Intelligent Non-Invasive Breathing Abnormality Perception By SDR Technology

Submitted by:

Zain-Ul-Abideen

Fa19-Bee-026

Waqar-Ul-Hassan

Fa19-Bee-001

Fatima Sattar

Fa19-Bee-004

Program: BS in Electrical Engineering

Supervised by:

Dr.Mubashir Rehman

Co-Supervised by:

Dr.Ali Mustafah

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Department of Electrical and Computer Engineering

COMSATS University Islamabad, Attock Campus, Pakistan.

Acknowledgements

In the name of ALLAH who is the omnipotent and the almighty All hails to Almighty,

He guided us to the precise path and fulfilled our hopes while we were going through ups and downs in this Project. As He is the one who blessed us with such abilities and power of doing the task at hand. May He keep his blessings and mercies on us as always, We can't thank Him enough but to give what He wants from us and that is being 'Patient and Thankful'.And after that, all thanks to Dr.Mubashir Rehman who favored us with such a distinctive Project which has a lot to offer in future. His will, motivation and efforts were right up there which helped us to go through all the intricacies with so much ease. His ability to motivate us to work with full efficiency was pre-eminent which certainly optimized and stimulated our working capacity. And we are also grateful to Dr.Ali Mustafah and appreciate his cooperative nature for raising our confidence and doing his finest to make us do our best.

Thank You!

Abstract

Breathing abnormalities have led to quite an increase in mortality rate in the past few decades due to excessive industrialization and environmental changes. A Software Defined Radio(SDR) based system is used to detect and analyze respiratory patterns, enabling non-contact monitoring of breathing. Afterwards Machine learning algorithm is applied to classify breathing patterns and detect abnormalities. The proposed system is a non-invasive, low cost and portable solution that has the potential to improve early detection of breathing abnormalities thus contributing to the safety of humanity through early tackling of any abnormality in breathing if detected. This is significant because current methods for monitoring breathing patterns are often invasive, uncomfortable for patients, and expensive. This study will demonstrate the potential of SDR based radar for remote non-invasive breath monitoring.

Contents

Chapter 1

Introduction

1.1 Background

In the recent years we have seen a global level pandemic called Covid-19 which took many lives.This pandemic was also prone to spreading through breathing and also caused breathing abnormalities within the targets[15].Also According to WHO survey for top 10 causes of deaths, the 3rd one is COPD and 4th one is lower respiratory infection[10].Breathing abnormalities like Apnea(temporary ceasing of breathing), Bradypnea (slower respiratory rate) and Tachypnea(abnormally Rapid breathing) are a significant cause of mortality world wide.As breathing abnormalites are quite common in the world, they can have huge consequences as mentioned before.

So there is a huge need to detect breathing abnormalities in an efficient manner.This will not only help in early detection of breathing illnesses but also reduce casualty count globally.

For the purpose of tackling such issues we require a smart and capable breathing abnormality perception system.The field of Wireless communication fulfils the criteria for such a system.In the past the only use of wireless communication was simply "communication". But in recent years it has emerged as a helpful tool in the field of medical sciences.Wireless communication offers greater accuracy, avoids the burden of manual tasks and one can access the data in real-time. The technologies based on Wireless communication can be employed in two ways:

