratory activities has been proposed in this study. This work presents a miniaturized sensor with electronics assembly fixed to the medical mask, using which respiratory activities such as normal breathing, deep breathing, rapid breathing and shallow breathing were assessed. **Materials and methods:** An ensemble model constructed with a combination of One Dimensional Convolutional Neural Network(1D CNN), Long Short-Term Memory(LSTM) deep neural network model, and Support Vector Machines(SVM) was deployed to classify the breathing status during different tasks using humidity signals from right and left nostrils individually and in combination. The study was conducted with 82 healthy volunteers with 2 trials after obtaining ethical clearance. **Results:** The integrated framework demonstrated an overall accuracy, F1-score, and Matthews Correlation Coefficient (MCC) of 92%, 0.91, and 0.894, respectively, for combined nostril data. For individual nostril data, the right nostril achieved 88%, 0.87, and 0.842, while the left nostril reached 63%, 0.61, and 0.505. **Conclusion:** These results highlight the superior performance of combined nostril data, showcasing the potential of this wearable system for real-time respiratory monitoring and emotional analysis.
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INTRODUCTION

Wearable breathing assessment tools that capture nasal airflow signals are crucial in monitoring respiratory health in real time. These devices provide continuous, non-invasive tracking of breathing patterns, enabling early detection of respiratory issues such as sleep apnea, asthma or chronic obstructive pulmonary diseases (COPD). By measuring nasal airflow, they offer precise insights into airflow obstruction or irregularities, which can be vital for timely medical intervention. Additionally, these tools enhance patient comfort and mobility, allowing for seamless integration into daily life while maintaining a close watch on respiratory health. Also, nasal-based wearable sensors provide researchers and clinicians with valuable data to study respiratory health patterns in various populations as it offers non-invasive tracking of breathing patterns, airflow signals and other respiratory vitals. This can lead to a better understanding of respiratory diseases and the development of new treatments and interventions (1-4). There are different nasal-based sensors available for the assessment of breathing patterns such as thermistor sensors, pressure sensors, carbon dioxide sensors, flow sensors, optical sensors, piezo-electric sensors, acoustic sensors, and humidity sensors (5). The humidity sensors provide a more accurate measurement of breath signals due to significant variations in the humidity of airflow signals between inhaled air and exhaled air. The exhaled air is saturated with moisture, and the humidity level and can provide direct information about the breath. Unlike other sensors that measure secondary effects (e.g., temperature changes, pressure fluctuations), humidity sensors directly detect the moisture content in exhaled air, making them more sensitive to certain respiratory changes, finding its application in monitoring chronic respiratory conditions like Asthma, COPD and other lung infections (6-9). Moreover, nasal-based wearable breathing assessment devices with humidity sensors support the tracking of athlete's respiratory health by giving them immediate feedback on their breathing patterns, assisting in the identification of any inefficiencies or irregularities, and helping them to optimize their breathing techniques for increased endurance and performance (10-13).

The investigation into creating a wearable with a variety of sensors for respiratory assessment is ongoing. Different methods have been presented by researchers to evaluate the nasal airflow signals. A printed graphite electrode-driven paper-based humidity sensor was designed and fabricated and was attached to a typical medical mask for respiratory monitoring (14). With off the shelf electronics components and a rechargeable 5V battery and Arduino microcontroller, a Bluetooth enabled device collects the respiratory signal and displays the pattern. Simulation was carried out for continuous monitoring while the subject was at rest and walking. Han-Sem Kim et al., proposed carbon nanotube-based humidity sensors for wearable respiratory monitoring applications. The proposed Nano composite materials showed good humidity properties and material characteristics and the study revealed the potential usage of the developed material for continuous respiratory monitoring. It was shown that the designed flexible humidity sensors outperformed other resistance-based humidity sensors that were already reported in the literature. The study doesn't reveal the microelectronic assembly used for the biopotential recordings. Activities like normal, fast, and deep breathing recordings were shown and the results were reported for mouth and nasal breathing (15). Yu pang et al., proposed a novel humidity sensor that makes use of graphene oxide, and polystyrene sulfonate silver nanoparticles (PEDOT: PSS and Ag colloids) to improve the conductivity capacity of the humidity sensor. They investigated the humidity properties of porous-based graphene networks at different relative humidity (RH) and concluded that porous based graphene sensors exhibited excellent capacity for monitoring different breathing patterns for different situations. The designed sensor was tested by varying the relative humidity and was tested for mouth as well as nose respiration with activities such as normal and deep breathing. The developed sensor was able to recognize the skin moisture, speaking and whistle rhythm (16). A thorough review on various respiration techniques that works on contact and non-invasive remote monitoring was reported by Mohammed Ali et. al.(17).The report suggested that the application of remote monitoring tool could be used as a potential screening aid to handle COVID-19-like situations. The study highlights the advantages as well as the disadvantages of contact as well as non-contact-based respiratory monitoring techniques. It was shown that remote photo plethysmography ultrasound radar and camera-based models could be deployed as a non-contact-based procedure to measure the respiratory airflow.

