A Project Report On

Estimation of Respiratory rate from Breathing Audio

Submitted in partial fulfillment of the requirement for the 8^{th} semester **Bachelor of Engineering**

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Computer Science and Engineering

DAYANANDA SAGAR COLLEGE OF ENGINEERING

(An Autonomous Institute affiliated to VTU, Belagavi, Approved by AICTE & ISO 9001:2008 Certified)

Accredited by National Assessment & Accreditation Council (NAAC) with 'A' grade

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CERTIFICATE

This is to certify that the project entitled **Estimation of Respiratory rate from Breathing Audio** is a bonafide work carried out by **Mahek Tajammul** [**1DS19CS083**], **Mandhalapu Dakshitha** [**1DS19CS085**],**Srivathsa N Rao** [**1DS19CS167**] **and** and **Karthik Raju R** [**1DS20CS409**] in partial fulfillment of 8th semester, Bachelor of Engineering in Computer Science and Engineering under Visvesvaraya Technological University, Belgaum during the year 2022-23.

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Abstract

Respiratory sound classification plays a crucial role in diagnosing respiratory diseases and monitoring patients' conditions. This project presents a code implementation for respiratory sound classification using machine learning techniques. The code utilizes audio processing libraries, including Librosa, to extract relevant features from respiratory sound recordings. These features are then used as input to a Convolutional Neural Network (CNN) model implemented using TensorFlow and Keras. The code's main functionality is to classify the respiratory sound recordings into different categories based on the extracted features. The provided code includes a Flask-based web application that allows users to upload respiratory sound recordings for classification. The uploaded audio file is processed using the pre-trained CNN model to predict the respiratory sound class. Additionally, the code determines the respiratory rate from the predicted class and classifies it as normal or abnormal based on a defined threshold.The system requirements for running the code include Python, along with the necessary libraries such as Flask, Librosa, NumPy, scikit-learn, TensorFlow, and Keras. An audio dataset is assumed to be present in a specific directory, and the code expects the path to the pre-trained model to be provided. The code can be adapted for different datasets and model architectures based on specific research requirements.Experimental evaluations can be conducted by modifying the code to train the CNN model using the provided dataset. The code splits the dataset into training and testing sets, performs preprocessing steps such as normalization and encoding of labels, and trains the CNN model on the training data. The model's performance is evaluated using accuracy metrics on the test set.The provided code serves as a valuable resource for researchers and practitioners working on respiratory sound classification. It offers a starting point for implementing similar systems and conducting experiments related to respiratory sound analysis. By leveraging the power of machine learning techniques, this code contributes to the advancement of respiratory healthcare by providing a tool for automated respiratory sound classification and analysis.

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Chapter 1

Introduction

1.1 The Problem

The COVID-19 pandemic has established the use of telemedicine as a critical health care delivery channel that is likely to expand in the future. A significant challenge faced in telemedicine care delivery is the accurate measurement of vital signs such as respiratory rate.Respiratory rate, defined as the number of breaths a person takes per minute, is one of four clinical vital signs. As such, it plays a central role in the physical examination and accurate diagnosis of patients. Changes in respiratory rate have been shown to be an important early indicator of clinical deterioration and increased mortality in a variety of disease states. Thus, an accurate measurement of respiratory rate is critical for assessing patient stability.

1.2 Real World Application

- Easy and Accurate measurement of respiratory rates of patients of any age groups
- Regular Monitoring of respiratory rates of patients with Breathing problems.
- Estimation of respiratory rates of patients with some serious lungs disorders.cv
- An application for easy validation of normal or abnormal respiratory rates in individuals.
- The overall application of the software is to detect the respiratory rates of Human beings, easy, accurate and early detection leading to early treatment and cure of the disease.

1.3 Organisation of Project Report

- Section 2 explains problem statement, proposed solution and system requirements.
- Section 3 explains the Literature Survey of the related papers.
- Section 4 explains the architecture and system design.
- Section 5 explains Implementation platforms, Implementation details and dataset.
- Section 6 explains Experimentation and Results.
- Section 7 provided the conclusion.

Chapter 2

Literature Survey

Azadeh Yadollahi,et al,[1]" Robust Method for Estimating Respiratory Flow Using Tracheal Sounds Entropy".

Due to the difficulties and inaccuracies of the majority of flow measurement methods, numerous researchers have tried to predict flow based on breathing sounds. However, the application of each of the suggested approaches is constrained by the requirement for various flow rates for the calibration of the model. In this paper, a novel and reliable approach to flow estimation is proposed by making use of the tracheal sounds which is a bandpass filter and whose Entropy is calculated and hence used. The proposed method can estimate any flow rate and only requires one breath to calibrate, regardless of the flow rate chosen for calibration, even when flow rates are outside the given limits of the calibration. After eliminating the sounds of the heart, which deforms the tracheal sounds' low-frequency parts, the efficacy of the method across a variety of frequency ranges is evaluated. In addition, the proposed method's effectiveness for calculating entropy was validated using six distinct segment sizes. Estimates were made for inhaling and exhaling with the best segment sizes.

Advantages: It shows a reliable method for estimating flow that can adapt to flow variability and doesn't need more than one breath to calibrate.

Ethan Grooby,et al,[2]“Neonatal Heart and Lung Sound Quality Assessment for Robust Heart and Breathing Rate Estimation for telehealth Applications”.

Chest sounds can be fetched easily and sent to the virtual cloud for monitoring remotely and diagnosing thanks to advancements in the processing of signals, ML, IOT, stethoscopes which are digital, and other technologies. But, for taking care of newly born specifically, poor-quality recordings are hindering remote monitoring and diagnostics. In order to improve the accuracy and dependency of estimations of rates of heart and breathing from chest sounds of newly born who are noisy, this paper presents a novel approach for automatically and specifically evaluating the quality of the signal. From 76 preterm and full-term infants, a total of 88 information sources and 10-second lengthy sounds of the chest were collected. The recordings' breathing times, the quality of the signal, and delectable beats were evaluated by observers. Heart sound contained 187 features and lung sound contained 182 features that were used for quality categorization.

A binary categorization model which is dynamic was tutored following the application of class balancing and hyperparameter optimization in addition to feature selection. After that, the chest sound was used to automatically estimate heart rates and breathing rates, and a comparison of many methods was made for the same thing. cross-validation done subject-wise and also leaving one out revealed that the high-quality recordings were] distinguished from the low-quality recordings by the model in the data which was used to test with a specificity of eighty-six percent, sensitivity of sixty-nine percent and accuracy of eighty-two percent for lung sounds and specificity of Ninety-six percent, sensitivity of Eighty-one percent and accuracy of Ninety-three percent for heart sounds, respectively. The sounds of high quality had estimations with a lower absolute error of median than those of low-quality sounds, with a difference of 4bpm and 12bpm, respectively.

Advantages: Both heart and lung sounds have had their signal quality accurately assessed. Additionally, the strategies applied here with Robotized chest sound recognition of newborns are valuable for future uses of telehealth.
Disadvantages: For high-quality sounds, the estimates have a lower median absolute error. As a result, more data must be trained and the median absolute error for low-quality sounds must also be reduced.

Mohammod Abdul Motin,et al,[3]"Selection of Empirical Mode Decomposition Techniques for Extracting Breathing Rate From PPG".

A huge biomarker that gives both predictive, as well as demonstrative data with the purpose of checking biological state, is the Breathing rate(BR). The harmless and ready-to-wear pulse oximeter-based photoplethysmogram (PPG) can be used to extract BR in addition to vital biomarkers like pulse rate and blood oxygen saturation. Empirical mode decomposition (EMD) and its types are frequently utilized for the decomposition of inclined, which are not linear and moving signals. The study looked into how each EMD variant affected the extraction of BR from PPG. BR was extracted from PPG using a hybrid model based on the EMD family and PCA. The datasets used to Validate each model's performances were MIMIC and Capno-base.The absolute error for the median ranged from 0 - 5.03 breaths per minute and from 2.47 - 10.55 breaths per minute for both datasets, respectively.

Advantages: Created best execution with relatively exact outcomes. Disadvantages: Since the hybrid model in this paper is based on a variety of EMD variants, it necessary to estimate each variant to determine its applicability. As a result, we require a setup for quick and simple respiratory rate estimation that takes time.

Chien-Lung Shen,et al,[4]"Respiratory Rate Estimation by Using ECG, Impedance and Motion Sensing in Smart Clothing".

Since the past decade, the demand for soft, lightweight, and smart clothing in-home care has increased. Automated biological and user-specific status recognition of the environment has been made possible by the development and application of numerous smart textile sensors. An affordable electrode fabric containing higher elasticity and lower resistance is considered the basis for the ready-to-wear multi-sensor clothing(smart) that is proposed in this study for homecare monitoring. Many bio signals of humans such as breathing rates, ECG, information on the gyro, and other things, can be measured by the ready-to-wear smart clothing's integration of multiple sensors.

Five free signals of respiration specifically, impedance plethysmography which is electric, actuated recurrence variety for respiration, incited adequacy variety for respiration, respiratory prompted power variety, and respiratory initiated development variety are bought.Using three distinct methods Kalman filter both Static, and dynamic, naive Bayes inference, the straightforward clothing can be used to accurately estimate respiratory rate. In the experiment of static, the frequency variation is respiratory induced performs best, while respiratory-induced amplitude variation performs best during the running experiment. The Guileless Bayes induction and dynamic Kalman channel have shown greatoutcomes.

Advantages: The novel smart clothes are washable, soft, and elastic, indicating that they are fitting for monitoring which is long-term in the service of medical which is home-care based, and in the healthcare industry.

Pedro Matias,et al,[5]“Clinically Relevant Sound-Based Features in COVID-19 Identification: Robustness Assessment With a Data-Centric Machine Learning Pipeline”

By developing a low-cost, non-invasive, and more decentralized technology that can educate people about the COVID-19 infection.The sensitivity scores varied between 60.00with their physiological significance, this study takes a data-centric approach. These findings are confirmed by an examination of two huge databases: The COVID-19 Sounds and Coswara datasets were used to explore the audio samples by enhancing the speech types in order to find disease-specific biomarkers. Since speech disturbances and respiratory problems (shortness of breath, dry cough) are some of the most common symptoms of COVID-19 disease, the best results were achieved with an SVM (Support Vector Machine) model (approximately 97).

Similarities: COVID-19 Identification Features Based on Breathing Sound.
Advantages: The COVID-19 detection model may be the most effective obtained performance when evaluating the COVID-19 Sounds dataset.

Claudia Floris,et al,[6]"Feasibility of Heart Rate and Respiratory Rate Estimation by Inertial Sensors Embedded in a Virtual Reality Headset"

Virtual reality (VR) headsets, with inbuilt micro-electromechanical systems, have the potential to assess the mechanical heart's functionality and respiratory activity of patients in a non-intrusive way and without additional sensors by utilizing the ballistocardiographic principle. To test the feasibility of this approach for physiological monitoring, thirty healthy volunteers were studied at rest in different body postures (sitting (SIT), standing (STAND) and supine (SUP)) and accelerometric and gyroscope data were recorded for 30 s using a VR headset and simultaneously with a 1-lead electrocardiogram (ECG) signal for mean heart rate (HR) estimation was done. To extract from the power spectral density and it's corresponding frequency, three frequencybased methods were evaluated. The obtained results, showed that the gyroscope outperformed the accelerometer in terms of accuracy with the gold standard. Also For Respiratory rate estimation,Supine position showed the best feasibility 98 obtaining a reliable value leading to the identification of the transversal direction as the one containing the largest breathing information.

Advantages: A good level of performance and evidence of feasibility

Kuo-Kai Shyu,et al,[7]"Detection of Breathing and Heart Rates in UWBRadar Sensor Data using FVPIEF Based Two-Layer EEMD".

The heartbeat signal is immaterial in light of the fact that it is covered by breathing sounds and messes. The EEMD technique is effective at separating the small heartbeat signal from the large breath signal and gradually enhancing the evaluation of heart and breathing rates as well as breathing conditions. When the UWB sensor is too close to the chest and too far from the person, it reflects a small echo pulse from the back cavity. The cardio-respiratory activity could be used to find this. The position of the first breath can be used to determine the heartbeat rate. The performance of heartbeat detection is unstable, despite the fact that the frequency window was previously selected based on knowledge of the heartbeat rate range.

Comparing the significance of a typical vital sign to the heartbeat signal of a healthy patient. The two-layer EEMD method, which selects the FTI and decomposes it into IMFs, makes it possible to effectively obtain both the breathing rate and the heart rate simultaneously.

Similarities: A non-contact monitor of vital signals or a tool for remote life detection.
Advantages: Effectively obtaining both breathing rate and heart rate simultaneously is possible. The UWB echo pulse used to simultaneously detect human breathing and heart activity demonstrates that the proposed detecting method is effective.

Alexis Martin,etal,[8]"In-Ear Audio Wearable: Measurement of Heart and Breathing Rates for Health and Safety Monitoring".

The subject of this study is the integration of vital sign monitoring functions in workplace hearing protection devices (HPDs). The testing subjects were approached to inhale at different rhythms and forces and they were reasonable sounds that were kept in the ear trench. For the purpose of measuring heart and breathing rates, digital signal processing algorithms are developed. Finally, an adjustable denoising filter was used to add industrial noise in the in-ear recorded signals in order to measure the algorithms' accuracy in a noisy environment. The HPD is also possible to run in high ambient noise after checking the heart rate and respiration rate with a closed ear canal. The absolute mean error of the algorithm is 2.7 cycles per minute (CPM).

Similarities: With an in-ear microphone-equipped wearable audio device, physiological sounds were recorded in the ear canal. As a reference, a commercial device was used to simultaneously record heartbeats and breathing.
Advantages: The noise disturbance has a clear impact on the performance of breathing rate detection, resulting in absolute errors below 7.4 CPM.

Xiangyu Xu,et al,[9] "Leveraging Acoustic Signals for Fine-grained Breathing Monitoring in Driving Environments".

The energy spectral density (ESD) of an acoustic signal describes how the energy of the acoustic signal is distributed in space with frequency, and environmental movement can be interpreted as changes in the energy distribution. This paper includes a fine-grained respiratory monitoring system called BreathListener. BreathListener uses your smartphone's audio device to estimate detailed breathing waveforms in a driving environment. BreathListener uses background subtraction and variational mode decomposition (VMD) to remove interference from the driving environment of the ESD signal and extract the respiratory cycle. A deep learning architecture based on a Generative Adversarial Network (GAN) is then developed to generate fine-grained respiratory waveforms from the Hilbert spectrum of the respiratory patterns extracted in the ESD signal. The RF card on smartphones cannot be used as an active RF radar, which is more powerful at tracking breathing patterns, because smartphones are embedded with NFC chips that support RF recognition.

Similarities: Using smartphone acoustic devices to estimate the fine-grained breathing waveform in driving conditions.
Advantages: Because the correlation coefficient is greater than 0.77, a deep learning architecture that uses a Generative Adversarial Network (GAN) to generate fine-grained. breathing waveforms indicates that BreathListener can still function in these circumstances, albeit with a decrease in accuracy.

Tianben Wang,et al,[10] "Contactless Respiration Monitoring using Ultrasound Signal with Off-the-shelf Audio Devices".

One of the most important ways to help older people live their best lives while they sleep is by monitoring their respiration in a real-time and continuous fashion.The model employs an MDL-based algorithm that is capable of capturing the Doppler effect brought on by exhaled airflow.

For respiration monitoring, this system has a median error of less than 0.3 breaths per minute or 2identify apnea. to make the system better so that it can lessen the effects of sporadic body movements while you sleep. Our system will be further evaluated in the future through larger-scale deployment in typical homes.

Advantages: Low respiration error detection (less than 0.3 breaths per minute, or 2 detected by a real-time and continuous respiration monitoring system.

Jyotibdha Acharya,et al,[11]“Deep Neural Network for Respiratory Sound Classification in Wearable Devices Enabled by Patient-Specific Model Tuning”.

Classification is carried out employing a Mel-spectrogram-based deep CNN-RNN model of respiratory sounds. With limited patient data, this model will first screen respiratory patients and create patient-specific classification models for anomaly detection. The weight quantization method will quadruple the cost of memory overall without sacrificing performance. The main contribution of the paper is the significant memory savings from local log quantization of trained weights. It gives a score of 66.31the four-class respiratory cycle classification on the 80–20 split. This model received a score of 71.81 percent in leave-one-out cross-validation, indicating that its results are significantly more reliable than those of the initial train-test split. Second, when pre-prepared with breathing information, profound learning models have been displayed to effectively obtain area explicit information and perform better compared to summed-up models.The hybrid CNN-RNN model may perform slightly worse than the VGG-16 model because the LSTM layer requires a higher bit precision than the CNN counterpart.

Similarities: Makes use of breathing audio as an input for enhancing data.
Advantages: This model reduces the minimum amount of memory required by four times without sacrificing performance or the ability to classify four classes of the respiratory cycle.

Tamer Elfaramawy,et al,[12]“A Wireless Respiratory Monitoring System Using a Wearable Patch Sensor Network”.

The severity of the cough is crucial when dealing with other conditions like chronic obstructive pulmonary disease (COPD).A remote respiratory observing framework with hack discovery is made to gauge the breathing rate and the recurrence of the hack. The respiratory frequency and coughing events are calculated using data processing and fusion algorithms. Through an SPI interface bus, the IMU transmits the data from the accelerometer and gyroscope to the MCU. The Savitzky-Golay smoothing filter was chosen because it is simple to use and works well in many systems. The thoracic and abdominal cages contain the two sensor nodes. A chest belt served as a point of reference. A performance test was carried out while the observer was moving around to demonstrate its robustness.