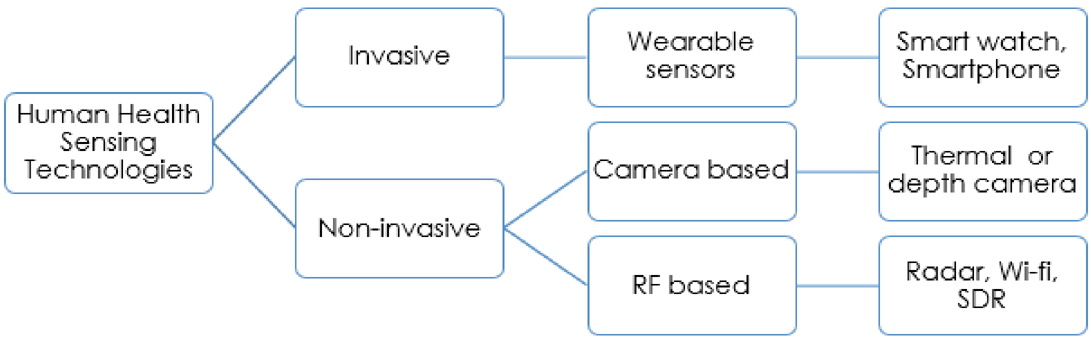

Figure 1.1: Health Sensing Technologies

Currently, the most common methods for monitoring breathing patterns involve invasive procedures or uncomfortable devices. Generally it would be quite uncomfortable for a person with chronic breathing abnormalities if he has to deal with invasive methods such as putting on certain sensors.Many researchers have recently developed and evaluated technologically advanced wearable inertial sensing-based sports activity monitoring systems for physical activities such as running, jumping, cycling, golf, tennis, and badminton[2].Invasive methods also carry the risk of infection or spread of disease.So a better choice is the approach of non-invasive breathing detection. Non-contact monitoring methods have emerged as a promising alternative for monitoring breathing patterns.These methods rely on sensors that can detect changes in motion caused by breathing without requiring any physical contact with the patient. They offer a range of advantages over invasive and non-invasive methods, including increased patient comfort and reduced risk of infection.

However even within non-invasive methods of breathing detection there are certain challenges such as accuracy and signal processing.In recent years though, the advancement in research on software defined radio(SDR) technology has enabled the development of SDR based radar systems for breath monitoring.The system uses radio waves and can be highly accurate when properly configured.
The need for more accurate and efficient methods for detecting breathing abnormalities, such as sleep apnea, which can lead to serious health issues if left untreated. The limitations of current methods for detecting breathing abnormalities, such as invasive procedures and wearable sensors, which can be uncomfortable,inconvenient,and expensive. The potential for SDR technology to provide a non-invasive and cost-effective solution for detecting breathing abnormalities, by leveraging the radio waves that are naturally emitted by the human body.

The study developed a non-contact SDR-based RF sensing platform to overcome limitations in RF-based sensing methods and enable monitoring of breathing abnormalities[9][21][12]. Two types of information are obtained and widely used in the time domain by RF-based sensing. The breathing pattern, which is essentially a detailed process of inhalation and exhalation over time, is one piece of information. The breathing rate is another piece of information[17].

1.2 Problem Statement

The applicable wireless based technologies face certain problems:
• Contact-based technologies may be a source of viral infection spread.
• Frequent use of contact-based health monitoring may cause inconvenience for patients.
• Difficulty in accurately diagnosing health problems through contact based technology.
• In hospitals, more resources are used for patient care and monitoring.

1.3 Project objectives

Following are the project's objectives:
• Designing SDR test bed for the measurement of breathing exercises .
• Breathing rates i-e Normal, slow, and fast are detected according to a defined standard.
• Analysing and classifying abnormalities in collected samples using machine learning with great accuracy.
• Make a comparison of the system proposed and the data present of the already used invasive technologies to evaluate the reliability, accuracy and effectiveness of the proposed system.
• Improve the machine learning and signal processing to increase the accuracy of breathing abnormality detection.
• Explore the scalability and feasibility of the proposed system for deployment in hospitals and other healthcare facilities.

1.4 Research Question

The thesis addresses following questions:

1. How can SDR be applied to measure and classify breathing abnormalities without the need of any physical contact?
2. What among the non-contact technologies is best for breathing abnormality detection?
3. What are the standards for the different breathing states of humans?
4. What are the most important features of SDR signals for detecting breathing abnormalities, and how can these features be extracted and analyzed?
5. How can machine learning algorithms be applied to SDR signals to accurately classify different types of breathing abnormalities?

1.5 Project Application For the Betterment of the Society

The project plays a vital role in the betterment of society.It is a secure and stable method for the detection of any abnormality in breathing of patients. It is also quite reliable and flexible. One of the most important advantages of the proposed system is its ability to provide continuous, real-time monitoring of breathing patterns. This can be especially useful in critical care settings, such as intensive care units, where patients require constant monitoring and timely intervention in case of any respiratory distress.

Moreover, the proposed system can also help to improve the accuracy of diagnosis and treatment of respiratory conditions. By providing objective and accurate assessments of breathing patterns, healthcare professionals can make more informed decisions about the appropriate course of treatment for patients. This can lead to better outcomes and a more efficient use of healthcare resources.

Another important advantage of the proposed system is its ability to be used in a variety of settings, including in-home care and remote monitoring. This can be especially useful for patients with chronic respiratory conditions, who may require regular monitoring but do not need to be hospitalized. With the non-contact system, patients can be monitored remotely, reducing the need for frequent hospital visits and improving their quality of life.