Various deep learning techniques have been applied to respiratory breathing pattern recognition. In one approach, a CNN-based model was utilized to classify six breathing patterns by transforming accelerometer signals into spectrograms, which were then fed into the network (18).

Study proposes a contactless breathing pattern recognition system using WiFi signals and a CNN-LSTM model to classify six respiratory patterns. Data preprocessing techniques are applied to extract accurate time-domain signals, achieving a classification accuracy of 97.8%. The results demonstrate the system's effectiveness for continuous respiratory monitoring and potential clinical applications (19).

The preceding literature indicates that a plethora of approaches are being proposed for the assessment of respiratory patterns. Nonetheless, the prospect for developing novel respiratory evaluation modalities is underscored by the limited constraints of sample size, dependability, robustness of sensor design and lack of integration of deep artificial intelligence approaches for analytics. Therefore, the goal aims to create a novel electronic wearable nasal mask that incorporates Deep AI methods for the analysis of humidity signals, or the changes in humidity in nasal airflow signals that characterize breathing patterns of normal breathing, deep breathing, rapid breathing and shallow breathing.

MATERIALS AND METHODS

Overall Frame Work

Fig.1 demonstrates the general structure for evaluating respiratory signals with the following breathing patterns: normal breathing, deep breathing, rapid breathing (climbing the stairs) and shallow breathing (recuperation). By inserting a wearable nasal mask with humidity sensors positioned beneath the nostrils, the humidity fluctuations indicating the breathing patterns from the right and left nostrils were detected. In order to prepare the raw data for future analysis, baseline drift was removed using a de-trending mechanism, and outliers were eliminated using IQR (Inter Quartile Range) techniques. To handle the non-stationary nature of the biomedical signals recorded, the data was normalized and divided into segments with 80% overlap. To evaluate and categorize the prepared data, an ensemble model comprising 1D-CNN, LSTM, and SVM classifiers was applied. The performance of the proposed integrated framework was evaluated in terms of Accuracy, F1- score and MCC values.

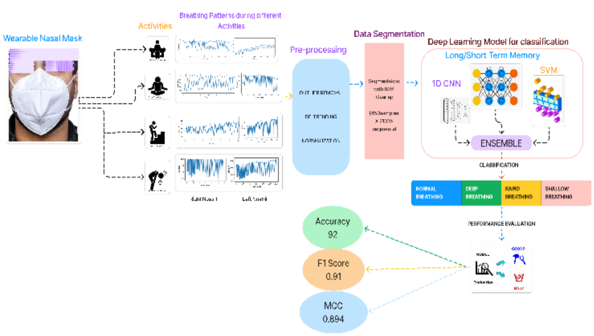

Fig. 1: Overall Framework of the proposed work

Sensor Design

The hardware configuration of the electronic wearable nasal mask developed at Ramaiah Institute of Technology ,Bangalore is illustrated in Fig. 2. It features a compact and lightweight design, a critical attribute that enhances its suitability for wearable applications. It is equipped with MEMS based sensor BME280 from Bosch that can read all of the three parameters, temperature, pressure and humidity variations which can be conditionally activated. Here we deactivated the temperature and pressure sensors leaving the humidity sensor active. The prototype integrates key components, including the ADC-ADS115, USB-C port, USB/battery power switcher, battery management system, low dropout (LDO) regulator, battery connector, ZIF connector, ESP32 microcontroller, and an indicator LED for user feedback. The motherboard, housing these components, is mounted on the mask, as shown in Fig. 2. A flexible sensor strip, connected to the motherboard via the ZIF connector, is positioned inside the mask, with sensors placed beneath the right and left nostrils to capture breathing patterns. The collected signals are transmitted to a mobile application via Bluetooth for further analysis.

