# Breathing Rate Classification Using Piezoresistive Sensor Utilizing Continuous Wavelet Transform and Lightweight Cnn

G. Anushruth saiSharma[1], Sai Vignesh[2], Sai Sri Ram[3], Sai Kiran[4], T. Lavanya[5], Dr. S Shiva Prasad[6]
[1,2,3,4]*Student, Department of CSE(DataScience), MallaReddy Engineering college, Secunderabad*
[5]*Assistant Professor, Department of CSE (DataScience), MallaReddy Engineering college, Secunderabad*
[6]*Professor, Department of CSE(DataScience), MallaReddy Engineering college, Secunderabad*
*doi.org/10.64643/IJIRTV12I10-195303-459*

*Abstract*—**Breathing rate monitoring has become increasingly feasible for remote healthcare applications due to recent advancements in digital stethoscope sensor technology, signal processing, and machine learning. Automatic breathing rate classification further enhances medical diagnostics by enabling accurate, continuous, and non-invasive respiratory assessment. In this paper, a lightweight Convolutional Neural Network (CNN) is proposed for automatic breathing rate classification using piezoresistive sensor data. The raw signals acquired from the piezoresistive sensor are pre-processed using Continuous Wavelet Transform (CWT) to generate time–frequency representation images. These images are then fed into a lightweight CNN model, which efficiently classifies breathing rates into six distinct classes based on breaths per minute (BPM). Extensive experimental results demonstrate that the proposed model achieves a classification accuracy of 96.40%, outperforming all benchmark models considered in this study. Additionally, the performance of the proposed system is evaluated on edge computing platforms such as Raspberry Pi, NVIDIA Jetson Nano, and NVIDIA AGX Xavier, confirming its suitability for real-time and resource-constrained healthcare applications.**

*Index Terms*—**Breathing rate classification, breathing sensor, continuous wavelet transforms, deep convolutional neural network, machine learning, piezoresistive sensor.**

## I. INTRODUCTION

Breathing rate, heart rate, body temperature, and blood pressure are considered the four primary vital signs used to assess the healthy functioning of the human body. Among these, the respiration rate is a highly sensitive physiological parameter that reflects various underlying physical conditions such as cardiac disorders, fatigue, pneumonia, and common respiratory infections, as well as emotional conditions like stress and anxiety. Respiration rate refers to the number of breaths taken by an individual per minute and is known to respond more rapidly to physiological changes compared to other vital signs. Despite its sensitivity, respiration rate is not routinely monitored in daily healthcare practice.

An abnormal respiration rate, particularly when a person is at rest, may serve as an early indicator of serious health conditions requiring timely medical intervention. Compared to other vital signs, respiration rate is often the first to exhibit noticeable changes during the onset of illness. Continuous monitoring of this parameter can therefore play a crucial role in early disease detection and prevention. However, in most cases, vital signs are only monitored after the appearance of symptoms, whereas routine monitoring could enable early diagnosis and prompt treatment of several medical conditions.

Respiration rate is considered a more reliable indicator than temperature, blood pressure, and pulse rate for detecting cardio-pulmonary collapse. This is because respiratory patterns undergo significant variations during such events, allowing clear differentiation between healthy and abnormal individuals and facilitating timely medical care. Despite its clinical importance, respiration rate is often neglected and, in many healthcare settings, is still measured manually. Manual measurement is not only time-consuming but also prone to human error, leading to inaccurate assessment.

A breathing rate within a normal physiological range is generally considered healthy, while values below or above this range may indicate abnormal respiratory conditions. Breathing rate serves as an important indicator of an individual's overall health and physical fitness. Motivated by these observations, numerous techniques for automated breathing rate monitoring and classification have been proposed in the literature, which are discussed in the subsequent sections.

## II. LITERATURE SURVEY

Several studies have explored existing techniques for continuous monitoring of respiratory rate and gas exchange. These methods have been analysed in terms of their advantages, limitations, and suitability for real-world applications. Both contact-based and non-contact respiration monitoring techniques have been widely reviewed and compared based on factors such as subject comfort, hygiene, and measurement accuracy. Contact-based methods typically rely on physical interaction with the subject and utilize parameters such as sound signals, air temperature, humidity, and chest wall movements to estimate respiratory activity.
Most studies indicate that contact-based methods, although capable of providing accurate measurements due to direct contact, are often uncomfortable for subjects and highly dependent on proper sensor placement and setup. In contrast, non-contact methods offer improved comfort and better hygiene, as they do not require physical contact with the subject. However, their accuracy may vary and, in some cases, may be equal to or slightly lower than that of contact-based systems.