Similarities: System for wirelessly monitoring the respiratory system and detecting coughing.
Advantages: The setup takes a lot less time and is easier to use. In order to provide maximum comfort, it makes use of electronic building blocks with low power consumption.

Saba Emrani,et al,[13]“Persistent Homology of Delay Embeddings and its Application to Wheeze Detection”.

The periodic structure of dynamical systems can be quantified through the use of topological methods. The proposed autocorrelation-like (ACL) function of the signals is used in the algebraic topological approach to analyze breathing sound signals for wheeze detection.For periodicity analysis in the time domain, which is a continuous piecewise sinusoidal function with various periods and phases and a time-varying amplitude, strict autocorrelation functions cannot be implemented because breathing sound signals are time-varying and non-stationary. A small number of data points from each point represent the sound signal. Using a subsampling method, the algorithm's computational complexity is reduced.

Similarities: Analyzing breathing sound signals in order to identify wheezes.
Advantages: The method we propose is 98.39 percent accurate.

Yolanda Castillo-Escario,et al,[14]"Entropy Analysis of Acoustic Signals Recorded With a Smartphone for Detecting Apneas and Hypopneas: A Comparison With a Commercial System for Home Sleep Apnea Diagnosis".

The majority of patients with obstructive sleep apnea (OSA) do not receive treatment or a diagnosis, despite the condition's prevalence. The algorithm for identifying silent events, classifying them as apneas or hypopneas, evaluating how well they work, and comparing the data from three different portable sleep monitors that are primarily based on nasal airflow. The smartphone correctly identifies and categorizes all OSA patients, and the predicted apnea-hypopnea indices are highly consistent between the two systems. Since the majority of hypopneas are heard to be snoring, there was no reduction in noise. OSA is a disease that affects a lot of people, especially the elderly and obese. One of the straightforward, non-invasive methods for determining blood oxygen saturation (SpO2) is pulse oximetry.

Similarities: To screen OSA patients at home, the model uses a smartphone that analyzes audio signals.
Advantages: The accuracy of the classification increased to 82.

Lukui Shi, Kang Du,et al,[15]"Lung Sound Recognition Algorithm Based on VGGish-BiGRU".

Since lung sounds are intricate and nonstationary signals, it is hard to ascertain their data utilizing regular highlights. The transient qualities of the lung sounds can't be separated by utilizing the traditional convolutional brain organization. BiGRU-VGGish is the lung sound acknowledgment calculation, which depends on move learning and joins the VGGish network with the BiGRU (bidirectional gated repetitive unit brain organization), which can successfully further develop the acknowledgment exactness of lung sounds utilizing state-of-the-art calculations, headways in computerized signal handling and man-made consciousness advances, and customary acoustic. The electronic stethoscope slowly replaces the stethoscope. The wavelet change is utilized to separate lung sound signs into recurrence subbands, and a bunch of measurable elements is taken from the subbands to address the wavelet coefficient dissemination. Rather than different strategies, BiGRU can catch the time series elements of the lung sounds, which works on the precision of the asthma sounds. Similarities: The lung sound data are used to retrain the BiGRU network, which then extracts the sounds from the lungs. Advantages: In contrast to the most recent algorithms, The proposed algorithm effectively improves lung sound recognition accuracy.

Advantages: Created best execution with relatively exact outcomes.
Disadvantages: Since the hybrid model in this paper is based on a variety of EMD variants, it necessary to estimate each variant to determine its applicability. As a result, we require a setup for quick and simple respiratory rate estimation that takes time.

Summary of the Literature Survey

The literature Survey was done for 30 papers. We evaluated the different methodologies used, the metrics used for evaluation and the advantages and disadvantages of those approaches. We analysed it and constructed a table [2.1] to evaluate the methodologies and metrics which we can consider. The existing methodologies are accurate but their efficiency is not providing the ideal accuracy.

For example: The early Fourier fusion algorithm gives efficient performance impact related to sleep. But the recognition algorithm needs to be improved for better results. The auto regressive spectrum gives good estimates but fails to remove all the background noise. Signal quality classification through XGBOOST presents an accurate and low cost monitoring of respiratory rate. But this approach has been evaluated for only unsupervised use and not for supervised as well. Hence to overcome all the disadvantages by getting an idea from advantages, here we implement a machine learning based Estimation of Respiratory rate through recorder/microphone of a mobile phone.

Paper name	Model/Algorithm used	Accuracy/Metrics
Deep Learning versus Professional Healthcare Equipment: A Fine-Grained Breathing Rate Monitoring Model	Deep learning as fine-grained breathing rate monitoring technique.	The TTR of DeepFilter is 0.77 DeepFilter can achieve 90% accuracy in 1 meter but lower than 80% in 2 meters.
Estimation of respiratory rate and exhale duration using audio signals recorded by smartphone microphones	Data acquisition through smart phone, respiration algorithm , inter- breather Interval detection, Signal quality classification using XGBOOST.	Respiratory rate was estimated with a mean absolute error (MAE) of 0.2 ± 0.27 bpm,Audio signal quality was classified with an area under the receiver operating characteristic of ±0.81 .
Breathing Rate Estimation from Head-Worn Photoplethysmography Sensor Data Using Machine Learning	Respiratory rate estimation algorithm which is based on advanced Signal processing and machine learning techniques. Also includes novel quality assessment and motion artifacts removals procedure.	The proposed algorithm outperforms the compared algorithms, achieving a mean absolute error of 1.38 breaths per minute and a Pearson's correlation coefficient of 0.86.
Multiparameter Respiratory Rate Estimation From the Photoplethysmogram	Smart Fusion RR estimation algorithm.	The Smart Fusion showed trends of improved estimation (mean root mean square error 3.0 breaths/min) compared to the individual estimation methods (5.8, 6.2, and 3.9 breaths/min).
Time-Reversal Breathing Rate Estimation and Detection	Contact-free breathing monitoring system, Root-MUSIC algorithm.	With only 10 seconds of measurement, a mean accuracy of 99% can be obtained for single-person breathing rate estimation under the non-line-of-sight (NLOS) scenario.
Breathing Rate Monitoring during Sleep from a Depth Camera under Real-life Conditions	Early Fourier Fusion algorithm.	Can achieve accuracy of 85.9%.

Figure 2.1. Literature Survey

Chapter 3

Problem Statement and Proposed Solution

3.1 Problem Statement

The challenges faced in accurately estimating respiratory rate during telemedicine visits pose significant obstacles to effective patient care. Factors such as poor lighting, low video quality, and camera angle can introduce uncertainties and inaccuracies in the manual assessment of respiratory rate. In telemedicine settings, where healthcare practitioners rely heavily on remote assessment, these challenges become even more pronounced.

The gold standard method of manually counting breaths over a 60-second interval is time-consuming and impractical in busy clinical or triage settings. The need to expedite the assessment process often leads to the adoption of shorter observation periods, such as 10 seconds. However, relying on these shorter intervals can result in unreliable respiratory rate estimates, as they may not capture the true breathing patterns of the patient accurately.

Furthermore, the awareness of being monitored can influence a patient's respiratory rate. This phenomenon, known as the observer effect, can lead to altered breathing patterns and, consequently, inaccurate estimates. This issue is particularly relevant in telemedicine settings, where patients may consciously or subconsciously modify their breathing due to anxiety, self-consciousness, or other factors.

To address these challenges, there is an urgent need for a robust and low-cost method to estimate respiratory rate in telemedicine settings. Such a method should be able to account for poor lighting conditions, low video quality, and varying camera angles. It should also provide accurate estimates within shorter observation periods while minimizing the influence of the observer effect. By overcoming these challenges, healthcare practitioners can rely on more accurate respiratory rate measurements, leading to improved patient care and more efficient telemedicine consultations.

In summary, the challenges posed by poor lighting, low video quality, camera angle variations, and the limitations of traditional respiratory rate estimation methods in telemedicine settings necessitate the development of a robust, low-cost solution. Overcoming these challenges will enable healthcare practitioners to accurately estimate respiratory rates, leading to more effective remote patient care and improved healthcare delivery in busy and remote telemedicine settings.

3.2 Existing Systems

An established automated approach for measuring respiratory rate in a clinical setting is impedance pneumography. This method involves the measurement of changes in transthoracic impedance, which is the resistance to the flow of electrical current through the chest, during the respiratory cycle using skin electrodes. By analyzing these impedance changes, the respiratory rate can be estimated. However, impedance pneumography requires specialized and expensive equipment that is typically available only in monitored clinical settings such as emergency departments, intensive care units, and some general medical wards. Consequently, this method is not suitable for remote or resource-limited settings where access to such equipment is limited.

Impedance pneumography offers several advantages in terms of accuracy and non-invasiveness. It provides real-time monitoring of respiratory rate without the need for direct contact with the patient's airways, making it a comfortable and safe option for continuous monitoring. However, the reliance on specialized equipment and the need for trained personnel to operate and interpret the measurements limit its widespread use beyond clinical settings.

In remote or resource-limited settings, the availability of impedance pneumography equipment is often restricted due to its high cost and technical requirements. This limitation hinders the ability to accurately assess respiratory rate during telemedicine visits or in situations where on-site monitoring is not feasible. Furthermore, the need for skilled personnel to perform the measurements and interpret the results adds to the challenges of implementing impedance pneumography in these settings.

Therefore, there is a clear gap in the existing systems when it comes to providing a robust and accessible method for estimating respiratory rate in remote or resource-limited settings. A solution is needed that overcomes the limitations of impedance pneumography, such as the requirement for expensive equipment and trained personnel, while still delivering accurate and reliable respiratory rate measurements. Such a solution would enable healthcare providers to remotely monitor respiratory rates in a cost-effective and efficient manner, facilitating timely interventions and improving patient outcomes in telemedicine and resource-constrained settings.

To address this gap, innovative approaches leveraging readily available technologies, such as smartphones or wearable devices, could be explored. These approaches should aim to provide accurate and reliable respiratory rate estimation while being affordable, user-friendly, and suitable for use in diverse environments. By developing a system that combines the convenience and accessibility of modern technology with the accuracy and reliability of respiratory rate measurement, healthcare providers can bridge the gap in remote or resource-limited settings, enabling effective and efficient delivery of healthcare services.

3.3 Proposed Solutions

To address the need for a robust and accessible method for estimating respiratory rate in remote or resource-limited settings, a proposed solution is to develop an estimation system that relies on audio signals alone. This system offers an automatic, remote, and cost-effective alternative for respiratory rate estimation, making it suitable for both hospital and telehealth settings.

Existing work in the field has explored various approaches for respiratory rate estimation using audio signals. These approaches can be broadly categorized into two categories: learning-based and signal processing-based techniques.

Learning-based techniques involve training machine learning models, such as convolutional neural networks (CNNs), to learn patterns and features from respiratory sound data. These models can then be used to estimate respiratory rate directly or related features, such as inspiration and expiration cycle boundaries, which can be used for the computation of respiratory rate.The proposed solution can leverage these learning-based techniques to develop a robust and accurate respiratory rate estimation model.

Our project demonstrates an implementation of a learning-based approach using a CNN model for respiratory sound classification. The code performs preprocessing of the audio data, feature extraction using mel spectrograms, model training, and estimation/classification. The trained model can then be used to estimate respiratory rate from uploaded audio files in a web application. This serves as a starting point for developing a comprehensive respiratory rate estimation system using audio signals.

In addition to learning-based techniques, signal processing-based techniques can also be utilized. These techniques involve analyzing the properties and characteristics of the audio signals to extract relevant information related to respiratory rate. For example, techniques such as peak detection, spectral analysis, or time-frequency analysis can be applied to identify respiratory patterns and estimate the rate. By combining both learning-based and signal processing-based approaches, the proposed solution can enhance the accuracy and reliability of respiratory rate estimation.

The advantage of using audio signals for respiratory rate estimation lies in its simplicity and accessibility. Audio signals can be easily captured using common devices such as smartphones, making it a widely available resource. This eliminates the need for specialized equipment and reduces the cost associated with respiratory rate measurement. Furthermore, audio-based estimation systems can be integrated into telehealth platforms, allowing remote monitoring of patients' respiratory rates without the need for direct physical contact.

In conclusion, the proposed solution of developing an estimation system based on audio signals offers a promising approach for respiratory rate estimation in remote or resource-limited settings. By leveraging both learning-based and signal processing-based techniques, accurate and reliable respiratory rate measurements can be obtained using readily available audio data. Implementing such a system can significantly improve the delivery of healthcare services, particularly in telehealth settings, by enabling remote monitoring and timely interventions based on respiratory rate measurements.

3.4 System Requirements

- Python
- Python Libraries: Flask, librosa, NumPy, scikit-learn, Keras and TensorFlow
- Audio Dataset: ICBHI

Python: Python is the programming language used to write the entire code. Python is a high-level, versatile programming language known for its simplicity and readability. It provides a wide range of libraries and frameworks that make it suitable for various applications, including machine learning and web development.

Flask: Flask is a popular micro web framework used for creating APIs in Python. It is designed to be simple and easy to use, allowing developers to quickly build web applications. In the provided code, Flask is utilized to create a web application interface where users can upload audio files for respiratory rate estimation.

Librosa: Librosa is a powerful library for music and sound analysis in Python. It provides functions and tools for working with audio files and extracting relevant features. In the context of the code, Librosa is used for loading audio files, computing mel spectrograms, and performing feature extraction on respiratory sound data.

Tensorflow: Tensorflow is an open-source library widely used for deep learning and machine learning applications. It offers a comprehensive ecosystem for building and training neural networks. In the code, Tensorflow is utilized for constructing and training a convolutional neural network (CNN) model for respiratory sound classification.

Numpy: Numpy is a fundamental library for numerical computing in Python. It provides powerful data structures and functions for efficient array operations and mathematical computations. In the code, Numpy is used to handle arrays and matrices, performing calculations, and manipulating the data for preprocessing and model training.

Scikit-learn: Scikit-learn is a versatile machine learning library in Python. It offers a wide range of tools and algorithms for data preprocessing, feature selection, and model training. In the provided code, Scikit-learn is employed for splitting the data into training and testing sets using the 'train-test-split' function.

Keras: Keras is a high-level neural network library that runs on top of Tensorflow. It provides a user-friendly API for building and training deep learning models. In the code, Keras is used to construct the CNN model architecture and compile it with appropriate loss and optimization functions.

Audio Dataset:

The ICBHI dataset is used in the code for respiratory sound classification. This dataset contains 5.5 hours of recordings with 6898 respiratory cycles. The recordings include various respiratory conditions such as crackles, wheezes, and a combination of both. The dataset consists of 920 annotated audio samples from 126 subjects. This dataset serves as the training and testing data for the respiratory sound classification model.

Overall, the code utilizes various Python libraries, including Flask, Librosa, Tensorflow, Numpy, Scikit-learn, and Keras, to develop a web application for respiratory rate estimation. These libraries provide the necessary functionalities for audio processing, feature extraction, model training, and prediction. The ICBHI dataset is employed to train and evaluate the respiratory sound classification model, enabling accurate estimation of respiratory rate from uploaded audio files.

Chapter 4

Architecture and System Design

4.1 System Architechture

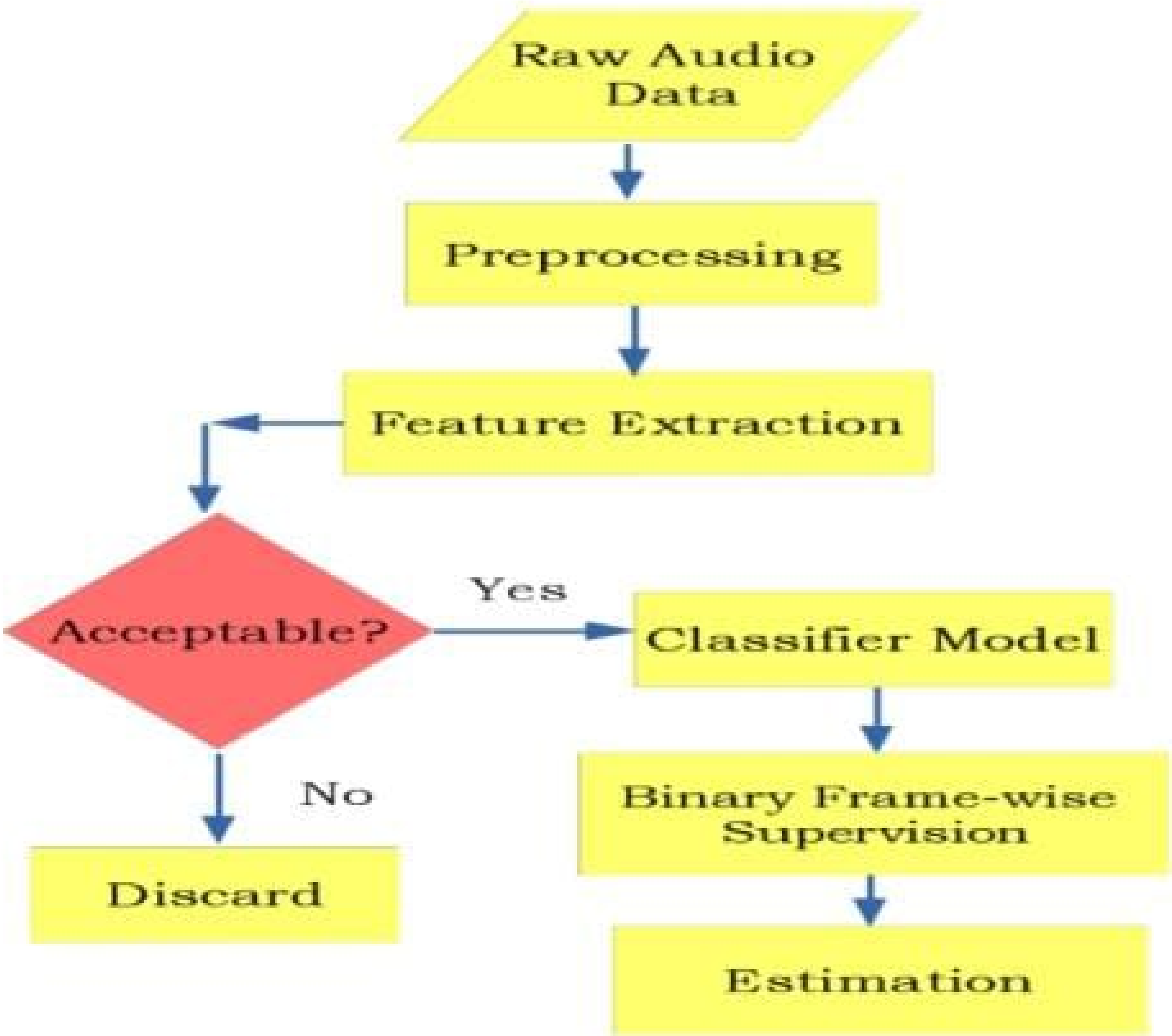

Figure 4.1. System Architechture

4.2 System Overview

The project aims to develop a web application for estimating respiratory rate using smartphone.The application provides an intuitive user interface where doctors or patients can upload audio and know the status about their respiratory rate.The system architecture [4.1] consists of several components that work together to perform respiratory sound classification. The architecture includes preprocessing, feature extraction, model training, estimation/classification, and a Flask-based web application.