Data Collection

A set of 164 samples of humidity signals indicating the breathing variations using an electronic wearable nasal mask that captures the humidity signals from right and left nostrils developed at Ramaiah Institute of Technology, Bangalore, India were collected for 2 trials from 82 healthy volunteers in normal weather conditions of 25°C. The study recruited participants from Ramaiah Institute of Technology, Bangalore, India, comprising 42 males and 40 females. The average age of the participants ranged from 30 to 32 years, with an approximate BMI of 29 for males and 25 for females. The sampling frequency of the device, 15 samples per second, yielded 11700 sample lengths per trial per subject, thus a total of 1,918,800 sample values were created for the analysis. The data collection was performed having ethics approval from Ramaiah Medical College and Hospitals, Bangalore India having the consent signed by all the participants. The subjects were initially asked to relax in a sitting posture and were made to wear the developed nasal mask. All the volunteers expressed a comfort fit of the wearable nasal mask. Subjects were then asked to perform a combination of tasks as per the timing diagram shown in Fig. 2. The recordings were saved in.txt format in a serial Bluetooth mobile application, which was later retrieved for analysis.

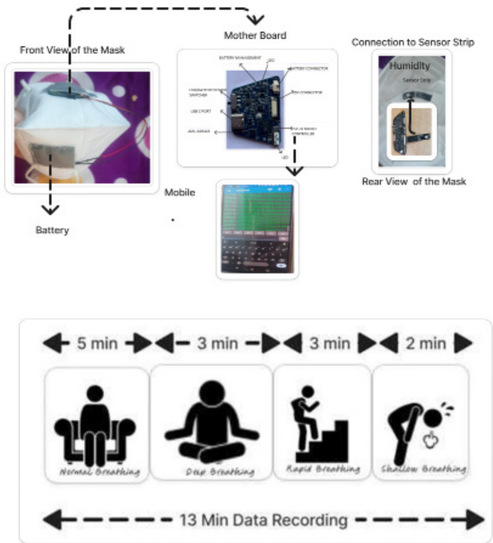

Fig. 2: Hardware Configuration and Timing Diagram

Pre-Processing

Fig. 3 shows the raw data plots of the humidity signals captured from both right and left nostrils for all the tasks considered for analysis. Raw signals are affected by some of the artifacts leading to the formation of outliers and baseline drift in the signals. To overcome this , the raw signals are subjected to data cleaning and de-trending procedures where the raw data is initially cleaned for the removal of outliers using IQR methods and de-trended for the removal of baseline drift in the signal using quadratic de-trending technique. Fig. 4 shows baseline drift removed and normalized signals of right and left nostrils for different activities considered.

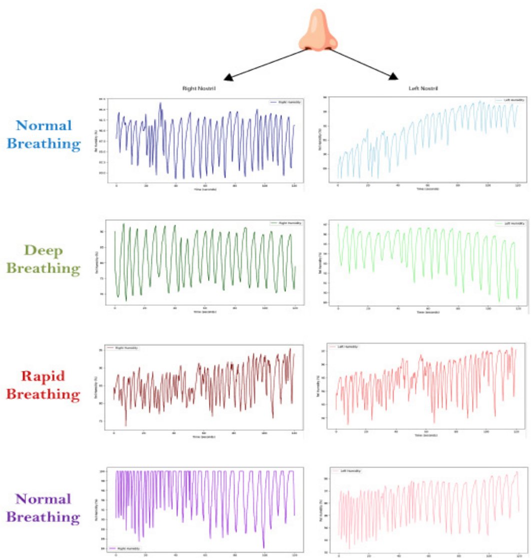

Fig. 3: Raw plots of humidity signals depicting breathing patterns in right and left nostrils for different activities considered

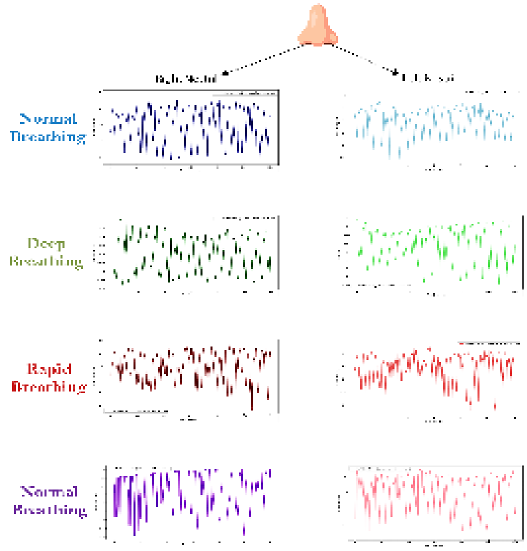

Fig 4: Pre-processed humidity signals with baseline drift removed of right and left nostrils for different activities considered.