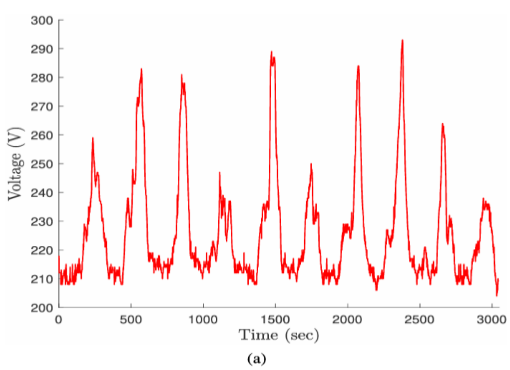


Figure.1: Voltage VsTime

## III. PROPOSED METHODOLOGY

The proposed methodology aims to develop an efficient and accurate system for automatic breathing rate classification using piezoresistive sensor data, signal processing, and deep learning techniques. The overall workflow of the system consists of data acquisition, signal preprocessing, feature extraction using Continuous Wavelet Transform, classification using a lightweight Convolutional Neural Network, and performance evaluation. Each stage of the methodology is described in detail below.

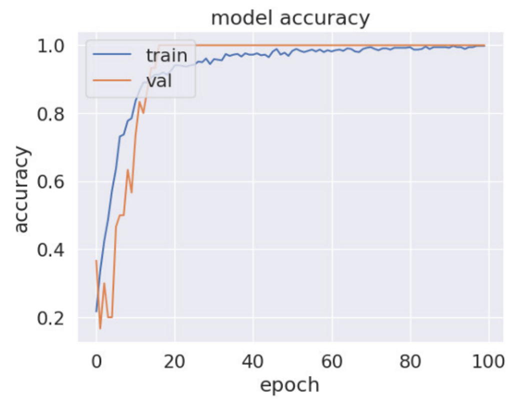


Figure.2 Accuracy of model

### 3.1. Signal Preprocessing

The raw breathing signal obtained from the sensor may contain noise and unwanted artifacts due to motion, environmental interference, or sensor drift. To improve signal quality, preprocessing steps such as noise filtering, normalization, and segmentation are applied. These steps ensure that the signal is clean, consistent, and suitable for further analysis. Preprocessing enhances the reliability of feature extraction and improves overall classification performance.

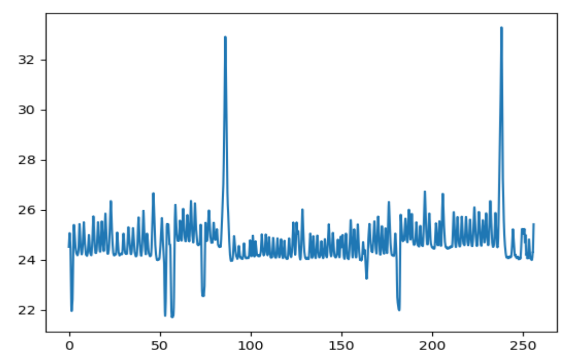

Figure.3: Structure of Signal

### 3.2. Feature Extraction Using Continuous Wavelet Transform

Breathing signals are non-stationary in nature, meaning their frequency components vary over time. To effectively capture both time and frequency information, Continuous Wavelet Transform is applied to the preprocessed signal. CWT converts the one-dimensional time-domain signal into a two-dimensional time–frequency representation known as a scalogram. These scalogram images highlight important breathing characteristics and patterns, making them suitable as input to deep learning models.