In addition to healthcare, the proposed system could have broader societal implications, such as in disaster response and recovery.In the aftermath of natural disasters(i.e. Earthquakes etc.) or conflicts, there is often a shortage of healthcare professionals and resources, making it difficult to provide adequate care for affected populations.The non-contact system, being portable and automated, can be quickly deployed to affected areas and used to assess and monitor the respiratory health of patients, thus facilitating more effective and efficient healthcare delivery.

Lastly, the proposed system can also contribute to the development of new technologies and innovations in the field of healthcare.The use of SDR-based radar technology and machine learning algorithms can pave the way for new applications and solutions in healthcare, such as the development of smart healthcare devices and systems that can be used for a variety of medical conditions and health monitoring.

In conclusion, the project on "intelligent non-contact breathing abnormality detection using SDR" has several potential benefits for society, including improved patient outcomes, more efficient use of healthcare resources, and the development of new healthcare technologies and innovations. Its ability to provide accurate, real-time monitoring of breathing patterns in a non-invasive and patient-friendly manner makes it a valuable addition to the healthcare field, with potential applications beyond healthcare as well.

1.6 UN Stainability Goals

The project meets the UN's sustainable development goals.

1.6.1 Good Health and Well-Being (Goal 3)

Ensure Healthy Life and Promote well-being for all at all ages.

By providing a non-invasive and accurate method for monitoring breathing patterns, the proposed system can help to improve the diagnosis and treatment of respiratory conditions, leading to better health outcomes for patients. Moreover, the system's portability and remote monitoring capabilities can improve access to healthcare, especially for those in remote or under-served areas.

Figure 1.2

1.6.2 Industry Innovation and Infrastructure (Goal 9)

Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation.

The use of SDR-based radar technology and machine learning algorithms in the proposed system can pave the way for new innovations in healthcare and contribute to the development of new technologies and industries.This can lead to economic growth and the creation of new jobs.

Figure 1.3

1.6.3 Sustainable Cities and Communities (Goal 11)

Make cities and human settlements inclusive, safe, resilient and sustainable.

By enabling remote monitoring of patients, the proposed system can reduce the need for frequent hospital visits, thereby reducing traffic congestion and air pollution in cities. Additionally, the project's potential application in disaster response and recovery can help to ensure the strength of cities and communities against natural disasters and conflicts.

Figure 1.4

1.7 Thesis Overview

The thesis begins with an introduction that provides background information on the challenges of contact-based health monitoring and the need for non-contact methods of detecting breathing abnormalities.The problem statement will be identified, highlighting the limitations of current monitoring techniques and the potential benefits of the proposed system.
The research objectives and questions will then be presented, outlining the specific goals and methods of the project.The literature review will follow, surveying the relevant literature on SDR-based radar technology, machine learning algorithms, and respiratory conditions.The methodology chapter will then describe the hardware and software components of the proposed system, as well as the data collection and analysis procedures.
The results of the experiments will be presented,including the accuracy of the system in detecting breathing abnormalities compared to current contact-based methods.The discussion section will interpret the results, addressing the project's limitations and potential for further development. Finally, the conclusion will summarize the project's contributions to the field and its potential applications in healthcare and disaster response.

1.8 Project Timeline

No.	STARTING WEEK DATE	DESCRIPTION OF MILESTONE	DURATION IN WEEK
1	15-09-22	Literature review for FYP proposal plus defence	2 weeks
2	01-10-22	Data set collection	4 weeks
3	01-11-22	Literature review related to project working	2 weeks
4	15-11-22	Feature extraction	4 weeks
5	15-12-22	Breathing abnormalities perception	6 weeks
6	01-02-23	Applying machine learning for classification	6 weeks
7	15-03-23	Performance analysis of project and its verification	4 weeks
9	15-04-23	Documentation and presentation work	4 weeks

Figure 1.5

Chapter 2

Literature Review

2.1 Breathing definition and importance

The process by which living organisms, including humans, exchange oxygen and carbon dioxide with their surroundings is known as breathing. It consists of inhaling oxygen-rich air into the lungs and then exhaling carbon dioxide. Breathing is a vital bodily function that provides oxygen for cellular respiration while also removing waste gases from the body.

Proper breathing is essential for overall health and well-being. It ensures that oxygen reaches the cells of the body, allowing energy production and supporting vital organ functions. Furthermore, efficient breathing aids in the regulation of the body's pH balance by controlling the levels of carbon dioxide in the bloodstream. Stress reduction, relaxation, and optimal mental and physical performance are all benefits of balanced breathing.