Data Segmentation

In order to address the non-stationary nature of the respiratory signals captured, the pre- processed signals are segmented for every 30 sec with 80% overlap and every 30 sec segments with (450 (sample values) X 21316 (no. of segments)) is considered for the model development. The prepared data is further subjected to deep learning algorithms to classify normal breathing, Deep breathing, Rapid breathing (Climbing the stairs) and shallow breathing (recovery).

Deep AI

Data collection was performed using electronic wearable nasal mask with humidity sensor. Data represents four distinct activities such as normal breathing, deep breathing ,rapid breathing(climbing the stairs) and shallow breathing (recovery).The study's primary objective was to develop a robust model capable of accurately classifying these activities based on the sensor data. To achieve this, the data first underwent a meticulous Exploratory Data Analysis (EDA) phase. During EDA, outliers were identified and removed, ensuring the dataset was both clean and reliable, which is critical for the subsequent steps in modeling. This preprocessing step was essential to eliminate noise and potential anomalies that could skew the model's learning process. Once the data was cleaned, it was segmented into 30-second windows at a sample rate of 15 samples per second. To enhance the number of training samples and ensure good temporal features, an 80% overlapping window strategy was employed. This overlap meant that, each new segment shared a significant portion of data with the previous one, effectively increasing the dataset's size and the richness of temporal information captured in each segment. The dataset was split into 80% for training and 20% for testing, ensuring a robust evaluation of the model's performance. Specifically, out of the total 1,918,800 samples, 1,535,040 samples are allocated for training, while 383,760 samples are reserved for testing. This split maintained a sufficient amount of data for learning complex patterns while providing a reliable assessment of generalization. To assess the contribution of individual features to the model's performance, the study tested three different feature combinations: using only right nostril humidity signals, only left nostril humidity signals and both right and left nostril humidity signals together. This comparative analysis provided insights into how each nasal breathing data influenced the classification accuracy, allowing to identify the most effective feature set for the final model.The challenge was in accurately classifying activities using multimodal sensor data, where patterns varied over time. To tackle this, a hybrid deep learning approach combining CNN, LSTM, and SVM was employed. CNN effectively extracted spatial features, LSTM captured temporal dependencies, and SVM ensured robust classification. Unlike traditional models like Random Forest, which lack temporal awareness, or standalone RNNs, which may struggle with vanishing gradients, this combination optimally balanced feature extraction, sequence modeling, and decision boundaries, enhancing classification performance. The 1D CNN-LSTM model was designed to first extract spatial features from the time-series data using 1D convolution layers. These layers were followed by max-pooling layers, which reduced the dimensionality of the data while retaining critical features. The model then transitioned into LSTM layers, which are particularly well-suited for handling sequential data.

The LSTM layers captured the temporal dependencies within the segmented windows, enabling the model to recognize patterns over time, that might be indicative of specific activities. The CNN-LSTM model was further enhanced by fully connected dense layers that progressively reduced the feature space, allowing the model to focus on the most relevant information. Dropout layers were included to prevent overfitting by randomly omitting neurons during training, thereby improving the model's generalizability to new data. The final output layer of the 1D CNN-LSTM model was a softmax layer, which produced a probability distribution over the four activity classes, enabling the model to predict the most likely activity for each data segment. After training the 1D CNN-LSTM model, an innovative approach was taken to further refine the classification process. Features were extracted from the penultimate dense layer of the 1D CNN- LSTM model, representing the learned spatial and temporal patterns within the data. These features were then used as input to a Support Vector Machine (SVM). The SVM, known for its effectiveness in creating robust decision boundaries, performed the final classification. This ensemble approach allowed the study to harness the feature extraction capabilities of deep learning with the precise classification strength of SVM, leading to a highly accurate and reliable activity recognition system based on breathing. The integration of these techniques—

spatial feature extraction via CNN, temporal pattern recognition via LSTM, and final classification via SVM—resulted in a powerful and comprehensive model. This ensemble method proved superior to using any single model approach, demonstrating the value of combining different methodologies to leverage their respective strengths. The result was a robust system capable of accurately classifying the four activities, highlighting the potential of such hybrid models in real-world applications, especially in domains requiring precise activity recognition based on sensor data. Fig. 5 shows the architecture of the ensemble model developed for classification which is configured with 3-convolutional layers,3-MaxPooling Layers, 3-Dropout Layers ,4-Dense Layers,2-LSTM Layers and ReLu, Softmax activation function.