1. Preprocessing: The system starts with preprocessing the respiratory sound data. The audio files are loaded using the 'librosa.load' function from the librosa library. The loaded audio files undergo feature extraction, specifically the computation of the mel spectrogram using the 'librosa.feature.melspectrogram' function. The mel spectrogram captures the frequency content of the audio signal over time. To ensure consistency, the extracted features are normalized by calculating the mean and standard deviation.

2. Feature Extraction: After preprocessing, the features are extracted from the audio files. In this case, the mel spectrogram is used as the feature representation. The mel spectrogram provides a representation of the audio signal in the frequency domain. It captures the distribution of frequencies over time and is commonly used in audio analysis tasks. The extracted features are then padded or truncated to a fixed length to ensure uniformity for model input.

3. Model Training: The next step in the system architecture is model training. The extracted features are split into training and testing sets using the 'train-test-split' function from scikit-learn. The labels associated with the audio files are encoded using the 'LabelEncoder' class. The training data undergoes further preprocessing by normalizing the features and reshaping them to match the input shape of the convolutional neural network (CNN). The CNN model is constructed using the TensorFlow Keras API. The model architecture consists of convolutional layers, pooling layers, and dense layers. The model is compiled with appropriate loss and optimization functions before being trained using the training data.

4. Estimation/Classification: Once the model is trained, it can be used for respiratory sound classification. The Flask-based web application provides an interface for users to upload audio files. The uploaded audio file is saved, and the trained model is loaded along with the label encoder. Features are extracted from the uploaded audio file using the same procedure as during training. The extracted features are preprocessed by normalizing them using the mean and standard deviation calculated from the training data. The preprocessed features are then fed into the trained model to obtain predictions.

The predicted class index is obtained using 'np.argmax', and the corresponding label is determined using the inverse transformation of the label encoder. Based on the predicted label, the respiratory rate is estimated using a mapping specific to each class. The estimated respiratory rate is then classified as normal or abnormal based on a threshold. The classification result, along with the uploaded audio playback, is displayed to the user.

5. Flask App: The system includes a Flask-based web application to provide a user-friendly interface for respiratory sound classification. The web application consists of HTML templates for the main page and the classification result page. The main page includes an audio file upload form, allowing users to select an audio file for classification. When the user submits the form, the uploaded audio file is sent to the server using a POST request. The Flask route '/classify-audio' handles the uploaded file, extracts features, performs classification using the trained model, and returns the classification result as JSON data. The classification result is then displayed on the webpage using JavaScript.

4.3 Data Flow Diagram:

1. User Interaction: The process begins when a user interacts with the Flask-based web application. They upload an audio file through the provided interface.

2. File Upload: The Flask application receives the uploaded file and saves it to the server's storage. This allows the file to be accessed and processed by the application.

3. Feature Extraction: The saved audio file is passed to the "extract-features" function, which preprocesses the audio data. This function utilizes the Librosa library to extract relevant features from the audio, such as the Mel spectrogram.

4. Preprocessing: The extracted features undergo preprocessing steps to ensure consistency with the training process. This includes normalization, where the mean and standard deviation calculated from the training dataset are used to normalize the testing features. Additionally, the features are reshaped to match the input shape of the trained model.

5. Model Prediction: The preprocessed features are fed into the trained model. The model utilizes its learned weights and architecture to predict the class probabilities for the given audio. The model predicts whether the audio sample is normal or abnormal based on the trained classification model.

6. Label Mapping: The predicted class index is converted back to the original label using the label encoder. This step allows the predicted label to be mapped back to its corresponding respiratory sound category.

7. Respiratory Rate Mapping: A respiratory rate mapping is applied to map the predicted label to a respiratory rate value. This mapping is based on predefined mappings, where each label corresponds to a specific respiratory rate value.

8. Classification Determination: Based on the predicted respiratory rate and a predefined threshold, the classification of the audio sample is determined as either "Normal" or "Abnormal." If the respiratory rate is below or equal to the threshold, it is classified as "Normal," otherwise, it is classified as "Abnormal."

9. User Feedback: The classification result, along with the uploaded audio file playback, is displayed to the user through the Flask web application. The user can see the classification outcome and listen to the uploaded audio file.

10. Cleanup: To ensure proper management of storage space, the uploaded audio file is deleted from the server's storage, freeing up resources and maintaining data privacy.

This data flow diagram[4.2] provides an overview of how the audio data is processed, classified, and presented to the user through the Flask web application.

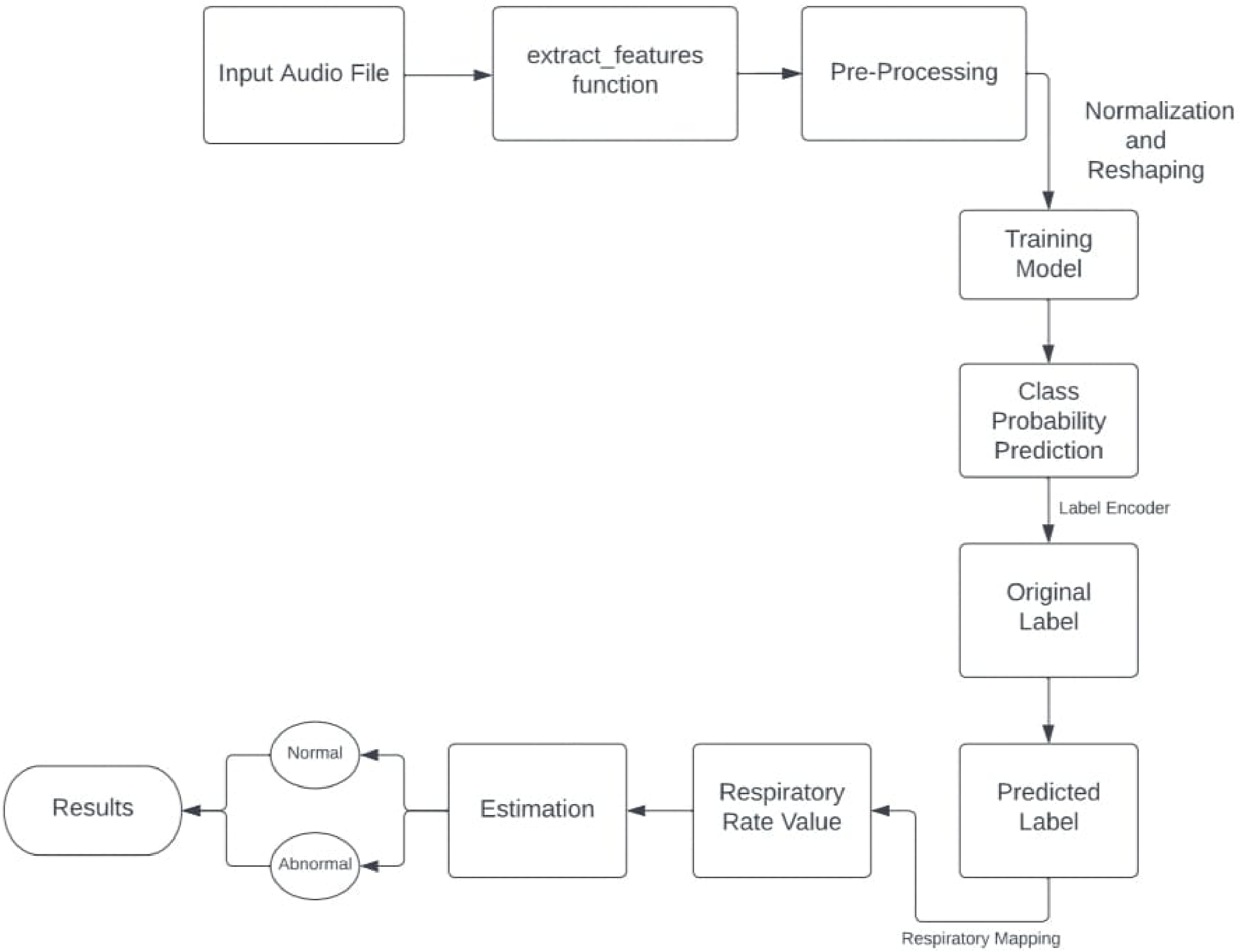

Figure 4.2. Data Flow Diagram

Chapter 5

Implementation

5.1 Software:

• Python • Flask • Librosa • TensorFlow • Keras • Python

• Python Libraries: Flask, librosa, NumPy, scikit-learn, and TensorFlow

• Audio Dataset : ICBHI

5.2 Implementation Details

To ensure the quality and reliability of the respiratory sound data used for analysis, a preprocessing step involves applying four constraints to filter out samples that do not meet the specified criteria. These constraints help identify and remove samples that contain irrelevant or undesirable characteristics. Let's expand on each of the four constraints:

1. Distinctly irregular heartbeats containing samples: This constraint focuses on identifying respiratory sound samples that contain distinctly irregular heartbeats. Irregular heartbeats may introduce noise or inconsistencies into the respiratory sound data, making it challenging to accurately estimate the respiratory rate. By detecting and excluding these samples, the preprocessing step ensures that the remaining data primarily captures the respiratory patterns without interference from irregular heartbeats.

2. Too many random background sounds in the samples: Random background sounds, such as ambient noise or unrelated sounds, can affect the accuracy of respiratory rate estimation. This constraint aims to identify samples that contain an excessive amount of random background sounds. By setting a threshold or criteria for the acceptable level of background noise, the preprocessing step filters out samples that surpass this threshold, ensuring that the remaining data focuses on the relevant respiratory sounds.

3. Excess clamor or murmur present in the sound sample: In some cases, respiratory sound samples may contain excess clamor or murmur, which can be attributed to various factors such as microphone interference, movement noise, or external disturbances. This constraint aims to identify samples that exhibit an excessive level of clamor or murmur. By establishing a threshold or characteristic of excessive noise, the preprocessing step removes these samples to enhance the accuracy of subsequent analysis.

4. Pattern of breathing that is not periodic or irregular: Respiratory sound samples with a non-periodic or irregular breathing pattern may introduce inconsistencies in the estimation of respiratory rate. This constraint identifies samples that deviate significantly from a typical periodic breathing pattern. By detecting and excluding samples with irregular breathing patterns, the preprocessing step ensures that the remaining data represents consistent and periodic respiratory sounds, facilitating accurate respiratory rate estimation.

By applying these four constraints during the preprocessing stage, the system aims to enhance the quality and reliability of the respiratory sound data used for further analysis. Removing samples that contain irregular heartbeats, excessive background noise, excess clamor or murmur, or irregular breathing patterns helps ensure that the subsequent steps, such as feature extraction and model training, are based on high-quality data, leading to more accurate respiratory rate estimation.

5.2.1 Feature Extraction

In the feature extraction step of the system, the 'extractfeatures' function utilizes the librosa library to extract audio features from the respiratory sound data. Specifically, it computes the Mel spectrogram for the audio file.

The Mel spectrogram is a representation of the audio signal in the frequency domain. It is derived by dividing the frequency range into mel-scale bins, which are perceptually uniform in relation to human hearing. This conversion from the linear frequency scale to the mel-scale helps better capture the characteristics of human auditory perception.

To compute the Mel spectrogram, the 'extractfeatures' function applies the appropriate librosa function, such as 'librosa.feature.melspectrogram', to the audio file. This function calculates the spectrogram using a specific set of parameters, including the window size, hop length, and number of mel bands.

After computing the Mel spectrogram, the extracted features are processed further to ensure consistency in length. This is achieved by padding or truncating the features to a fixed length defined by the 'maxlength' parameter. Padding involves adding zeros to the features to match the desired length, while truncation involves removing excess frames if the features exceed the desired length.

By performing feature extraction using the Mel spectrogram and adjusting the feature length to a fixed size, the system prepares the data for subsequent steps, such as model training and classification. The Mel spectrogram captures important frequency information from the respiratory sound data, while the fixed-length feature representation ensures compatibility with the model's input requirements.

5.2.2 Model Training

The model training encompasses several essential steps to prepare the data, define the model architecture, and train the model. Here is a detailed explanation of each step:

1. Loading and Extracting Features: The code loads the audio files from the dataset directory and applies the 'extract-features' function to extract features for each file. The features are calculated using the Mel spectrogram or other relevant audio analysis techniques. The extracted features are stored in the 'features' array.

2. Storing Features and Labels: The extracted features are paired with their corresponding labels, which are obtained from the filenames or metadata. The features are stored in the 'features' array, and the labels are stored in the 'labels' array.

3. Label Encoding: To work with categorical labels in a numerical format, the label encoder is employed. The label encoder converts the categorical labels into numerical values, allowing the model to process them effectively.

4. Train-Test Split: The dataset is divided into training and testing sets using the 'train-test-split' function from the scikit-learn library. This step ensures that the model is trained on a portion of the data and evaluated on unseen data to assess its generalization performance.

5. Feature Normalization: Normalization is performed on the features to bring them to a similar scale and facilitate model training. The mean of the features is subtracted, and the result is divided by the standard deviation. This process ensures that all features have zero mean and unit variance.

6. Label One-Hot Encoding: The labels are one-hot encoded using the 'to-categorical' function. One-hot encoding transforms categorical labels into binary vectors, where each vector represents a unique label. This encoding is necessary for multi-class classification tasks.

7. Reshaping Input Data: The input data, including the features, needs to be reshaped to match the expected input shape of the CNN model. The reshaping is performed to ensure that the data is compatible with the model's input layer, which typically expects a specific shape, such as (batch-size, height, width, channels).

8. Defining the CNN Model: The CNN model is defined using the Keras Sequential API. The model architecture typically consists of convolutional layers, max pooling layers, flatten layers, and dense (fully connected) layers. These layers are added sequentially to build the model's architecture.

9. Model Training: Once the model is defined, it is compiled with appropriate loss and optimization functions. The model is then trained using the training data, which includes the preprocessed features and corresponding one-hot encoded labels. During training, the model adjusts its internal parameters based on the optimization algorithm and the provided loss function, aiming to minimize the discrepancy between predicted and actual labels.

CNN Model consists of:

• "tf.keras.Sequential": This is a linear stack of layers. It allows you to build the model layer by layer.

• "tf.keras.layers.Input": This layer defines the input shape of the data. In this case, it expects input data of shape "(X-train.shape[1], X-train.shape[2], 1)".
The "X-train" is a placeholder for the training data, and "X-train.shape[1]" represents the number of rows in the input data, "X-train.shape[2]" represents the number of columns, and "1" represents the number of channels (in this case, grayscale images with one channel).

• "tf.keras.layers.Conv2D": This is a convolutional layer with 32 filters, each of size "(3, 3)". The activation function used is the Rectified Linear Unit (ReLU), which introduces non-linearity to the model.

• "tf.keras.layers.MaxPooling2D": This layer performs max pooling operation on the output of the previous convolutional layer. It helps reduce the spatial dimensions of the input and extract the most important features.

• "tf.keras.layers.Flatten": This layer flattens the multi-dimensional output from the previous layer into a one-dimensional vector. It prepares the data for the fully connected layers.

• "tf.keras.layers.Dense": This layer is a fully connected layer with 64 units/neurons. The activation function used is ReLU.

• "tf.keras.layers.Dense": This is the final fully connected layer with "num-classes" units, where "num-classes" is the number of output classes in the classification task. The activation function used is softmax, which computes the probability distribution over the classes.

This model takes 2D input data (such as images) and applies convolutional and pooling operations to extract relevant features. It then flattens the feature maps and passes them through fully connected layers to make predictions on the input classes using the softmax activation function.

10. Compiling the Model: After defining the model architecture, the next step is to compile the model. This involves specifying the optimizer, loss function, and evaluation metric to be used during training. The optimizer determines how the model's parameters are updated based on the computed gradients. Common optimizers include Adam, RMSprop, and Stochastic Gradient Descent (SGD). The loss function measures the discrepancy between the predicted and actual labels and serves as the objective to be minimized during training. The evaluation metric provides additional metrics to evaluate the model's performance during training. Examples of evaluation metrics include accuracy, precision, recall, and F1-score.