2.2 Breathing abnormalities and causes

Breathing abnormalities are deviations from normal respiration patterns and rhythms. These abnormalities can be caused by a variety of factors, including physiological, psychological, and environmental factors. Common causes of breathing problems include:

- Respiratory problems:
  Asthma, chronic obstructive pulmonary disease (COPD), pneumonia, and bronchitis can all cause abnormal breathing patterns. These conditions can cause shortness of breath, wheezing, or difficulty properly exhaling or inhaling.

- Anxiety and stress:
  Emotional factors such as anxiety, stress, and panic attacks can all have an impact on breathing. Hyperventilation is a common reaction to intense stress or anxiety, characterised by rapid and shallow breathing.

- Sleep disorders:
  Sleep apnea and other sleep-related disorders can disrupt normal breathing while sleeping. These disorders frequently cause periods of interrupted breathing, resulting in oxygen deprivation and death.

- Medications and substances:
  Some medications, such as opioids and sedatives, can impair respiratory function, resulting in slow or shallow breathing. Substance abuse, such as alcohol and drug use, can also have an impact on breathing patterns.

- Neurological disorders:
  Neurological disorders such as Parkinson's disease, multiple sclerosis, or spinal cord injuries can impair respiratory muscle control, resulting in breathing difficulties.
- Environmental factors:
  Pollutants, allergens, and irritants in the air can cause respiratory symptoms and interfere with breathing. Breathing abnormalities can be exacerbated by poor air quality, smoking, or occupational hazards.

It is critical to determine the underlying cause of breathing problems and seek appropriate medical attention. Medication, breathing exercises, lifestyle changes, or addressing the underlying condition causing the abnormal breathing patterns are all treatment options.

2.3 SDR

Software Defined Radio (SDR) is a game-changing technology that has changed the face of wireless communication. Unlike traditional radios, which rely on fixed hardware components to perform specific functions, SDR defines and controls its operations through software. Because of its adaptability and flexibility, SDR has become an indispensable tool in a variety of domains, including telecommunications, military applications, and research.

- Functionality of SDR:
  SDR's functionality is derived from its ability to manipulate radio signals using software. SDR can process, modify, and transmit data using various modulation schemes, such as amplitude modulation (AM), frequency modulation (FM), and phase modulation (PM), by digitising analogue signals. Furthermore, SDR supports dynamic spectrum allocation, allowing multiple wireless standards to coexist on the same hardware.
- SDR Advantages:
  SDR radios have several advantages over traditional radios. For starters, because it is software-based, it allows for simple upgrades and enhancements, eliminating the need for costly hardware replacements. Second, SDR enables rapid prototyping and development of new communication systems, thereby shortening the time to market for innovative technologies. Furthermore, SDR facilitates interoperability between various wireless standards, allowing for seamless communication between disparate networks.
- Limitation of SDR:
  While SDR has numerous advantages, it also has some limitations. One significant challenge is the increased vulnerability to cyber threats as a result of software reliance. To protect against unauthorised access and potential attacks, SDR systems must implement strong security measures. Furthermore, the computational requirements of SDR can be demanding, necessitating powerful hardware to ensure real-time data processing and transmission.
- SDR platform design consideration:
  Creating an effective SDR platform necessitates taking into account a number of factors. Selecting appropriate hardware components, such as analog-to-digital converters (ADCs) and digital-to-analog converters (DACs), to ensure accurate signal conversion is one of them. Furthermore, the platform's architecture should be capable of high-speed data transfer and signal processing. To accommodate

evolving communication standards, power consumption, cost-effectiveness, and scalability must all be carefully considered.

- Software environments for SDR:
  There are several software environments available for developing and deploying SDR applications. GNU Radio, a free and open-source software development toolkit, and MATLAB/Simulink, a proprietary software suite widely used in research and industry, are two popular options. These environments offer a variety of signal processing, modulation, and demodulation tools and libraries, making them invaluable for SDR prototyping and experimentation.

2.4 The USRP Platform

Ettus Research, a subsidiary of National Instruments, created the Universal Software Radio Peripheral (USRP) platform, which is a popular SDR hardware solution. For researchers, engineers, and enthusiasts, USRP provides a versatile and configurable platform. It consists of a motherboard and daughterboard combination that provides a flexible framework for signal transmission and reception.