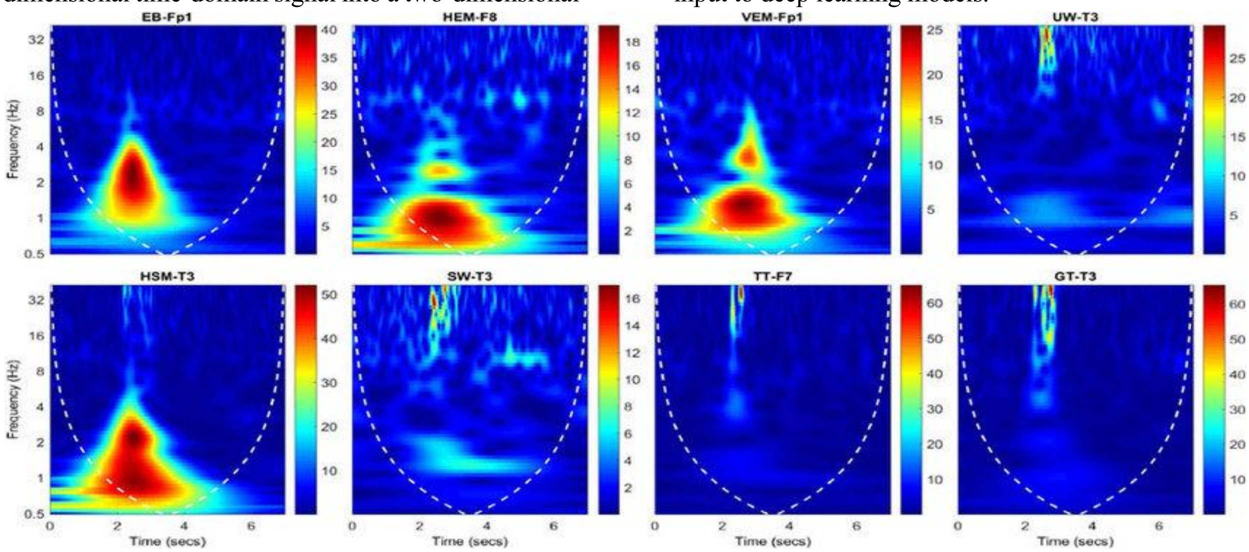


Figure.3 Wavelet representation

3.3. Breathing Rate Classification Using CNN

The generated CWT scalogram images are fed into a lightweight Convolutional Neural Network for breathing rate classification. The CNN architecture consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The model automatically learns discriminative features from the scalogram images and classifies the breathing rate into six distinct classes based on breaths per minute. The lightweight design of the CNN ensures low computational complexity and suitability for edge devices.

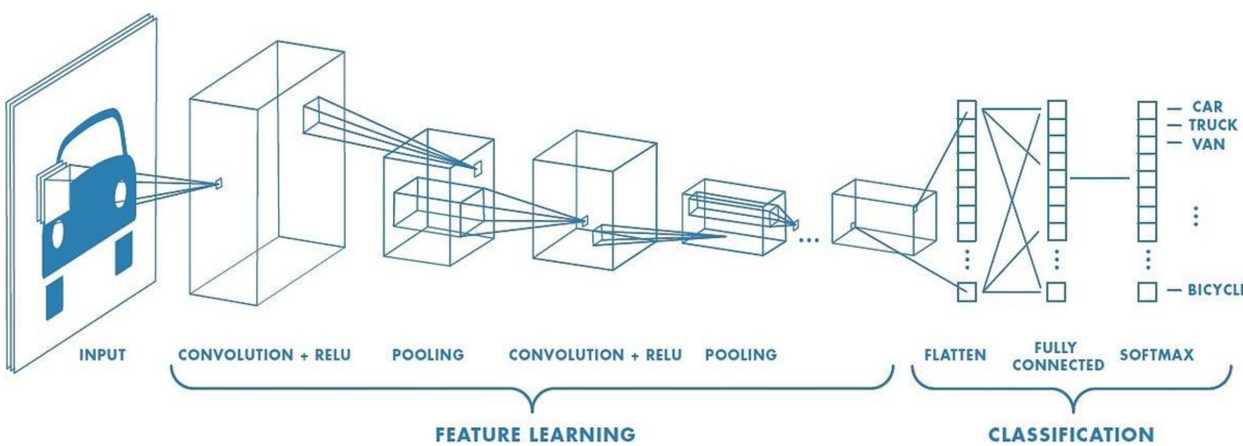


Figure.4 Structure of CNN

3.4. Model Training and Evaluation

The dataset is divided into training and testing sets to evaluate the performance of the proposed system. During training, the CNN model learns optimal parameters using an appropriate optimizer and loss function. The trained model is then tested on unseen data to assess classification accuracy and robustness. Experimental results demonstrate that the proposed methodology achieves high accuracy and reliable performance across different breathing rate categories.