11. Training the Model: Once the model is compiled, it is ready to be trained on the training data. The training process is initiated by calling the 'fit' function on the model object. The 'fit' function takes the preprocessed training features and labels as input. During training, the model adjusts its internal parameters using the optimization algorithm specified during compilation. The training process iterates over the dataset for a specified number of epochs, where each epoch represents a complete pass through the entire dataset. The model learns to make better predictions by minimizing the specified loss function. The training progress and performance metrics are typically displayed during training, such as the loss and accuracy for each epoch.

During training, the model learns to generalize patterns from the training data and improves its ability to make accurate predictions on unseen data. The duration of training depends on the complexity of the model, the size of the dataset, and other factors such as computational resources. It is common practice to monitor the model's performance on a separate validation set to assess its generalization and prevent overfitting, where the model becomes too specialized to the training data and performs poorly on new data.

By compiling the model with an optimizer, loss function, and evaluation metric, and subsequently training it using the 'fit' function, the code enables the model to learn and optimize its parameters based on the provided training data.

5.2.3 Audio Classification

The Flask web application provides an interface for uploading audio files and classifying them using the trained model:

• Preprocessing and Reshaping: After the audio file is uploaded, the Flask web application passes it to the 'extract-features' function to obtain the audio features. These features are then preprocessed by normalizing them using the mean and standard deviation calculated from the training data. Additionally, the features are reshaped to match the input requirements of the trained model. This ensures that the input data has the correct dimensions and format expected by the model.

• Prediction and Label Conversion: Once the features are preprocessed and reshaped, they are fed into the trained model using the 'predict' method. The model predicts the class probabilities for the given audio based on its learned patterns and weights. The predicted class index is obtained by finding the index with the highest probability, indicating the most likely class.

To obtain the predicted label, the label encoder object is used to invert the encoding process. It maps the predicted class index back to the original label, providing a human-readable interpretation of the prediction.

• Respiratory Rate Mapping and Classification: To determine the respiratory rate based on the predicted label, a respiratory rate mapping is defined. This mapping associates each class with a corresponding respiratory rate value. By using the predicted label as a key, the mapping retrieves the associated respiratory rate.

Next, a classification decision is made based on the respiratory rate and a specified threshold. If the respiratory rate is below or equal to the threshold, the classification is considered "Normal." Otherwise, it is labeled as "Abnormal." This decision is based on domain-specific knowledge or medical guidelines.

• JSON Response and File Cleanup: The classification result, along with the uploaded audio playback, is returned as a JSON response to the frontend. The frontend can then display the classification result to the user.

Finally, to clean up temporary storage and maintain data privacy, the uploaded audio file is deleted after the classification process is completed.

By following these steps, the Flask web application enables users to upload audio files, preprocess them, classify them using the trained model, and provide the classification result as a JSON response.

5.3 DATASET

Respiratory Sound Database ICBHI1 2017

The dataset used in the project is the "Respiratory Sound Database ICBHI1 2017." This dataset is specifically designed for respiratory sound analysis and classification tasks. It contains a collection of audio recordings of respiratory sounds captured from patients with different respiratory conditions.

The Respiratory Sound Database ICBHI1 2017 includes recordings from multiple sources, such as clinics and hospitals, to ensure a diverse range of respiratory conditions and variations in the sound patterns. The recordings are performed using electronic stethoscopes or other suitable audio capturing devices.

Each audio recording in the dataset is associated with a specific respiratory condition or pathology, such as asthma, bronchiolitis, chronic obstructive pulmonary disease (COPD), and pneumonia, among others. These labels provide valuable information for training and evaluating the respiratory sound classification model.

The dataset also includes additional metadata and annotations, such as the age and gender of the patients, clinical history, and expert annotations for specific events or patterns in the audio recordings. This information can be useful for further analysis and research purposes.

By using the Respiratory Sound Database ICBHI1 2017, the project benefits from a comprehensive and curated collection of respiratory sound recordings, allowing for the development and evaluation of robust classification models. The dataset enables researchers and developers to explore various respiratory conditions, study their acoustic characteristics, and develop innovative solutions for respiratory sound analysis and diagnosis.

It is worth noting that the dataset may require proper data preprocessing, including cleaning, noise removal, and feature extraction, to ensure optimal performance and accurate classification results.

Chapter 6

Testing

The testing process is an important step in evaluating the performance of the trained model on unseen data. In the project, the testing phase involves the following steps:

1. Dataset Split: The testing dataset is prepared by splitting the features and corresponding labels into X-test and y-test, respectively, using the 'train-test-split' function from the scikit-learn library. This ensures that the model is evaluated on data it hasn't seen during training, providing an unbiased assessment of its generalization capabilities.

2. Preprocessing: Before feeding the testing data to the model, the features undergo preprocessing to maintain consistency with the training process. This includes normalizing the features using the mean and standard deviation calculated from the training dataset. The purpose of normalization is to scale the features to a similar range and prevent any bias introduced by different feature scales. Additionally, the testing features are reshaped to match the input shape of the CNN model.

3. Model Prediction and Evaluation: Once the preprocessing is completed, the preprocessed testing features, 'X-test', are used to make predictions using the trained model. The model's 'evaluate' method is called, passing the testing features 'X-test' and the corresponding one-hot encoded labels 'y-test-categorical'. This evaluation step calculates the loss and accuracy of the model on the testing dataset.

4. Test Loss and Test Accuracy: The test-loss and test-accuracy are obtained as the outputs of the 'evaluate' method. The test-loss quantifies the discrepancy between the predicted and actual labels, providing a measure of how well the model performs on the testing data. The test-accuracy, on the other hand, represents the percentage of correctly classified samples in the testing dataset. A higher test-accuracy indicates better performance in accurately classifying respiratory sounds.

The test-loss and test-accuracy values serve as essential metrics for evaluating the model's performance. They provide insights into the model's effectiveness in classifying respiratory sounds and can be used to compare different models or baselines. By analyzing these metrics, researchers and developers can assess the model's performance, identify areas for improvement, and determine its suitability for respiratory sound classification tasks.

In summary, the testing process plays a crucial role in assessing the trained model's performance on unseen data. The test-loss and test-accuracy metrics provide valuable information about the model's classification capabilities and serve as benchmarks for evaluating its effectiveness in respiratory sound analysis.

Chapter 7

Experimentation and Results

7.1 Training and Validation Loss:

The graph[7.1] shows the trend of the model's loss (error) during training and validation. The training loss represents the error on the training data, while the validation loss reflects the error on a separate validation dataset. The graph helps us understand how the model's loss changes over epochs. A decreasing loss indicates that the model is learning and converging towards better performance. If the training loss continues to decrease while the validation loss increases or remains stagnant, it may indicate overfitting, suggesting that the model is not generalizing well to unseen data.

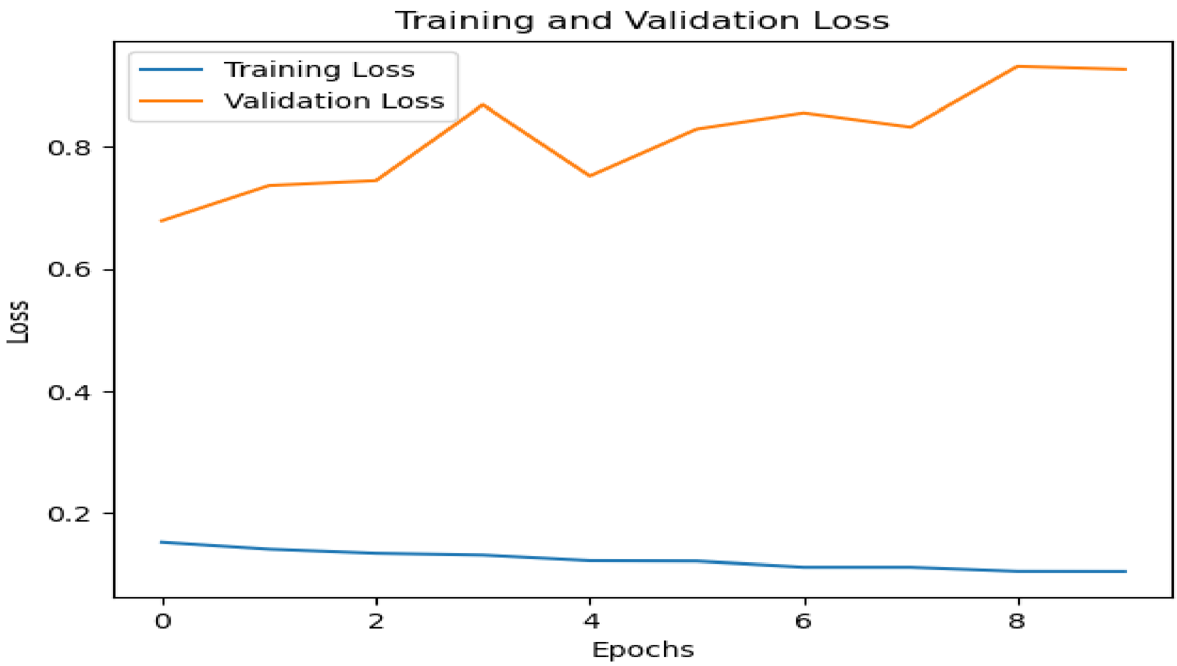

Figure 7.1. Training and Validation Loss

7.2 Training and Validation Accuracy:

The graph[7.2] displays the model's accuracy during training and validation. Accuracy measures the percentage of correctly classified instances. Similar to the loss graph, the training accuracy represents the model's performance on the training data, while the validation accuracy indicates its performance on the validation dataset. An increasing accuracy signifies that the model is improving its ability to correctly classify instances. It is desirable to see both the training and validation accuracies increasing, indicating that the model is learning and generalizing well. However, a large gap between the training and validation accuracies may suggest overfitting.

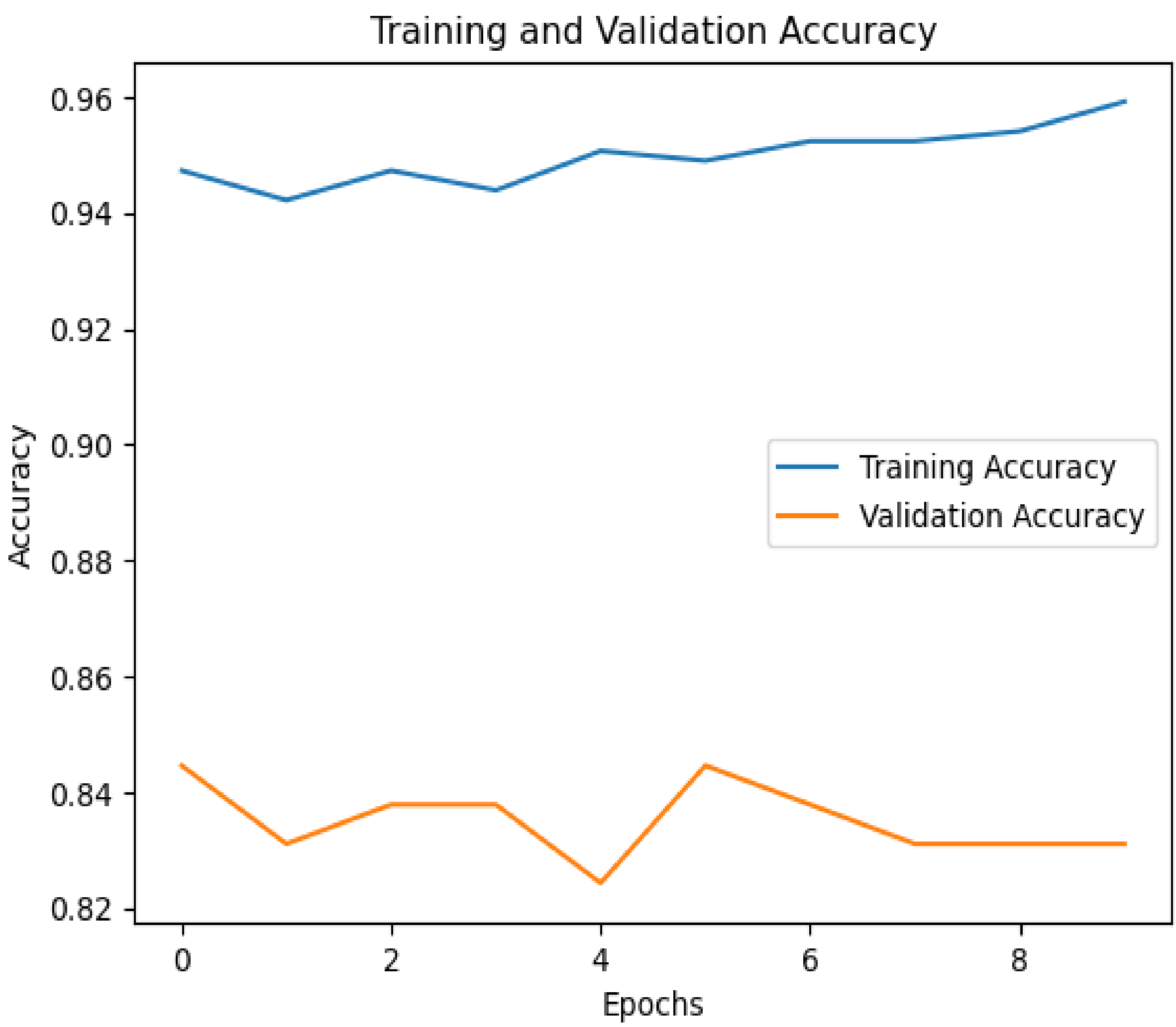

Figure 7.2. Training and Validation Accuracy

7.3 Testing Accuracy and loss:

The trained model achieved a Test Loss of 0.6009, indicating its ability to minimize the error when making predictions on unseen data. Additionally, the model achieved a Test Accuracy of 0.8043, showcasing its proficiency in correctly classifying instances from the test dataset as shown in figure [7.3].

```
8243
Epoch 5/10
19/19 [==============================] - 23s 1s/step - loss: 0.2522 - accuracy: 0.9116 - val_loss: 0.5586 - val_accuracy: 0.
8243
Epoch 6/10
19/19 [==============================] - 25s 1s/step - loss: 0.2229 - accuracy: 0.9082 - val_loss: 0.5701 - val_accuracy: 0.
8243
Epoch 7/10
19/19 [==============================] - 26s 1s/step - loss: 0.2008 - accuracy: 0.9235 - val_loss: 0.6013 - val_accuracy: 0.
8311
Epoch 8/10
19/19 [==============================] - 26s 1s/step - loss: 0.1859 - accuracy: 0.9337 - val_loss: 0.6159 - val_accuracy: 0.
8446
Epoch 9/10
19/19 [==============================] - 27s 1s/step - loss: 0.1750 - accuracy: 0.9320 - val_loss: 0.7014 - val_accuracy: 0.
8311
Epoch 10/10
19/19 [==============================] - 27s 1s/step - loss: 0.1618 - accuracy: 0.9371 - val_loss: 0.6582 - val_accuracy: 0.
8378
Test Loss: 0.6009
Test Accuracy: 0.8043
```

Figure 7.3. Testing Accuracy and loss

7.4 Confusion Matrix:

The confusion matrix [7.4] provides detailed information about the model's classification performance for each class. It visualizes the number of correct and incorrect predictions made by the model. Each row represents the true labels, while each column represents the predicted labels. The diagonal elements of the matrix indicate the number of correct predictions for each class, while the off-diagonal elements represent the misclassifications. Analyzing the confusion matrix allows for insights into specific classes where the model may struggle. For example, you can identify classes with high false positive or false negative rates. Additionally, the overall accuracy of the model can be calculated from the confusion matrix by summing up the correct predictions and dividing by the total number of instances.