- Transmitter:
  The transmitter functionality of the USRP platform allows for the generation and transmission of radio signals. It employs digital-to-analog converters (DACs) to convert digital signals into transmission-ready analogue waveforms. The transmitter module provides programmable options for modulation schemes, power levels, and signal conditioning techniques. This adaptability enables users to tailor their transmissions to specific needs.

- Receiver:
  The USRP platform's receiver module is in charge of capturing and processing incoming radio signals. Analog-to-digital converters (ADCs) are used to convert received analogue signals into digital data for further processing. To improve the quality of received signals, the receiver supports various signal demodulation techniques and includes signal conditioning capabilities. The USRP receiver is capable of operating over a wide frequency range, making it suitable for a variety of wireless communication applications.

2.5 Wireless channel state information

Wireless Channel State Information (CSI) is the knowledge or estimation of a wireless communication channel's characteristics. It includes parameters like channel gain, phase, and noise, all of which are important for optimising signal transmission and reception. CSI estimation is critical in techniques such as beamforming, adaptive modulation, and channel equalisation, allowing for efficient use of the wireless channel's capacity.

2.6 Orthogonal frequency division multiplexing OFDM

(Orthogonal Frequency Division Multiplexing) is a modulation technique that is widely used in modern wireless communication systems. It divides the available frequency spectrum into multiple orthogonal subcarriers. OFDM achieves high data rates while mitigating the effects of multipath fading and frequency-selective channel impairments by transmitting data symbols simultaneously on these subcarriers.

2.7 Van de Beek algorithm

The Van de Beek algorithm is a critical component of OFDM systems, addressing the problem of inter-symbol interference (ISI) caused by multipath propagation. To eliminate ISI, this algorithm employs a cyclic prefix, which is a copy of the last portion of the OFDM symbol. By appending this cyclic prefix before each OFDM symbol, the receiver can discard multipath echoes and successfully recover the transmitted data.

2.8 Artificial intelligence

Artificial intelligence (AI) is the simulation of human intelligence in machines that allows them to perform tasks that would normally require human cognition. Machine learning, natural language processing, computer vision, and expert systems are all subfields of AI. With the introduction of powerful hardware and sophisticated algorithms, AI has made remarkable advances, revolutionising a wide range of industries and applications.

2.9 Machine learning

Machine learning is a branch of artificial intelligence that focuses on teaching computers to learn from data and make predictions or decisions without being explicitly programmed. It entails the creation of algorithms and models that automatically improve their performance as a result of experience or training. Machine learning techniques are classified into three types: supervised learning, unsupervised learning, and reinforcement learning.

- Supervised learning:
  To learn a mapping function, supervised learning involves training a model on labelled input-output pairs. The model learns from a dataset in which each input is associated with a desired output. The model generalises from the training data through iterative optimisation to make accurate predictions on unseen inputs. Supervised learning is frequently used for classification, regression, and time series analysis tasks.

- Unsupervised learning:
  The goal of unsupervised learning is to find patterns or structures in unlabeled data. Unsupervised learning, unlike supervised learning, has no predefined output labels. The model, on the other hand, identifies inherent patterns or clusters in the input data, allowing for insights and knowledge discovery. Unsupervised learning is commonly used for clustering, dimensionality reduction, and anomaly detection.

- Systematic workflow for machine learning model:
  Creating a machine learning model follows a systematic workflow that usually consists of several stages. Data collection and preprocessing, feature selection or extraction, model selection, training, validation, and testing are examples of these stages. Furthermore, hyperparameter tuning and model evaluation are critical steps in optimising the model's performance and assessing its generalizability.

- Evaluation of machine learning model:
  A machine learning model's performance and generalisation abilities are assessed during its evaluation. Depending on the task, common evaluation metrics can

include accuracy, precision, recall, F1 score, mean squared error, and area under the receiver operating characteristic curve (AUC-ROC). Model evaluation aids in determining the effectiveness of the model, identifying potential issues, and guiding improvements in the learning process.

Non-contact sensing methods have gained significant attention in recent years for various applications.In the context of the COVID-19 pandemic,the monitoring of physical activities and respiratory patterns remotely has become a critical need.This literature review aims to summarize and compare multiple research papers that propose non-contact sensing methods for monitoring physical activities and respiratory patterns.