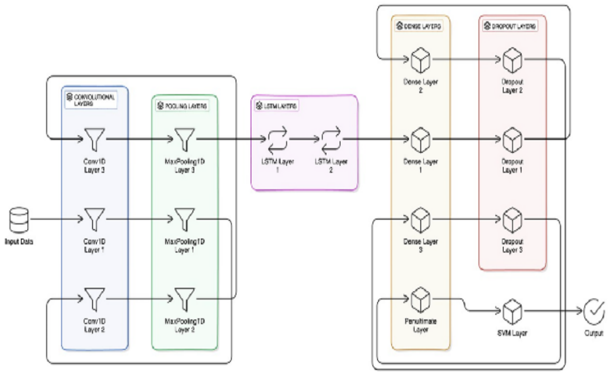

Fig 5: Architecture of Ensemble model

Performance Evaluation Metrics

In this study, the evaluation of the model was conducted using three key metrics: Accuracy, F1 Score, and Matthews Correlation Coefficient (MCC). Accuracy, a widely used metric, measures the proportion of correct predictions out of the total predictions made by the model. While it offers a general overview of performance, it can be misleading in cases of class imbalance, where the model might achieve high accuracy by favoring the majority class. To address this, the F1 Score was also employed, providing a balanced measure of precision and recall, particularly valuable in scenarios with uneven class distributions. The F1 Score, being the harmonic mean of precision and recall, ensures that the model is evaluated on both its ability to correctly identify positive instances and its completeness in doing so. Additionally, the Matthews Correlation Coefficient (MCC) was utilized as a more robust metric that considers all elements of the confusion matrix, including true positives, true negatives, false positives, and false negatives. The MCC provides a comprehensive assessment of the model's performance, particularly in imbalanced datasets, where it delivers a more nuanced understanding than accuracy or F1 Score alone. By incorporating these three metrics, the study ensured a thorough evaluation of the model's effectiveness, capturing both overall accuracy and its ability to handle different classes with precision and balance. In addition to these metrics, further analysis was conducted using accuracy and loss curves, ROC and precision-recall curves to comprehensively assess the model's performance.

Ethical Clearance

This study was approved by the Ethics Committee, Ramaiah Medical College, Bangalore , Ref No. ECR/215/Inst/KA/2013/RR-19

RESULTS

In this study, a proposed ensemble model combining 1D CNN, LSTM, and SVM was developed to capitalize on the unique strengths of each technique for accurately recognizing breathing patterns. The model was tested using three different feature combinations: left humidity alone, right humidity alone, and a combination of both. The findings highlighted that, using both nasal humidity data together, resulted in superior performance across all evaluation metrics. When relying solely on right humidity data, the model achieved strong results, with an accuracy of 0.88, an F1 Score of 0.87, and an MCC of 0.844, indicating that right humidity was a reliable predictor that led to balanced and accurate classifications. Conversely, the model's performance dropped considerably when only left humidity was used, showing an accuracy of 0.63, an F1 Score of 0.61, and an MCC of 0.505. This suggests that left humidity alone was less effective in differentiating between breathing activities, leading to lower classification success. The most significant improvement was observed when both right and left humidity data were considered. The model achieved an accuracy of 0.92, an F1 Score of 0.91, and an MCC of 0.894, indicating that the integration of data from both nostrils provided complementary insights that enhanced the model's ability to accurately classify breathing patterns.

DISCUSSION

In the discussion of these results, the analysis of the accuracy and loss curves shown in Fig. 6(a,b) highlights the enhanced performance of the model when both left and right humidity features are used in combination. The model with combined features exhibited a consistent increase in accuracy and decrease in loss over time, contrasting with the instability observed when relying solely on left humidity. The superiority of the combined feature model is further supported by its highest F1 Score, indicating its effectiveness in identifying true positive instances.