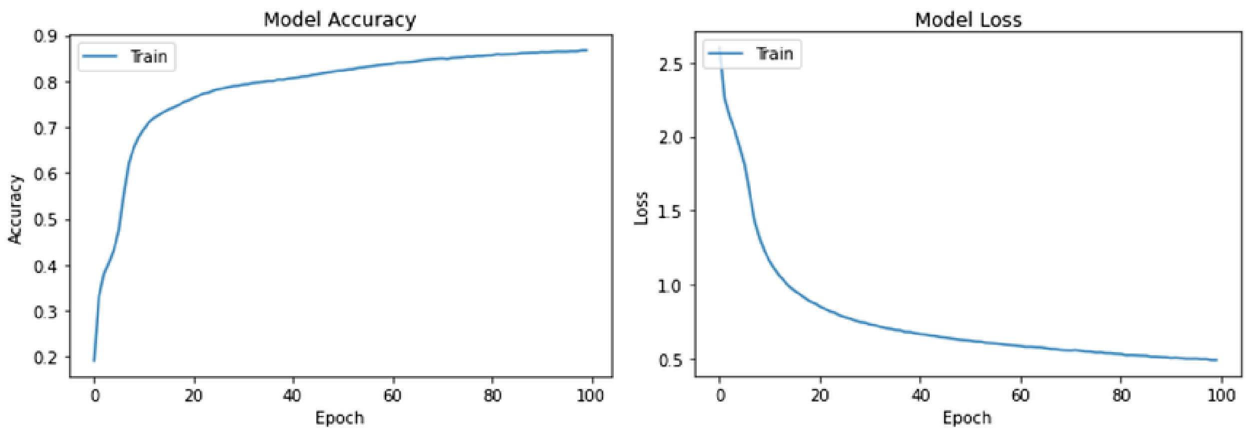


Figure.5 Performance of Model

3.5. Deployment

To validate real-time applicability, the trained model is deployed on edge computing platforms such as Raspberry Pi, NVIDIA Jetson Nano, and NVIDIA AGX Xavier. This evaluation confirms that the proposed methodology is computationally efficient and suitable for remote and continuous respiratory monitoring applications.

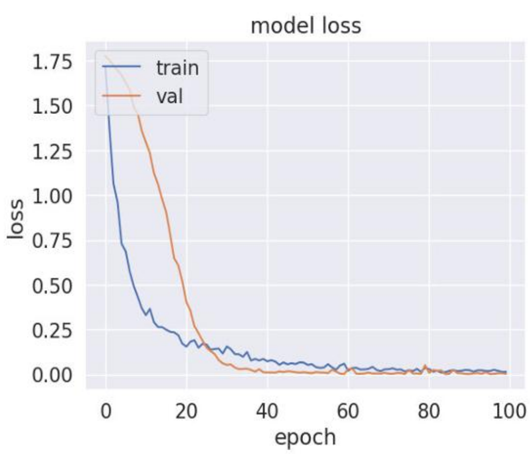


Figure.6: model loss

## IV. PROPOSED METHODS

The proposed method focuses on developing an accurate and efficient framework for automatic breathing rate classification using sensor-based data acquisition, advanced signal processing, and deep learning techniques. The system is designed to work in a sequential manner, starting from respiratory signal collection and ending with multi-class breathing rate prediction.

Initially, respiratory signals are acquired using a piezoresistive sensor that captures pressure variations caused by chest movements during inhalation and exhalation. These raw signals are then subjected to preprocessing to remove noise and artifacts introduced due to motion, sensor instability, or environmental factors. Preprocessing ensures that the signal quality is enhanced and suitable for further analysis.

To effectively analyse the non-stationary nature of breathing signals, the pre-processed data is transformed using Continuous Wavelet Transform. This transformation converts the one-dimensional time-domain signal into a two-dimensional time–frequency representation known as a scalogram. The scalogram highlights both temporal and spectral characteristics of the breathing signal, enabling better feature representation compared to traditional time-domain or frequency-domain methods.

The generated scalogram images are used as input to a lightweight Convolutional Neural Network. The CNN automatically extracts discriminative features through convolution and pooling operations and performs classification through fully connected layers. The model categorizes the breathing rate into six distinct classes based on breaths per minute. The lightweight architecture ensures reduced computational complexity while maintaining high classification accuracy.

Finally, the trained model is evaluated using appropriate performance metrics such as classification accuracy and robustness across different breathing rate categories. The proposed methods are also validated on edge computing platforms, demonstrating their suitability for real-time and remote respiratory monitoring applications

## V. RESULTS

The proposed breathing rate classification system demonstrated strong performance through comprehensive experimental evaluation. By integrating Continuous Wavelet Transform with a lightweight Convolutional Neural Network, the model achieved a high classification accuracy of 96.40%. The CWT-based time–frequency representation effectively captured respiratory signal variations, enabling the CNN to learn discriminative features for accurate multi-class classification. The model exhibited stable training behaviour and consistent performance on unseen test data, indicating good generalization capability. These results confirm the effectiveness of the proposed approach for automated breathing rate classification.