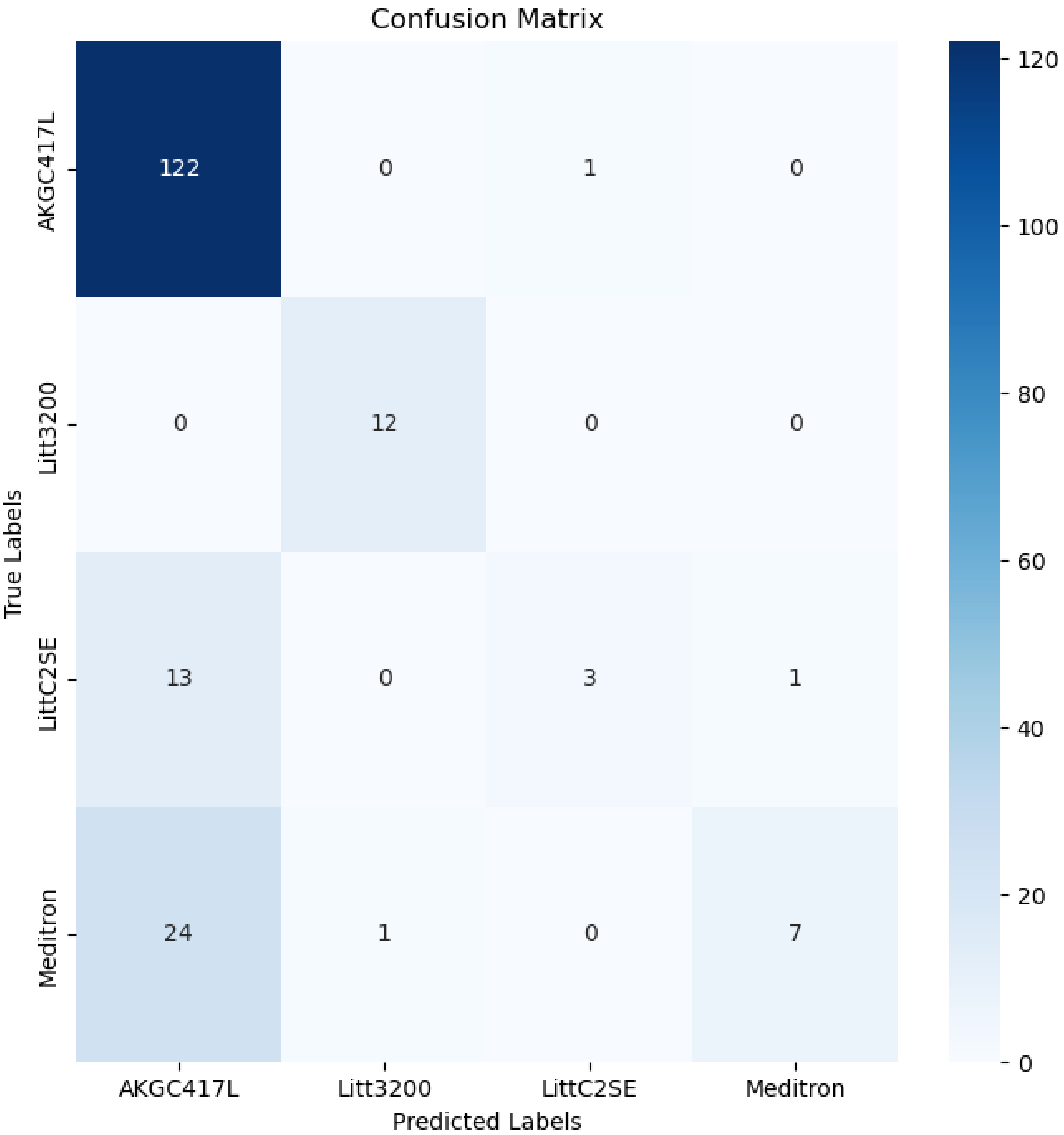

Figure 7.4. Confusion Matrix

7.5 Normal Vs Abnormal:

The pie chart [7.5] represents the distribution of normal and abnormal samples in the test dataset. Here's a description of the results:
Normal Samples: The pie chart shows that approximately 66.7of the samples in the test dataset are classified as "Normal." This corresponds to a count of 20 samples.

Abnormal Samples: The remaining 33.3of the samples in the test dataset are classified as "Abnormal." This corresponds to a count of 10 samples.

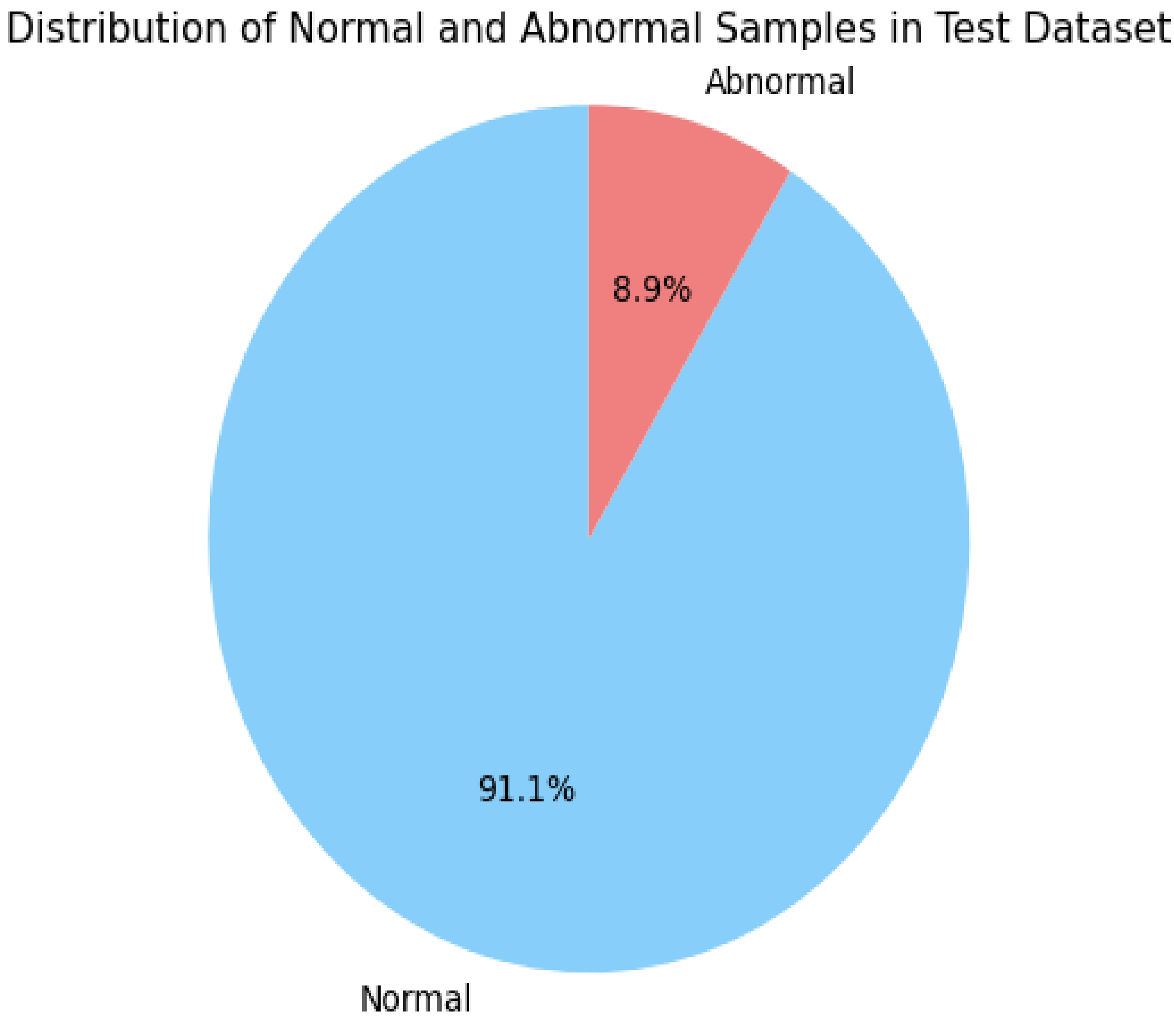

Figure 7.5. Normal Vs Abnormal

Chapter 8

ScreenShots

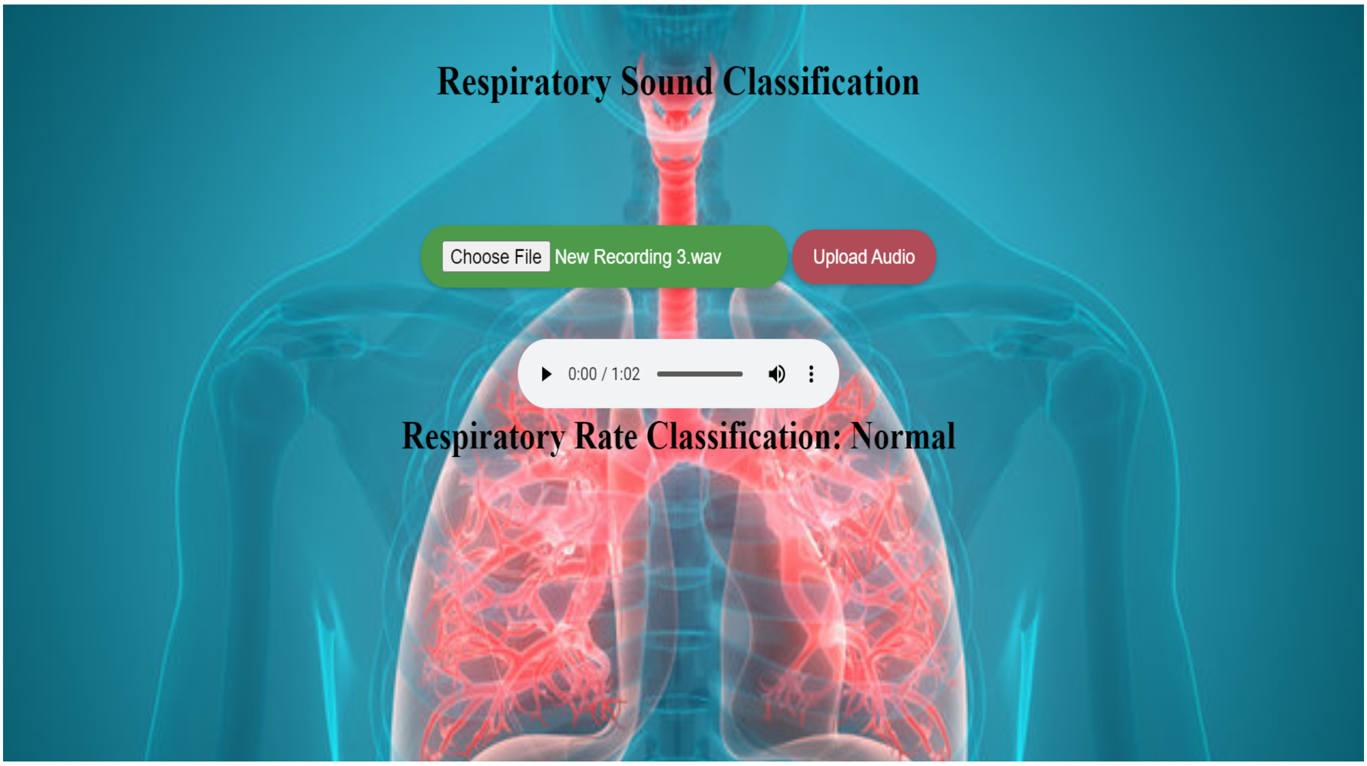

Figure 8.1. Result 1

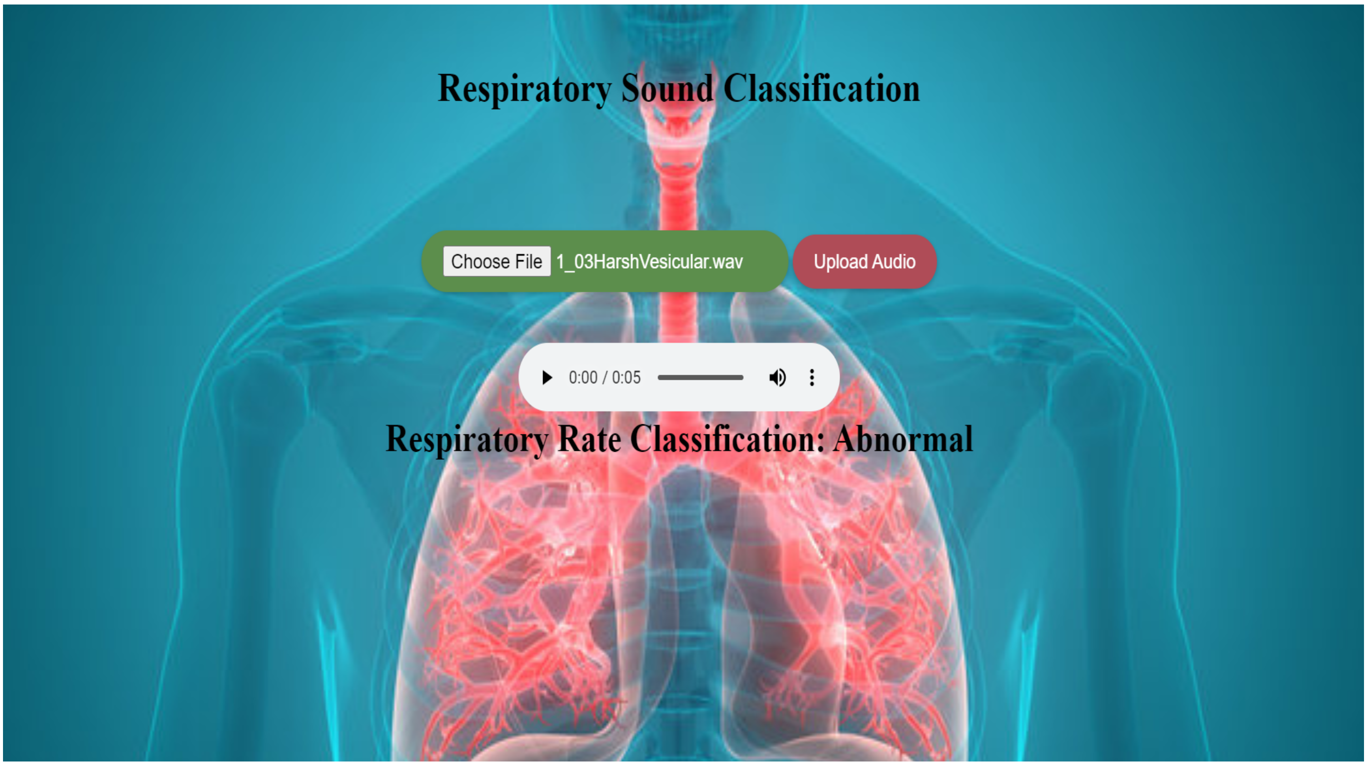

Figure 8.2. Result 2

Chapter 9

Conclusion

The project implements a respiratory sound classification system using machine learning techniques. The code processes audio files containing respiratory sounds and classifies them into different categories, along with determining the respiratory rate and classifying it as normal or abnormal. The system utilizes a deep learning model trained on a dataset of respiratory sound recordings.

To summarize the implementation and its implications:

In this work, we developed a respiratory sound classification system using machine learning. The system processes audio files containing respiratory sounds and applies feature extraction techniques to extract relevant information. A deep learning model, specifically a convolutional neural network (CNN), is trained on a dataset of respiratory sound recordings to perform the classification task.

The implemented system demonstrates promising results, achieving a Test Accuracy of 0.8043 on unseen data. The model's performance is further analyzed using visualizations, including the training and validation loss/accuracy graphs, which showcase the model's learning progress and generalization ability. Additionally, a confusion matrix provides insights into the classification performance for each class, allowing for a detailed evaluation.

The system's ability to classify respiratory sounds and determine the respiratory rate has practical applications in healthcare and medical diagnosis. It can assist healthcare professionals in identifying abnormal respiratory patterns and potentially aid in the early detection of respiratory disorders. Furthermore, the system can be expanded and customized to accommodate different classification tasks or integrate with existing healthcare systems.

Future work can involve enhancing the model's performance by incorporating more advanced deep learning architectures or exploring alternative feature extraction methods. Additionally, expanding the dataset with a larger variety of respiratory sound recordings can improve the model's robustness and generalization. Integration with real-time data collection systems or wearable devices can also be explored to enable continuous monitoring of respiratory sounds.

Overall, the developed respiratory sound classification system demonstrates the potential for leveraging machine learning techniques to assist in the analysis and interpretation of respiratory sounds, contributing to improved healthcare outcomes and respiratory disorder management.

Chapter 10

Future Work

In terms of future work, one area of focus could be on improving the feature engineering process. While the current model utilizes the mel spectrogram as the feature representation, there are several other audio features that could be explored. For example, incorporating features such as MFCCs (Mel-frequency cepstral coefficients) or wavelet transforms may provide additional insights and enhance the model's ability to capture relevant information from respiratory sounds. By experimenting with different feature extraction techniques, we can uncover more effective representations that improve the model's classification performance.

Additionally, investigating methods to handle class imbalance in the dataset would be beneficial. The pie chart analysis revealed a noticeable difference between the number of normal and abnormal samples. Addressing class imbalance is crucial because an imbalanced dataset can bias the model towards the majority class and lead to suboptimal performance in classifying the minority class. Techniques such as oversampling, undersampling, or data augmentation tailored specifically for the minority class (abnormal samples) can help balance the dataset and improve the model's ability to accurately classify abnormal respiratory sounds.

By focusing on these areas, we can enhance the model's feature representation capabilities and address potential biases in the dataset, ultimately improving the accuracy and robustness of the respiratory sound classification system.

References

[1].Azadeh Yadollahi(Student Member), Zahra M. K. Moussavi(Senior Member) IEEE, "A Robust Method for Estimating Respiratory Flow Using Tracheal Sounds Entropy", 12 May 2014.

[2].Ethan Grooby, Jinyuan He, Julie Kiewsky, Davood Fattahi, Lindsay Zhou, Arrabella King, Ashwin Ramanathan, Atul Malhotra, Guy A. Dumont(Life Fellow), Faezeh Marzbanrad,(Member) IEEE "Neonatal Heart and Lung Sound QualityAssessment for Robust Heart and Breathing Rate Estimation for telehealth Applications", May 31, 2021.

[3].Mohammod Abdul Motin(Student Member), Chandan Kumar Karmakar(Member), and Marimuthu Palaniswami(Fellow) IEEE "Selection of Empirical Mode Decomposition Techniques for Extracting Breathing Rate From PPG", April 2019.

[4].Chien-Lung Shen, Tzu-Hao Huang, Po-Chun Hsu, Ya-Chi Ko, Fen-Ling Chen, Wei-Chun Wang, Tsair Kao, Chia-Tai Chan "Respiratory Rate Estimation by Using ECG, Impedance and Motion Sensing in Smart Clothing",1 July 2017.

[5].Pedro Matias, Joao Costa, Andre V. Carreiro, Hugo Gamboa, Ines Sousa, Pedro Gomez, Joana Sousa, Nuno Neuparth, Pedro Carreiro-Martins and Filipe Soares "Clinically Relevant Sound-Based Features in COVID-19 Identification: Robustness Assessment With a Data-Centric Machine Learning Pipeline",3 October 2022.

[6].Claudia Floris, Sarah Solbiati, Federica Landreani, Gianfranco Damato, Bruno Lenzi, Valentino Megaleand Enrico Gianluca Caiani "Feasibility of Heart Rate and Respiratory Rate Estimation by Inertial Sensors Embedded in a Virtual Reality Headset",14 December 2020.