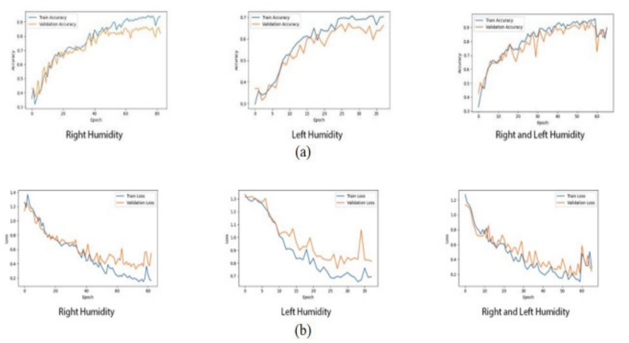

Fig 6: a. Accuracy curve and b. Loss curve of ensemble model obtained using humidity signals

Additionally, the MCC values corroborate this finding, showing that the combined features lead to the most robust performance across all classes. The ROC and precision-recall curves shown in Fig. 7(a,b) demonstrate that the model's ability to distinguish between classes is significantly improved with the inclusion of both humidity features, as reflected in the higher AUC scores. These metrics confirm that the combined model achieves better precision and recall compared to models using individual features.

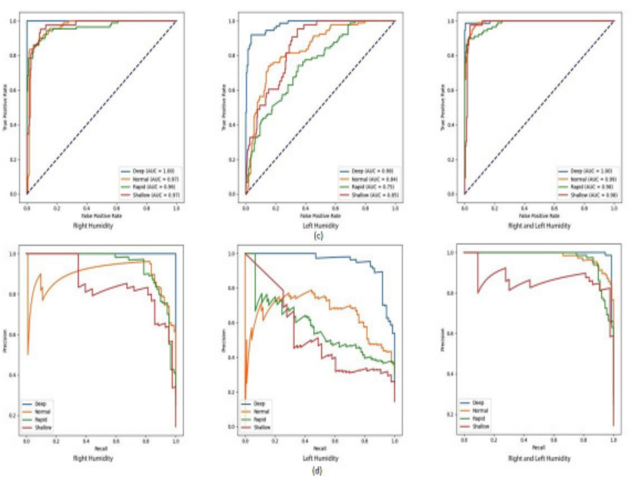

Fig 7: a. ROC and b. Precision Recall curves of ensemble model obtained using humidity signals.

These findings underscore the value of incorporating both humidity signals from the right and left nostrils, resulting in more subtle pattern detection and more accurate activity recognition. Overall, the combined feature approach leads to superior performance across all key metrics, demonstrating its efficacy in enhancing the model's reliability and accuracy in recognizing breathing activities.

CONCLUSION

To identify the humidity signals representing the pulmonary breathing patterns collected from electronic wearable nasal mask among four activities normal breathing, deep breathing, rapid breathing, and shallow breathing an ensemble model utilizing 1D CNN, LSTM and SVM classifiers has been developed.82 individuals participated in two trials for the purpose of gathering data, and recordings lasting 2132 minutes were produced. The accuracy, F1 score, and MCC of the suggested Ensemble models, multiclass classification of all breathing patterns were used to assess its overall effectiveness. The classification of activities was performed considering the humidity variations from individual nostril i.e right nostril alone, left nostril alone and both right and left nostrils together. Experimental results showed that, an efficient classification was obtained when both right and left nostril humidity signals were used together as input to the model. Varied emotions fluctuates breathing patterns, for example, quick breathing and shallow breathing suggest anxiety or tension, whereas deep breathing is associated with calm. Few of the recent research indicates the development of humidity based sensors for the acquisition of respiratory signals that highlights the importance of humidity sensors for capturing the breath signals[20-22],however the current paper presents the integration of deep AI analytics onto the respiratory signals captured using novel wearable mask developed inhouse. Breathing analysis throughout the various tasks considered in this paper assists individuals in developing self-regulation techniques by providing a variety of physical, psychological, and physiological benefits. Classifying distinct breathing patterns can help to acquire insights into overall health and mental well-being, as well as improve self-awareness. From the research experimental work, the novel Ensemble model performed very well in the classification of breathing pattern for normal breathing, deep breathing, rapid breathing and shallow breathing with highest accuracy.

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