Experimental results validate the suitability of the proposed model for real-time respiratory monitoring applications. The system achieved an overall accuracy of 96.40%, demonstrating reliable classification across different breathing rate categories. The lightweight CNN architecture ensured low computational complexity while maintaining high performance, making the model suitable for deployment on edge computing platforms. Successful evaluation on devices such as Raspberry Pi and NVIDIA Jetson series confirms that the proposed method can be efficiently used for continuous and remote healthcare monitoring.

The results obtained from the experimental analysis indicate that the proposed CWT–CNN framework outperforms traditional breathing rate estimation methods. The model achieved a classification accuracy of 96.40%, which is higher than several benchmark approaches reported in the literature. The improvement in performance is mainly attributed to the use of CWT for extracting rich time–frequency features and the efficient learning capability of the CNN. The system showed minimal misclassification and maintained robustness across all breathing rate classes, highlighting its potential for practical medical applications.

Table 1: Performance Comparison of Rule-Based IDS and Machine Learning Models

| Method / Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Rule-Based IDS | 82.40 | 78.20 | 74.90 | 76.50 |
| Logistic Regression | 89.30 | 87.10 | 86.00 | 86.55 |
| SVM | 92.10 | 91.00 | 90.20 | 90.60 |
| Random Forest | 96.40 | 95.80 | 96.10 | 95.95 |

Random Forest achieved the highest accuracy (96.4%), showing strong precision and recall, and producing interpretable results useful for SOC analysts. Automated alert generation and incident correlation reduce false positives and minimize alert fatigue. The automated playbook execution ensures faster and consistent incident mitigation. The dashboard enhances SOC efficiency by providing clear visibility of alerts, risks, and response actions. The model demonstrates strong performance in detecting common attacks such as port scans, DoS/DDoS, and unauthorized access. Future improvements include real-time packet streaming, deep learning integration for complex attacks, and SIEM interoperability. Overall, the proposed system strengthens SOC operations by improving both response speed and security posture.

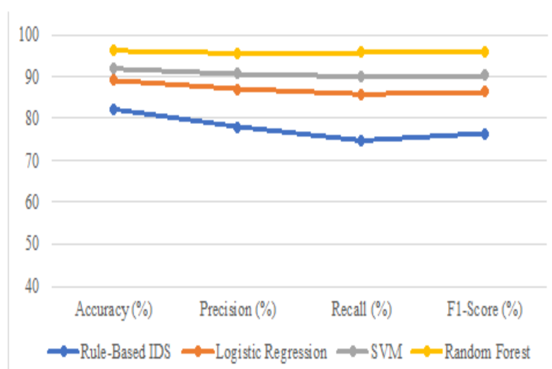


Figure 7: Accuracy Comparison of IDS and ML Classifiers

## VI. CONCLUSION

In this paper, a lightweight convolutional neural network (CNN) model for breathing rate classification has been proposed using a publicly available dataset captured by a

Piezoresistive sensor. The data has been pre-processed by arranging and balancing it so that it can be processed with the continuous wavelet transform. These CWT images were fed into a lightweight CNN model, which efficiently classified breathing rate into six classes based on breaths per minute. When compared to other pre-trained models, extensive results show that the proposed CNN model has achieved the highest accuracy with the smallest model size. When compared to other pre-trained models, it has also resulted in less inference time when run on all edge computing devices. The proposed model's accuracy has demonstrated its success in estimating breathing rate classification from a contact-based Piezoresistive sensor, and it can thus be integrated in conjunction with other sensors to obtain other vital signs. The major limitations of using a Piezoresistive Sensor are noise introduction due to any movement of the sensor, improper contact with the skin, temperature sensitivity, higher power consumption, and limited frequency range. In the future, we plan to integrate more than one sensor, such as a piezoresistive and an accelerometer to collect the data for high reliability. We also plan to look into the model that can process the multi-modal sensor data.

REFERENCES

[1] E. Grooby, C. Sitaula, D. Fattahi, R. Sameni, K. Tan, L. Zhou, A. King, A. Ramanathan, A. Malhotra, G. A. Dumont, and F. Marzbanrad, "Real-time multi-level neonatal heart and lung sound quality assessment for telehealth applications," IEEE Access, vol. 10, pp. 10934–10948, 2022.