[7].Kuo-Kai Shyu, Luan-Jiau Chiu, Po-Lei Lee, Tzu-Han Tung and Shun-Han Yang "Detection of Breathing and Heart Rates in UWBRadar Sensor Data using FVPIEF Based Two-Layer EEMD",2018.

[8].Alexis Martin, Jérémie Voix*" In-Ear Audio Wearable: Measurement of Heart and Breathing Rates for Health and Safety Monitoring", 2016.

[9].Xiangyu Xu, Jiadi Yu, Yingying Chen "Leveraging Acoustic Signals for Fine-grained Breathing Monitoring in Driving Environments", 2020.

[10].Tianben Wang, Daqing Zhang, Leye Wang, Yuanqing Zheng, Tao Gu, Bernadette Dorizzi, Xingshe Zhou "Contactless Respiration Monitoring using Ultrasound Signal with Off-the-shelf Audio Devices", 2018.

[11].Jyotibdha Acharya, "Deep Neural Network for Respiratory Sound Classification in Wearable Devices Enabled by Patient Specific Model Tuning",3 June 2020.

[12].Tamer Elfaramawy, Cheikh Latyr Fall, Soodeh Arab, Martin Morissette, Francois Lellouche

and Benoit Gosselin “A Wireless Respiratory Monitoring System Using a Wearable Patch Sensor Network”,2018.

[13].Saba Emrani, Thanos Gentimis, Hamid Krim “Persistent Homology of Delay Embeddings and its Application to Wheeze Detection”, April 2014.

[14]. Yolanda Castillo-Escario, Ignasi Ferrer-lluis, Josep Maria Montserrat and Raimon Jane “Entropy Analysis of Acoustic Signals Recorded With a Smartphone for Detecting Apneas and Hypopneas: A Comparison With a Commercial System for Home Sleep Apnea Diagnosis”, September 5, 2019.

[15].ukui Shi, Kang Du, Chaozong Zhang, Hongqi Ma, and Wenjie Yan “Lung Sound Recognition Algorithm Based on VGGishBiGRU”, September 19, 2019.

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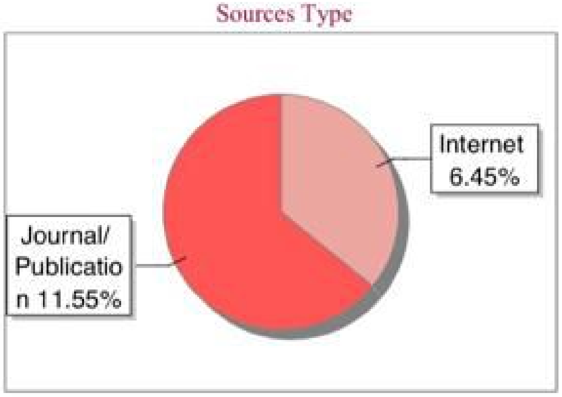

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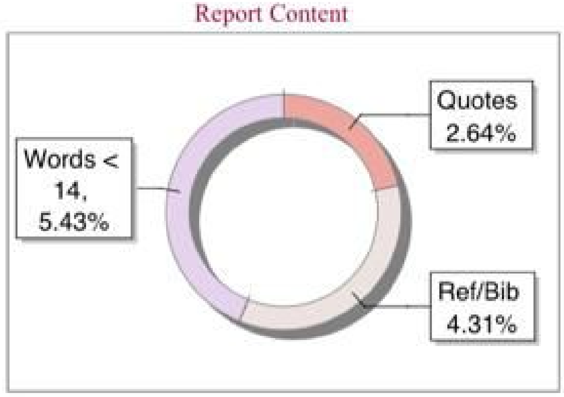

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Estimation of Respiratory Rate through Breathing Audio

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Abstract: To overcome the major obstacle posed by a lack of access to physical examination, which includes inexpensive and accurate remote measurements of vital signs. Here, we use audio to estimate the patient's respiratory rate using machine learning. There are other strategies (non-learning based), but their precision is restricted, and the research we realize about utilizing ML is either not straightforwardly valuable or non-public datasets are used. There is only one accessible dataset that is public, hence it is used for the evaluation of the Proposed methods.

Considering the above, we propose a novel data augmentation technique to increase its effective size to avoid the overfitting issue. Our calculation utilizes the depiction of the spectrum of frequencies and the need for names for relaxing cycles, which are used to make a repetitive neural network that can see the cycles. Using only the breathing audio of the patient, our augmentation technique makes use of the independence of the majority of the spectrogram's periodic frequency components and their order is calculated for generating multiple signals representing it. The smartphone is used to collect those signals allowing doctors to accurately and automatically determine the respiratory rate of patients from a distance.

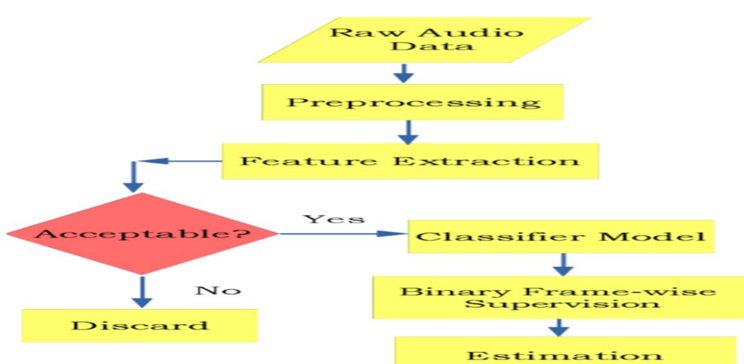
Keywords: Vital signs, raw audio data, respiration rates, a classifier model, binary framewise supervision, and inspiration and expiration.

I. INTRODUCTION

Respiratory rate is among four clinical vital signs, stated as the number of times a person breathes in a minute. Due to Covid-19, telemedicine is considered an essential mode of health care delivery. The majority of covid-19 patients were admitted to hospitals and were not able to breathe by themselves, resulting in abnormal respiratory rates. A common symptom of covid-19 found was respiratory distress. In various diseases, changes in respiratory rate were found to be a detector of clinical declination and an increase in the number of deaths. As a result, determining a patient's stability necessitates a precise rate of breathing. Counting a patient's breaths over 60 seconds is the widely used standard for determining their breathing rates. This method will be ineffective in a crowded clinic or triage setting and frequently shortens by observing breaths for shorter periods, such as 10 seconds, which can result in inaccurate estimates. To overcome the major obstacle posed by a lack of access to physical examination, which includes inexpensive and accurate remote measurements of vital signs.

Here, we use audio to estimate the patient's respiratory rate using machine learning. An alternative that is accurate, highly efficient, and easy to use, for respiratory rate estimation that is suitable for both hospitals and telemedicine (remote) is provided by an estimation system that relies solely on audio signals.

II. SYSTEM DESIGN



III. METHODOLOGY

To determine whether the audio data satisfies the specified constraints, a breathing data sample is taken for preprocessing, and manually samples are removed by the following 4 Constraints:

(1) Distinctly irregular heartbeats containing samples.
(2) Too many random background sounds in the samples.
(3) An excess clamor or murmur present in the sound sample.
(4) Pattern of breathing that is not periodic or irregular.

As a result, the audio samples that meet the above criteria are taken out and put into the classifier model. The dataset is then sent to a technique called Binary Frame Supervision. The supervision signals should be kept as simple as possible, due to limited training datasets. We hypothesize that rather than estimating the number of inspire/expire regions in the sample, representing transitions between different points at the frame level shall give the supervision better, due to respiration's periodic nature. The breathing signal's fundamental periodicity dictates that each of its many frequency parts ought to be periodic. To avoid overfitting, and to propose a different type of data augmentation, frequency independence is used. Rather than giving the spectrogram with no guarantees, we haphazardly permute the recurrence parts each time we elapse a preparing information test to our model. After permutation, the input still contains periodicity information, but the training data sample's exact form will vary from time to time. Not being able to overfit any frequency-related data pattern, we hypothesize that the model finds periodicity by learning and finding for periodicity in each channel.

The respiration rate must be calculated using the model's framewise class probabilities after training is finished. There is a good chance that the output classes 0 and 1 will alternate in this sequence. For the earlier inspiration/expiration regions, it is empirically observed whether the predictions are confident and accurate, and over time, we become less confident. As a result, we decided to predict the underneath breath duration based on the length of the first region. A model is also trained separately in which the audio is flipped and the same estimations are made to improve the prediction. As a result, the test set is used to estimate the respiratory rate for all methods and depending upon the estimated lengths of the first and last parts of the inspiration or expiration known as breathing intervals to arrive at the final estimation, which is the average of estimations made by both the models individually.

IV. COMPONENTS

Available datasets: ICBHI 2017 Respiratory Sound Database

V. LITERATURE SURVEY

[A]. Azadeh Yadollahi(Student Member), Zahra M. K. Moussavi(Senior Member) IEEE "A Robust Method for Estimating Respiratory Flow Using Tracheal Sounds Entropy",12 May 2014. Due to the difficulties and inaccuracies of the majority of flow measurement methods, numerous researchers have tried to predict flow based on breathing sounds. However, the application of each of the suggested approaches is constrained by the requirement for various flow rates for the calibration of the model. In this paper, a novel and reliable approach to flow estimation is proposed by making use of the tracheal sounds which is a bandpass filter and whose Entropy is calculated and hence used. The proposed method can estimate any flow rate and only requires one breath to calibrate, regardless of the flow rate chosen for calibration, even when flow rates are outside the given limits of the calibration. After eliminating the sounds of the heart, which deforms the tracheal sounds' low-frequency parts, the efficacy of the method across a variety of frequency ranges is evaluated. In addition, the proposed method's effectiveness for calculating entropy was validated using six distinct segment sizes. Estimates were made for inhaling and exhaling with the best segment sizes.

Keywords: Tracheal sounds, Entropy, heart sound, flow prediction.

Advantages: It shows a reliable method for estimating flow that can adapt to flow variability and doesn't need more than one breath to calibrate.

[B].Ethan Grooby, Jinyuan He, Julie Kiewsky, Davood Fattahi, Lindsay Zhou, Arrabella King, Ashwin Ramanathan, Atul Malhotra, Guy A. Dumont(Life Fellow), Faezeh Marzbanrad,(Member) IEEE "Neonatal Heart and Lung Sound QualityAssessment for Robust Heart and Breathing Rate Estimation for telehealth Applications", May 31, 2021. Chest sounds can be fetched easily and sent to the virtual cloud for monitoring remotely and diagnosing thanks to advancements in the processing of signals, ML, IOT, stethoscopes which are digital, and other technologies. But, for taking care of newly born specifically, poor-quality recordings are hindering remote monitoring and diagnostics. In order to improve the accuracy and dependency of estimations of rates of heart and breathing from chest sounds of newly born who are noisy, this paper presents a novel approach for automatically and specifically evaluating the quality of the signal.

From 76 preterm and full-term infants, a total of 88 information sources and 10-second lengthy sounds of the chest were collected. The recordings' breathing times, the quality of the signal, and delectable beats were evaluated by observers. Heart sound contained 187 features and lung sound contained 182 features that were used for quality categorization.

A binary categorization model which is dynamic was tutored following the application of class balancing and hyperparameter optimization in addition to feature selection. After that, the chest sound was used to automatically estimate heart rates and breathing rates, and a comparison of many methods was made for the same thing. cross-validation done subject-wise and also leaving one out revealed that the high-quality recordings were distinguished from the low-quality recordings by the model in the data which was used to test with a specificity of eighty-six percent, sensitivity of sixty-nine percent and accuracy of eighty-two percent for lung sounds and specificity of Ninety-six percent, sensitivity of Eighty-one percent and accuracy of Ninety-three percent for heart sounds, respectively. The sounds of high quality had estimations with a lower absolute error of median than those of low-quality sounds, with a difference of 4bpm and 12bpm, respectively.

Keywords: Newborn monitoring, Heart and respiration rates, assessment of Quality, dynamic selection classification.

Advantages: Both heart and lung sounds have had their signal quality accurately assessed. Additionally, the strategies applied here with Robotized chest sound recognition of newborns are valuable for future uses of telehealth.

Disadvantages: For high-quality sounds, the estimates have a lower median absolute error. As a result, more data must be trained and the median absolute error for low-quality sounds must also be reduced.

[C].Mohammod Abdul Motin(Student Member), Chandan Kumar Karmakar(Member), and Marimuthu Palaniswami(Fellow) IEEE "Selection of Empirical Mode Decomposition Techniques for Extracting Breathing Rate From PPG", April 2019.

A huge biomarker that gives both predictive, as well as demonstrative data with the purpose of checking biological state, is the Breathing rate(BR). The harmless and ready-to-wear pulse oximeter-based photoplethysmogram (PPG) can be used to extract BR in addition to vital biomarkers like pulse rate and blood oxygen saturation. Empirical mode decomposition (EMD) and its types are frequently utilized for the decomposition of inclined, which are not linear and moving signals. The study looked into how each EMD variant affected the extraction of BR from PPG. BR was extracted from PPG using a hybrid model based on the EMD family and PCA. The datasets used to Validate each model's performances were MIMIC and Capno-base. The absolute error for the median ranged from 0 - 5.03 breaths per minute and from 2.47 - 10.55 breaths per minute for both datasets, respectively.

Keywords: Pulse oximeter, EMD, and variants.

Advantages: Created best execution with relatively exact outcomes.

Disadvantages: Since the hybrid model in this paper is based on a variety of EMD variants, it is necessary to estimate each variant to determine its applicability. As a result, we require a setup for quick and simple respiratory rate estimation that takes time.

[D]. Chien-Lung Shen, Tzu-Hao Huang, Po-Chun Hsu, Ya-Chi Ko, Fen-Ling Chen, Wei-Chun Wang, Tsair Kao, Chia-Tai Chan "Respiratory Rate Estimation by Using ECG, Impedance and Motion Sensing in Smart Clothing",1 July 2017.

Since the past decade, the demand for soft, lightweight, and smart clothing in-home care has increased. Automated biological and user-specific status recognition of the environment has been made possible by the development and application of numerous smart textile sensors. An affordable electrode fabric containing higher elasticity and lower resistance is considered the basis for the ready-to-wear multi-sensor clothing(smart) that is proposed in this study for homecare monitoring. Many biosignals of humans such as breathing rates, ECG, information on the gyro, and other things, can be measured by the ready-to-wear smart clothing's integration of multiple sensors. Five free signals of respiration specifically, impedance plethysmography which is electric, actuated recurrence variety for respiration, incited adequacy variety for respiration, respiratory prompted power variety, and respiratory initiated development variety are bought. Using three distinct methods Kalman filter both Static, and dynamic, naive Bayes inference, the straightforward clothing can be used to accurately estimate respiratory rate. In the experiment of static, the frequency variation is respiratory induced performs best, while respiratory-induced amplitude variation performs best during the running experiment. The Guileless Bayes induction and dynamic Kalman channel have shown great outcomes.

Keywords: Many sensors, Clothing which is smart, electrode(textile).

Advantages: The novel smart clothes are washable, soft, and elastic, indicating that they are fitting for monitoring which is long-term in the service of medical which is home-care based, and in the healthcare industry.

[E]. Carlo Massaroni, Daniela Lo Presti, Domenico Formica, Sergio Silvestri and Emiliano Schena "Non-Contact Monitoring of Breathing Pattern and Respiratory Rate via RGB Signal Measurement",19 June 2019.

The intrusiveness of the sensors that are typically used means that the breathing rate is measured least frequently in a number of situations. This is why contactless monitoring systems in general are receiving more and more recognition.

A computing system for the extraction of breath-by-breath respiratory rate, also a contactless measurement of the respiratory pattern is proposed in the paper. An algorithm and built-in camera(RGB) of the laptop are used in this system to post-process video data. A waveform indicating the respiratory pattern is produced by recording the chest movements and analyzing the Switching in pixel intensity. 12 men and women were asked to sit in front of the laptop's camera and we were asked to wear both slim and loose-fit t-shirts to test the proposed system. Recording of the signal consisting of a drop in pressure was done at the point of the nostrils using ready-to-wear devices fixed to the head(head-mounted), which served as the reference for the pattern of breathing. The percentage, standard and absolute error mean are used to compare the two approaches. In addition, a plot was utilized to interrogate the method bias known as Bland-Altman. Slim and loose fit clothing with both of them, the system was able to accurately record respiratory rate, as demonstrated by the results. Females perform better on the measuring system.

Keywords: Built-in RGB camera, head-mounted device.

[F]. Claudia Floris, Sarah Solbiati, Federica Landreani, Gianfranco Damato, Bruno Lenzi, Valentino Megaleand Enrico Gianluca Caiani "Feasibility of Heart Rate and Respiratory Rate Estimation by Inertial Sensors Embedded in a Virtual Reality Headset",14 December 2020.

Using the ballistocardiographic principle, Headsets known as Virtual reality headsets with built-in microelectromechanical systems can assess the mechanical heart's functionality and respiratory activity without the need for additional sensors. 30 people with good health, at rest in various body positions were studied. The body positions were standing, supine, and sitting Using a virtual reality (VR) headset, gyroscope and accelerometer data were recorded for a duration of thirty seconds, and a 1-lead electrocardiogram (ECG) signal was used simultaneously to estimate mean heart rate (HR). 3 approaches based on frequency have been validated for the purpose of extracting the PSD and its corresponding frequency to it. The results showed that the gyroscope was more accurate than the accelerometer when a comparison was done with the gold standard. Additionally, the position which is supine demonstrated the greatest feasibility (98 percent) for estimating the respiratory rate, through which it was identified that the one which contains the most breathing information is the transversal direction. Findings also demonstrated that the feasibility of the proposed strategy is dependent on the posture and this strategy can be carried out the performance of some degree.