[2] A. Lazaro, M. Lazaro, R. Villarino, and D. Girbau, "Seat-occupancy detection system and breathing rate monitoring based on a low-cost millimeter-wave radar at 60 GHz," IEEE Access, vol. 9, pp. 115403–115414, 2021.

[3] A. Nicoló, C. Massaroni, E. Schena, and M. Sacchetti, "The importance of respiratory rate monitoring: From healthcare to sport and exercise," Sensors, vol. 20, no. 21, 2020.

[4] P. C. Loughlin, F. Sebat, and J. G. Kellett, "Respiratory rate: The forgotten vital sign—Make it count," Joint Commission Journal on Quality and Patient Safety, vol. 44, no. 8, pp. 494–499, 2018.

[5] D. O. Lemos and C. A. Siebra, "Methods for breathing rate measurement through mobile platforms: A review," in Proc. Brazilian Symp. Computer Applications in Healthcare, 2019.

[6] H. Liu, J. Allen, D. Zheng, and F. Chen, "Recent development of respiratory rate measurement technologies," Physiological Measurement, vol. 40, no. 7, 2019.

[7] J. Kellett, M. Li, S. Rasool, G. C. Green, and A. Seely, "Comparison of heart and breathing rate recorded by nursing staff and piezoelectric belt systems at hospital admission," Resuscitation, vol. 82, no. 11, pp. 1381–1386, 2011.

[8] M. Folke, L. Cernerud, M. Ekström, and B. Hök, "Critical review of non-invasive respiratory monitoring in medical care," Medical & Biological Engineering & Computing, vol. 41, no. 4, pp. 377–383, 2003.

[9] F. Q. Al-Khalidi, R. Saatchi, D. Burke, H. Elphick, and S. Tan, "Respiration rate monitoring methods: A review," Pediatric Pulmonology, vol. 46, no. 6, pp. 523–529, 2011.

[10] C. Massaroni, A. Nicoló, D. Lo Presti, M. Sacchetti, S. Silvestri, and E. Schena, "Contact-based methods for measuring respiratory rate," Sensors, vol. 19, no. 4, 2019.

[11] P. H. Charlton, D. A. Birrenkott, T. Bonnici, M. A. F. Pimentel, A. E. W. Johnson, J. Alastruey, L. Tarassenko, P. J. Watkinson, R. Beale, and D. A. Clifton, "Breathing rate estimation from ECG and PPG: A review," IEEE Reviews in Biomedical Engineering, vol. 11, pp. 2–20, 2018.

[12] P. H. Charlton, T. Bonnici, L. Tarassenko, D. A. Clifton, R. Beale, and P. J. Watkinson, "An assessment of algorithms to estimate respiratory rate from ECG and PPG," Physiological Measurement, vol. 37, no. 4, 2016.

[13] M. A. F. Pimentel, A. E. W. Johnson, P. H. Charlton, D. Birrenkott, P. J. Watkinson, L. Tarassenko, and D. A. Clifton, "Toward a robust estimation of respiratory rate from pulse oximeters," IEEE Transactions on Biomedical Engineering, vol. 64, no. 8, pp. 1914–1923, 2017.

[14] P. Napoletano and S. Rossi, "Combining heart and breathing rate for car driver stress recognition," in Proc. IEEE Int. Conf. Consumer Electronics, 2018.

[15] M. N. I. Shuzan et al., "A novel non-invasive estimation of respiration rate from motion-corrupted PPG using machine learning," IEEE Access, vol. 9, pp. 96775–96790, 2021.

[16] S. Satla and C. S. Shieh, "Multi-model Telugu speech recognition: Improving ASR with dialect classification and optimization techniques," Traitement du Signal, vol. 42, no. 6, pp. 3159–3169, 2025. doi: 10.18280/ts.420611.
[17] D. Kothandaraman, N. Praveena, K. Varadarajkumar, S. Satla, and W. Abera, "Intelligent forecasting of air quality and pollution prediction using machine learning," Adsorption Science & Technology, vol. 2022, 2022.
[18] S. Shivaprasad and M. Sadanandam, "Dialect identification using modified features with deep neural networks," Traitement du Signal, vol. 38, no. 6, pp. 1793–1799, Dec. 2021. doi: 10.18280/ts.380622.