1) Virtual reality device provides a reference for linear and rotational accelerations.
2) During the acquisition of VR signals, a device monitoring the heart rate was utilized in the experiment to obtain the gold standard ECG measurement: For the first measurement, its placement was on the chest (ECG-Chest), and for the second measurement, Between the middle fingers and thumb it was held(ECG-Thumb).

Keywords: VR headsets, gyroscope, accelerometer, power spectral density PSD ballistocardiography.

Advantages: A good level of performance and evidence of feasibility.

[G]. Jorge Brieva, Hiram Ponce, and Ernesto Moya-Albor "A Contactless Respiratory Rate Estimation Method Using a Hermite Magnification Technique and Convolutional Neural Networks", 15 January 2020.

In both medical applications and everyday activities, it is difficult to monitor the respiratory rate.In most cases, contact sensors were used as a direct solution. They have also been shown to be effective, but have some drawbacks, such as not working well on the sensitive skin of burn victims.As a result, more and more people are using contactless breath detection and looking for a monitoring system.In this paper, a system is based on a Convolutional Neural Network (CNN) and the Eulerian motion video magnification technique with Hermite transform which is a novel non-contact method that estimates respiratory rate. The subject's chest movements are tracked by the system using two methods.By using manually selected ROI and not selecting the ROI in the image box. Using CNN, the system determines whether a frame is an inhalation or an exhalation. The mean average error and a Bland and Altman analysis are used to compare how well the methods for detecting respiratory rate work together.

Keywords: Non-contact monitoring, motion video magnification, respiratory rate estimation, and the Hermite transform.

[H].Alexis Martin, Jérémie Voix*" In-Ear Audio Wearable: Measurement of Heart and Breathing Rates for Health and Safety Monitoring", 2016.

The subject of this study is the integration of vital sign monitoring functions in workplace hearing protection devices (HPDs). The testing subjects were approached to inhale at different rhythms and forces and they were reasonable sounds that were kept in the ear trench. For the purpose of measuring heart and breathing rates, digital signal processing algorithms are developed. Finally, an adjustable denoising filter was used to add industrial noise in the in-ear recorded signals in order to measure the algorithms' accuracy in a noisy environment. The HPD is also possible to run in high ambient noise after checking the heart rate and respiration rate with a closed ear canal. The absolute mean error of the algorithm is 2.7 cycles per minute (CPM).

Keywords: Biosignals, in-ear wearables, processing of acoustic signals, monitoring of health and safety, and heart and breathing rates.

Similarities: With an in-ear microphone-equipped wearable audio device, physiological sounds were recorded in the ear canal. As a reference, a commercial device was used to simultaneously record heartbeats and breathing.

Advantages: The noise disturbance has a clear impact on the performance of breathing rate detection, resulting in absolute errors below 7.4 CPM.

[I].Xiangyu Xu, Jiadi Yu, Yingying Chen "Leveraging Acoustic Signals for Fine-grained Breathing Monitoring in Driving Environments", 2020.

The energy spectral density (ESD) of an acoustic signal describes how the energy of the acoustic signal is distributed in space with frequency, and environmental movement can be interpreted as changes in the energy distribution. This paper includes a fine-grained respiratory monitoring system called BreathListener. BreathListener uses your smartphone's audio device to estimate detailed breathing waveforms in a driving environment. BreathListener uses background subtraction and variational mode decomposition (VMD) to remove interference from the driving environment of the ESD signal and extract the respiratory cycle. A deep learning architecture based on a Generative Adversarial Network (GAN) is then developed to generate fine-grained respiratory waveforms from the Hilbert spectrum of the respiratory patterns extracted in the ESD signal. The RF card on smartphones cannot be used as an active RF radar, which is more powerful at tracking breathing patterns, because smartphones are embedded with NFC chips that support RF recognition.

Similarities: Using smartphone acoustic devices to estimate the fine-grained breathing waveform in driving conditions.

Advantages: Because the correlation coefficient is greater than 0.77, a deep learning architecture that uses a Generative Adversarial Network (GAN) to generate fine-grained breathing waveforms indicates that BreathListener can still function in these circumstances, albeit with a decrease in accuracy.

[J].Tianben Wang, Daqing Zhang, Leye Wang, Yuanqing Zheng, Tao Gu, Bernadette Dorizzi, Xingshe Zhou "Contactless Respiration Monitoring using Ultrasound Signal with Off-the-shelf Audio Devices", 2018.

One of the most important ways to help older people live their best lives while they sleep is by monitoring their respiration in a real-time and continuous fashion. The model employs an MDL-based algorithm that is capable of capturing the Doppler effect brought on by exhaled airflow. For respiration monitoring, this system has a median error of less than 0.3 breaths per minute or 2%, and it can accurately identify apnea. to make the system better so that it can lessen the effects of sporadic body movements while you sleep. Our system will be further evaluated in the future through larger-scale deployment in typical homes.

Keywords: Acoustic sensing, the Doppler effect, respiration detection, and contactless sensing.

Advantages: Low respiration error detection (less than 0.3 breaths per minute, or 2 %) can be detected by a real-time and continuous respiration monitoring system.

[K].Jyotibdha Acharya, "Deep Neural Network for Respiratory Sound Classification in Wearable Devices Enabled by Patient-Specific Model Tuning",3 June 2020.

Classification is carried out employing a Mel-spectrogram-based deep CNN-RNN model of respiratory sounds. With limited patient data, this model will first screen respiratory patients and create patient-specific classification models for anomaly detection. The weight quantization method will quadruple the cost of memory overall without sacrificing performance. The main contribution of the paper is the significant memory savings from local log quantization of trained weights. It gives a score of 66.31% for the four-class respiratory cycle classification on the 80–20 split. This model received a score of 71.81 percent in leave-one-out cross-validation, indicating that its results are significantly more reliable than those of the initial train-test split. Second, when pre-prepared with breathing information, profound learning models have been displayed to effectively obtain area explicit information and perform better compared to summed-up models. The hybrid CNN-RNN model may perform slightly worse than the VGG-16 model because the LSTM layer requires a higher bit precision than the CNN counterpart.

Keywords: Weight quantization, respiratory audio analysis, CNN, LSTM, and a patient-specific model.

Similarities: Makes use of breathing audio as an input for enhancing data.

Advantages: This model reduces the minimum amount of memory required by four times without sacrificing performance or the ability to classify four classes of the respiratory cycle.

[L].Tamer Elfaramawy, Cheikh Latyr Fall, Soodeh Arab, Martin Morissette, Francois Lellouche and Benoit Gosselin "A Wireless Respiratory Monitoring System Using a Wearable Patch Sensor Network",2018.

The severity of the cough is crucial when dealing with other conditions like chronic obstructive pulmonary disease (COPD). A remote respiratory observing framework with hack discovery is made to gauge the breathing rate and the recurrence of the hack. The respiratory frequency and coughing events are calculated using data processing and fusion algorithms. Through an SPI interface bus, the IMU transmits the data from the accelerometer and gyroscope to the MCU.

The Savitzky-Golay smoothing filter was chosen because it is simple to use and works well in many systems. The thoracic and abdominal cages contain the two sensor nodes. A chest belt served as a point of reference. A performance test was carried out while the observer was moving around to demonstrate its robustness.

Keywords: Coughing detection, breathing rate, inertial measurement unit, wireless, low-power, real-time, wearable, patch sensor network, and data fusion.

Similarities: System for wirelessly monitoring the respiratory system and detecting coughing.

Advantages: The setup takes a lot less time and is easier to use. In order to provide maximum comfort, it makes use of electronic building blocks with low power consumption.

[M].Saba Emrani, Thanos Gentimis, Hamid Krim "Persistent Homology of Delay Embeddings and its Application to Wheeze Detection", April 2014.

The periodic structure of dynamical systems can be quantified through the use of topological methods. The proposed autocorrelation-like (ACL) function of the signals is used in the algebraic topological approach to analyze breathing sound signals for wheeze detection. For periodicity analysis in the time domain, which is a continuous piecewise sinusoidal function with various periods and phases and a time-varying amplitude, strict autocorrelation functions cannot be implemented because breathing sound signals are time-varying and non-stationary. A small number of data points from each point represent the sound signal. Using a subsampling method, the algorithm's computational complexity is reduced.

Keywords: Coughing detection, breathing rate, inertial measurement unit, wireless, low-power, real-time, wearable, patch sensor network, and data fusion.

Similarities: Analyzing breathing sound signals in order to identify wheezes.

Advantages: The method we propose is 98.39 percent accurate.

[N]. Yolanda Castillo-Escario, Ignasi Ferrer-lluis, Josep Maria Montserrat and Raimon Jane "Entropy Analysis of Acoustic Signals Recorded With a Smartphone for Detecting Apneas and Hypopneas: A Comparison With a Commercial System for Home Sleep Apnea Diagnosis", September 5, 2019.

The majority of patients with obstructive sleep apnea (OSA) do not receive treatment or a diagnosis, despite the condition's prevalence. The algorithm for identifying silent events, classifying them as apneas or hypopneas, evaluating how well they work, and comparing the data from three different portable sleep monitors that are primarily based on nasal airflow. The smartphone correctly identifies and categorizes all OSA patients, and the predicted apnea-hypopnea indices are highly consistent between the two systems. Since the majority of hypopneas are heard to be snoring, there was no reduction in noise. OSA is a disease that affects a lot of people, especially the elderly and obese. One of the straightforward, non-invasive methods for determining blood oxygen saturation (SpO2) is pulse oximetry.

Keywords: Biomedical signal processing, mHealth, acoustics, smartphone, monitoring, and sleep apnea.

Similarities: To screen OSA patients at home, the model uses a smartphone that analyzes audio signals.

Advantages: The accuracy of the classification increased to 82%.

[O]. Lukui Shi, Kang Du, Chaozong Zhang, Hongqi Ma, and Wenjie Yan "Lung Sound Recognition Algorithm Based on VGGish-BiGRU", September 19, 2019.

Since lung sounds are intricate and nonstationary signals, it is hard to ascertain their data utilizing regular highlights. The transient qualities of the lung sounds can't be separated by utilizing the traditional convolutional brain organization. BiGRU-VGGish is the lung sound acknowledgment calculation, which depends on move learning and joins the VGGish network with the BiGRU (bidirectional gated repetitive unit brain organization), which can successfully further develop the acknowledgment exactness of lung sounds utilizing state-of-the-art calculations, headways in computerized signal handling and man-made consciousness advances, and customary acoustic. The electronic stethoscope slowly replaces the stethoscope. The wavelet change is utilized to separate lung sound signs into recurrence subbands, and a bunch of measurable elements is taken from the subbands to address the wavelet coefficient dissemination. Rather than different strategies, BiGRU can catch the time series elements of the lung sounds, which works on the precision of the asthma sounds.

Keywords: Mel spectrogram, BiGRU, lung sound recognition, transfer learning, and VGGish.

Similarities: The lung sound data are used to retrain the BiGRU network, which then extracts the sounds from the lungs.

Advantages: In contrast to the most recent algorithms, The proposed algorithm effectively improves lung sound recognition accuracy.

[P]. Pedro Matias, Joao Costa, Andre V. Carreiro, Hugo Gamboa, Ines Sousa, Pedro Gomez, Joana Sousa, Nuno Neuparth, Pedro Carreiro-Martins and Filipe Soares "Clinically Relevant Sound-Based Features in COVID-19 Identification: Robustness Assessment With a Data-Centric Machine Learning Pipeline",3 October 2022.

By developing a low-cost, non-invasive, and more decentralized technology that can educate people about the COVID-19 infection. The sensitivity scores varied between 60.00% and 80.00% in Coswara and between 51.43% and 77.14% in COVID-19 Sounds. By validating the quality of the samples, segmenting the speech events, and examining interpretable features with their physiological significance, this study takes a data-centric approach. These findings are confirmed by an examination of two huge databases: The COVID-19 Sounds and Coswara datasets were used to explore the audio samples by enhancing the speech types in order to find disease-specific biomarkers. Since speech disturbances and respiratory problems (shortness of breath, dry cough) are some of the most common symptoms of COVID-19 disease, the best results were achieved with an SVM (Support Vector Machine) model (approximately 97% and 98% of sensitivity, respectively). the objective of collecting additional meta-data and describing the respiratory tract using various speech sounds like cough, breath, and voice.

Keywords: Signal processing, feature extraction, data-centric, machine learning, COVID-19, speech, vocal tract.

Similarities: COVID-19 Identification Features Based on Breathing Sound.

Advantages: The COVID-19 detection model may be the most effective obtained performance when evaluating the COVID-19 Sounds dataset.

[Q]. Heng Zhao (Student Member), Hong Hong(Member), Dongyu Miao (Student Member), Yusheng Li, Haitao Zhang, Yingming Zhang, Changzhi Li(Senior Member), and Xiaohua Zhu(Member) IEEE "A Noncontact Breathing Disorder Recognition System Using 2.4-GHz Digital-IF Doppler Radar".

This paper proposes a noncontact breathing confusion acknowledgment framework for recognizing sporadic breathing examples. A sensor module based on Doppler radar and a breathing disorder recognition module is used in this system. A custom 2.4GHz continuous wave(CW) digital-IF Doppler radar is used as the radar sensor module to precisely record the time-domain breathing waveform. After that, optimized classifiers and selected features are incorporated into a recognition module. In order to provide a comprehensive evaluation of the proposed system, four sets of experiments have been carried out. A linear SVM classifier with seven selected features is used in the proposed system's laboratory experiments to achieve a classification accuracy of 94.7 percent.

Keywords: Non-contact vital sign detection, doppler radar, breathing disorder, and support vector machine.

Advantages: The system's robustness and accuracy in the long-term diagnosis of breathing disorders are demonstrated by clinical experiment results. also demonstrates the possibility of auxiliary disease diagnosis under the proposed solution.

Disadvantages: Only 2.4 GHz is the frequency used in this case. As a result, the procedure can only be carried out with sufficient bandwidth.

[R]. David C. Mack, James T. Patrie, Paul M. Suratt, Robin A. Felder, and Majd Alwan "Development and Preliminary Validation of Heart Rate and Breathing Rate Detection Using a Passive, Ballistocardiography-Based Sleep Monitoring System",1 JANUARY 2009.

A BCG-based monitoring system is the NAPS system for the analysis of physiological signals. Measurements of heart rate, breathing rate, and musculoskeletal movements are taken with the NAPS Heart Rate Algorithm, the ECG and Pulse Oximetry Heart Rate Algorithm, and the Breathing Rate Algorithm. This demonstrates their potential as a general tool for studying sleep. The NAPS system's measurements of heart rate and breathing rate are compared to the ECG, pulse oximetry, and respiratory inductance plethysmography (RIP).

The BCG system isn't as important for monitoring sleep as other applications like activity tracking because it can't provide data 24 hours a day. The oximeter tracks the oxygen saturation. A SANDMAN computerized sleep system stores all of the data. The NAPS system has difficulty analyzing the data due to the assumption made by the algorithm that heart rate variability is relatively normal.

Keywords: Sleep, home health care, long-term monitoring, and ballistocardiography (BCG).

Similarities: Respiration rate detection monitoring system

Advantages: Accurately measure heart rate.

[S]. Georges Matar, Georges Kaddoum, Member, IEEE, Julie Carrier, Jean-Marc-Lina "Kalman filtering for posture-adaptive in-bed breathing rate monitoring using bed-sheet pressure sensors",2017.

Abdominal belts are also used to detect breathing movements, while esophageal pressure is typically used to measure breathing effort. The wired thermistor must be attached to the Bucco-nasal area for BR monitoring to measure airflow, causing the subject discomfort. In order to carry out the Kalman filter optimization step, the four-bed postures are identified by means of an artificial neural network (ANN) model.

Following a Bland-Altman (BA) analysis, the Pearson Correlation Coefficient (PCC) is utilized to evaluate the linear relationship that exists between the belt data and the pressure. An unobtrusive method of monitoring one's breathing that makes use of a pressure sensor mattress and can be utilized both at home and in a medical setting. The station-installed developed algorithm and a control interface are included in the software.

Keywords: Unobtrusive monitoring, breathing rate, a mattress with a pressure sensor, respiration, and breathing movements.

Similarities: Respiratory rate monitoring.

Advantages: It is easy to use in clinical settings because there is no obstruction in the field of view (FOV), which prevents patients from being covered.

[T]. Kuo-Kai Shyu, Luan-Jiau Chiu, Po-Lei Lee, Tzu-Han Tung and Shun-Han Yang “Detection of Breathing and Heart Rates in UWBRadar Sensor Data using FVPIEF Based Two-Layer EEMD”,2018.

The heartbeat signal is immaterial in light of the fact that it is covered by breathing sounds and messes. The EEMD technique is effective at separating the small heartbeat signal from the large breath signal and gradually enhancing the evaluation of heart and breathing rates as well as breathing conditions. When the UWB sensor is too close to the chest and too far from the person, it reflects a small echo pulse from the back cavity. The cardio-respiratory activity could be used to find this. The position of the first breath can be used to determine the heartbeat rate. The performance of heartbeat detection is unstable, despite the fact that the frequency window was previously selected based on knowledge of the heartbeat rate range. Comparing the significance of a typical vital sign to the heartbeat signal of a healthy patient. The two-layer EEMD method, which selects the FTI and decomposes it into IMFs, makes it possible to effectively obtain both the breathing rate and the heart rate simultaneously.

Keywords: Remote sensing, ultra-wideband (UWB) radar, heart rate, breathing rate, and ensemble empirical mode decomposition (EEMD).

Similarities: A non-contact monitor of vital signals or a tool for remote life detection.

Advantages: Effectively obtaining both breathing rate and heart rate simultaneously is possible. The UWB echo pulse used to simultaneously detect human breathing and heart activity demonstrates that the proposed detecting method is effective.

Paper name	Author	Model/Algorithm used	Advantages	Disadvantages
Estimation of Respiratory Rates Using the Built-in Microphone of a Smartphone or Headset	Yunyoung Nam, Bersain A. Reyes(Student Member) and Ki H. Chon(Senior Member) IEEE	The Welch periodogram and the autoregressive spectrum.	Feasibility of using smartphones together with their built-in and standard headset recorded from smartphone microphones.	Randomly occurring background noise or other noise during acquisition, so the estimation of respiratory rate became difficult.
Tidal Volume and Instantaneous Respiration Rate Estimation using a Volumetric Surrogate Signal Acquired via a Smartphone Camera	Bersain A. Reyes(Student Member), Natasa Reljin, Youngsun Kong(Student Member), Yunyoung Nam(Member) and Ki H. Chon (Senior Member) IEEE.	Acquisition protocol, chest movement recording algorithm.	Implemented an algorithm that is able to track chest movements directly on a smartphone and found promising results in terms of average RR estimation.	Recording of the breathing activity while the subjects were standing still.This method requires further studies to enable practical implementation of the proposed approach.
Deep Learning versus Professional Healthcare Equipment: A Fine-Grained Breathing Rate Monitoring Model	Bang Liu , Xili Dai , Haigang Gong, Zihao Guo, Nianbo Liu, Xiaomin Wang, and Ming Liu.	Deep learning as fine-grained breathing rate monitoring technique.	They are not just monitoring respiratory rates but also the changes in the Respiratory rate while sleeping as well and using various devices such as mobile phones, earbuds.	More data is required to train DeepFilter. It implies that DeepFilter needs to suit more smartphones from different manufacturers.
Estimation of respiratory rate and exhale duration using audio signals recorded by smartphone microphones	Emer P. Doheny, Ben P.F.O'Callaghana, Vit´oriaS.Fahed, J´er´emy Liegey, Cathy Goulding, Silke Ryan, Madeleine M.Lowery.	Data acquisition through smart phone, respiration algorithm , inter- breather Interval detection, Signal quality classification using XGBOOST.	The method presented accurate, low-cost remote monitoring of respiration in large populations frequency of the audio signal.	The system has been evaluated for unsupervised use, Evaluation has to be carried out to check if the system will gives efficiency in supervised use as well or not.
Breathing Rate Estimation from Head-Worn Photoplethysmography Sensor Data Using Machine Learning	Simon Stankoski*, Ivana Kiprijanovska, Ifigeneia Mavridou, Charles Nduka, Hristijan Gjoreski and Martin Gjoreski.	Respiratory rate estimation algorithm which is based on advanced Signal processing and machine learning techniques. Also includes novel quality assesment and motion artifacts removals procedure.	This algorithm uses a window size of 20 s, which is shorter than state-of-the-art approaches, making our algorithm more responsive to physiological changes.	Inability to detect out-of-distribution breathing rate.Because they are trained with data that covers only the normal range of breathing rate.
Multiparameter Respiratory Rate Estimation From the Photoplethysmogram	Walter Karlen∗, Member, IEEE, Srinivas Raman, J. Mark Ansermino, and Guy A. Dumont, Fellow.	Smart Fusion RR estimation algorithm.	The Smart Fusion algorithm is being implemented in mobile phone pulse oximeter device to facilitate the diagnosis of severe childhood pneumonia in remote areas.	Detection of lower rates was poor not designed to detect such events.
Time-Reversal Breathing Rate Estimation and Detection	Chen Chen(Student Member) Yi Han, Yan Chen(Senior Member), Hung-Quoc Lai, Feng Zhang(Student Member), Beibei Wang, Senior Member, and K. J. Ray Liu(Fellow)IEEE.	Contact-free breathing monitoring system, Root-MUSIC algorithm.	Demonstrates a perfect detection rate of breathing. A mean accuracy of 99% can be obtained for single-person breathing rate with only 10 seconds of measurement.	The way to detect and discard CSI samples significantly affected by subject andambient motions need to be investigated ,so as to further enhance the robustness of TR-BREATH.
Breathing Rate Monitoring during Sleep from a Depth Camera under Real-life Conditions	Manuel Martinez, Rainer Stiefelhagen.	Early Fourier Fusion algorithm.	Efficient Performance impact related to different sleep conditions, like apnea, position and staging.	Recognition algorithm need to be improved for better results.
Respiratory Rate Estimation from the Built-in Cameras of Smartphones and Tablets	Yunyoung Nam, Jinseok Lee, Ki H.Chon.	The autoregressive (AR)model,variable-frequencycomplex demodulation (VFCDM), and continuous wavelet transform (CWT) approaches.	Both heart rates and breathing rates can be accurately derived from a video signal obtained from smartphones, an MP3 player and tablets with or without a flashlight.	CWT and VFCDM methods gave good estimates but their accuracy degraded with increase in respiratory rates. It test only with the above mentioned mobile devices, whether it will work with the mobile devices of other companies is unknown.
Estimation of Respiratory Rate From Photoplethysmogram Data Using Time–Frequency Spectral Estimation	Ki H. Chon(Senior Member) IEEE, Shishir Dash and Kihwan Ju.	VFCDM algorithm.	The VFCDM method provided the best results in terms of accuracy,consistency(smaller range of the median value) and computational efficiency (less than 0.3 s on 1 min of data) with breathing rates that varied from 12–36 breaths/min.	Breathing rates higher than 26 breaths/min and the real-time performance of these algorithms are not tested yet.

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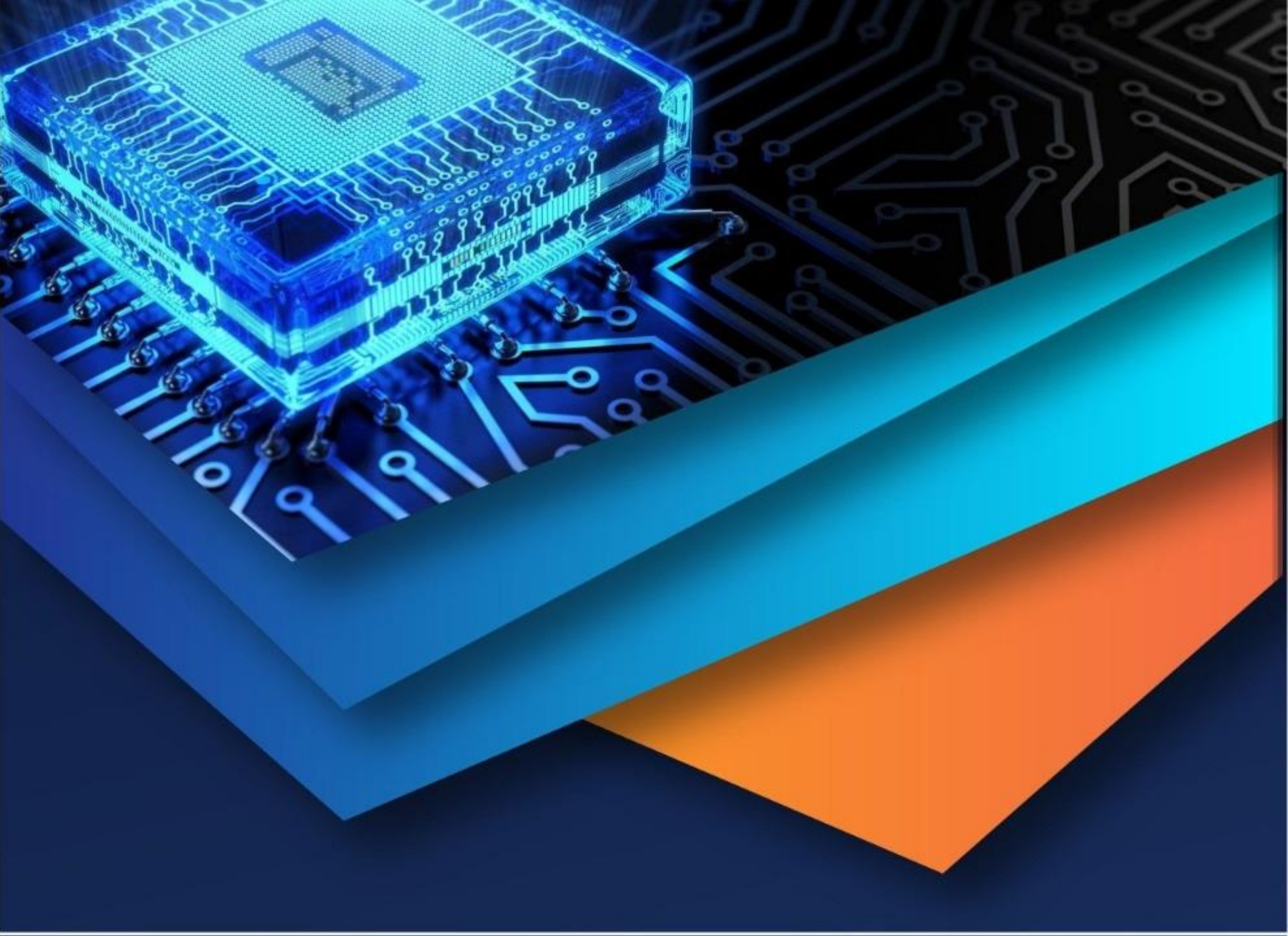
VI. CONCLUSION

The advantages of our proposed method, which performs exceptionally well with very few labeled training examples, are enhanced by the fact that the ICBHI Respiratory Sounds Database is the only publicly available database of labeled respiratory sounds. Using the proposed method, a supervised respiratory rate estimation system can be built with little data. As a consequence of this, the creation of this software might lead to an estimation of human respiration rates that is simple, precise, and highly efficient.

REFERENCES

[1] Azadeh Yadollahi(Student Member), Zahra M. K. Moussavi(Senior Member) IEEE "A Robust Method for Estimating Respiratory Flow Using Tracheal Sounds Entropy",12 May 2014.
[2] Ethan Grooby, Jinyuan He, Julie Kiewsky, Davood Fattahi, Lindsay Zhou, Arrabella King, Ashwin Ramanathan, Atul Malhotra, Guy A. Dumont(Life Fellow), Faezeh Marzbanrad,(Member) IEEE "Neonatal Heart and Lung Sound QualityAssessment for Robust Heart and Breathing Rate Estimation for telehealth Applications", May 31, 2021.
[3] Mohammod Abdul Motin(Student Member), Chandan Kumar Karmakar(Member), and Marimuthu Palaniswami(Fellow) IEEE "Selection of Empirical Mode Decomposition Techniques for Extracting Breathing Rate From PPG", April 2019.
[4] Chien-Lung Shen, Tzu-Hao Huang, Po-Chun Hsu, Ya-Chi Ko, Fen-Ling Chen, Wei-Chun Wang, Tsair Kao, Chia-Tai Chan "Respiratory Rate Estimation by Using ECG, Impedance and Motion Sensing in Smart Clothing",1 July 2017.
[5] Carlo Massaroni, Daniela Lo Presti, Domenico Formica, Sergio Silvestri and Emiliano Schena "Non-Contact Monitoring of Breathing Pattern and Respiratory Rate via RGB Signal Measurement",19 June 2019.
[6] Claudia Floris, Sarah Solbiati, Federica Landreani, Gianfranco Damato, Bruno Lenzi, Valentino Megaleand Enrico Gianluca Caiani "Feasibility of Heart Rate and Respiratory Rate Estimation by Inertial Sensors Embedded in a Virtual Reality Headset",14 December 2020.
[7] Jorge Brieva, Hiram Ponce, and Ernesto Moya-Albor "A Contactless Respiratory Rate Estimation Method Using a Hermite Magnification Technique and Convolutional Neural Networks", 15 January 2020.
[8] Alexis Martin, Jérémie Voix* "In-Ear Audio Wearable: Measurement of Heart and Breathing Rates for Health and Safety Monitoring", 2016.
[9] Xiangyu Xu, Jiadi Yu, Yingying Chen "Leveraging Acoustic Signals for Fine-grained Breathing Monitoring in Driving Environments", 2020.
[10] Tianben Wang, Daqing Zhang, Leye Wang, Yuanqing Zheng, Tao Gu, Bernadette Dorizzi, Xingshe Zhou"Contactless Respiration Monitoring using Ultrasound Signal with Off-the-shelf Audio Devices", 2018.
[11] Jyotibdha Acharya, "Deep Neural Network for Respiratory Sound Classification in Wearable Devices Enabled by Patient-Specific Model Tuning",3 June 2020.
[12] Tamer Elfaramawy, Cheikh Latyr Fall, Soodeh Arab, Martin Morissette, Francois Lellouche and Benoit Gosselin"A Wireless Respiratory Monitoring System Using a Wearable Patch Sensor Network",2018.
[13] Saba Emrani, Thanos Gentimis, Hamid Krim " Persistent Homology of Delay Embeddings and its Application to Wheeze Detection", April 2014.
[14] Yolanda Castillo-Escario, Ignasi Ferrer-lluis, Josep Maria Montserrat and Raimon Jane "Entropy Analysis of Acoustic Signals Recorded With a Smartphone for Detecting Apneas and Hypopneas: A Comparison With a Commercial System for Home Sleep Apnea Diagnosis", September 5, 2019.
[15] Lukui Shi, Kang Du, Chaozong Zhang, Hongqi Ma, and Wenjie Yan "Lung Sound Recognition Algorithm Based on VGGish-BiGRU" September 19, 2019.
[16] Pedro Matias, Joao Costa, Andre V. Carreiro, Hugo Gamboa, Ines Sousa, Pedro Gomez, Joana Sousa, Nuno Neuparth, Pedro Carreiro-Martins and Filipe Soares "Clinically Relevant Sound-Based Features in COVID-19 Identification: Robustness Assessment With a Data-Centric Machine Learning Pipeline",3 October 2022.
[17] Heng Zhao (Student Member), Hong Hong(Member), Dongyu Miao(Student Member), Yusheng Li, Haitao Zhang, Yingming Zhang, Changzhi Li(Senior Member) and Xiaohua Zhu(Member) IEEE "A Noncontact Breathing Disorder Recognition System Using 2.4-GHz Digital-IF Doppler Radar".
[18] David C. Mack, James T. Patrie, Paul M. Suratt, Robin A. Felder, and Majd Alwan "Development and Preliminary Validation of Heart Rate and Breathing Rate Detection Using a Passive, Ballistocardiography-Based Sleep Monitoring System",1 JANUARY 2009
[19] Georges Matar, Georges Kaddoum, Member, IEEE, Julie Carrier, Jean-Marc-Lina "Kalman filtering for posture-adaptive in-bed breathing rate monitoring using bed-sheet pressure sensors",2017.
[20] Kuo-Kai Shyu, Luan-Jiau Chiu, Po-Lei Lee, Tzu-Han Tung and Shun-Han Yang "Detection of Breathing and Heart Rates in UWBRadar Sensor Data using FVPIEF Based Two-Layer EEMD",2018.
[21] Yunyoung Nam, Bersain A. Reyes(Student Member) and Ki H. Chon(Senior Member) IEEE "Estimation of Respiratory Rates Using the Built-in Microphone of a Smartphone or Headset" November 2016.
[22] Bersain A. Reyes(Student Member), Natasa Reljin, Youngsun Kong(Student Member), Yunyoung Nam(Member) and Ki H. Chon (Senior Member) IEEE "Tidal Volume and Instantaneous Respiration Rate Estimation using a Volumetric Surrogate Signal Acquired via a Smartphone Camera"2015.
[23] Bang Liu, Xili Dai, Haigang Gong, Zihao Guo, Nianbo Liu, Xiaomin Wang, and Ming Liu"Deep Learning versus Professional Healthcare Equipment: A Fine-Grained Breathing Rate Monitoring Model",1 March 2018.
[24] Emer P. Doheny, Ben P.F.O'Callaghana, Vit´oriaS.Fahed, J´er´emy Liegey, Cathy Goulding, Silke Ryan, Madeleine M.Lowery "Estimation of respiratory rate and exhale duration using audio signals recorded by smartphone microphones",8 October 2022.
[25] Simon Stankoski*, Ivana Kiprijanovska, Ifigeneia Mavridou, Charles Nduka, Hristijan Gjoreski and Martin Gjoreski "Breathing Rate Estimation from Head-Worn Photoplethysmography Sensor Data Using Machine Learning",8 March 2022.
[26] Walter Karlen∗, Member, IEEE, Srinivas Raman, J. Mark Ansermino, and Guy A. Dumont, Fellow, IEEE "Multiparameter Respiratory Rate Estimation From the Photoplethysmogram",8 February 2013
[27] Chen Chen(Student Member) Yi Han, Yan Chen(Senior Member), Hung-Quoc Lai, Feng Zhang(Student Member), Beibei Wang, Senior Member, and K. J. Ray Liu(Fellow)IEEE "Time-Reversal Breathing Rate Estimation and Detection",2017.
[28] Yunyoung Nam, Jinseok Lee, Ki H.Chon "Respiratory Rate Estimation from the Built-in Cameras of Smartphones and Tablets",23 November 2013.
[29] Manuel Martinez, Rainer Stiefelhagen "Breathing Rate Monitoring during Sleep from a Depth Camera under Real-life Conditions"

[30] Ki H. Chon(Senior Member) IEEE, Shishir Dash and Kihwan Ju "Estimation of Respiratory Rate From Photoplethysmogram Data Using Time–Frequency Spectral Estimation", August 2009.



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