Wireless communication technologies are used in many of the papers to transmit data from sensors to a processing unit or display device. The most commonly used wireless communication technology is Bluetooth. For example, in the paper the authors use Bluetooth to transmit data from a microcontroller to a laptop for signal processing[1]. The authors use Bluetooth to transmit data from an accelerometer sensor to a smartphone app for physical activity monitoring[6].
Another wireless communication technology used in the papers is ZigBee, which is a low-power wireless communication protocol designed for wireless sensor networks. In the paper the authors use ZigBee to transmit data from a breathing pattern sensor to a processing unit[14].

2.10 RF Sensing Technologies

RF sensing is used in non-invasive monitoring of breathing patterns.RF signals are transmitted towards the subject's body and the reflected signals are analyzed to detect changes in amplitude caused by breathing.The author used RF sensing to detect changes in the amplitude of RF signals reflected from the human body, which can be used to monitor breathing patterns. The authors achieved an accuracy of 96.2percentage in detecting breathing patterns using this method[14].Various SDR platforms are currently used for research; the most commonly used is the USRP developed by Ettus research[11], which has become a popular[20] and appropriate choice for wireless research and education[4][19].

2.11 Previous Technologies

Its types are mentioned as follows:

2.11.1 Software-Defined Radio (SDR) Technology

SDR technology is used for non-invasive monitoring of breathing and physical activity. SDR technology allows for the creation of custom radio waveforms, making it an ideal choice for non-contact sensing applications. SDR technology creates a radar system that can detect changes in chest wall motion caused by breathing.The authors use SDR technology to detect changes in the amplitude of radio frequency (RF) signals reflected from the human body, which can be used to monitor breathing patterns[14].
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2.11.2 Radar Technology

Doppler Radar

Doppler radar is a device that uses the Doppler effect to measure the velocity of an object.Doppler radar has been used in several research papers related to non-invasive breathing perception.For example,The author used a Doppler radar to detect breathing rate and pattern without physical contact with the subject.The authors transmitted signals at a frequency of 5.8 GHz, which were then received by a radar sensor. The received signals were then processed using MATLAB to estimate the subject's breathing rate and pattern. The authors reported a high accuracy of their system, with a correlation coefficient of 0.99 and an average error rate of 1.53perc. The authors also emphasized the advantages of using Doppler radar, including high accuracy and low cost[3].

Ultra-Wideband (UWB) Radar

Ultra-wideband (UWB) radar is a device that uses signals with a large bandwidth to transmit and receive data. UWB radar has been used in several research papers related to non-invasive breathing perception. For example, UWB radar is used to monitor physical activities during the quarantine period. The authors used a UWB radar with a frequency range of 3.1 to 10.6 GHz to transmit and receive signals, which were then processed using MATLAB to estimate the subject's physical activities.The authors reported a high accuracy of their system, with an average classification accuracy[7].

Frequency Modulated Continuous Wave (FMCW) Radar

Frequency modulated continuous wave (FMCW) radar is a device that continuously transmits a signal with a varying frequency. FMCW radar has been used in several research papers related to non-invasive breathing perception. For example,FMCW radar is used to monitor breathing patterns without physical contact with the subject. The authors transmitted signals at a frequency of 24 GHz, which were then received by a radar sensor. The received signals were then processed using MATLAB to estimate the subject's breathing rate and pattern. The authors reported a high accuracy of their system, with a correlation coefficient of 0.92 and an average error rate of 1.75percent[18].

2.11.3 Wi-Fi

Human breathing and heartbeat can result in weak motions in the abdomen and chest. Thesemotions can have some effect on the propagation of WiFi signals and the WiFi CSI can record these effects. In the paper the authors setup the systems to enhance these effects based on Fresnel diffraction models and signal propagation theory, and extract CSI from WiFi physical layer to obtain vital signs[5].

There were a few other technologies that were also previously used:

2.11.4 Video-Based Methods

They are used for monitoring breathing and physical activity.These methods use cameras to capture images or videos of the subject, which are then processed using computer vision algorithms to extract features related to breathing or physical activity. Author uses a smartphone camera to capture video of a subject performing physical activities, which is then processed using computer vision algorithms to estimate the

subject's heart rate and breathing rate. The authors achieved an accuracy of 97.4 percentage in estimating breathing rates and 94.4percentage in estimating heart rates using this method[7].
Some of its types are:

Thermal Camera

Thermal imaging can be used to measure both breathing rate and exhaled air temperature to provide useful information about the body load during physical activity and to study potential symptoms of certain respiratory diseases.The respiratory rate is an important indicator for monitoring of a person's health[7].

Depth Camera

Depth cameras have proved adept at capturing the motion associated with respiration. From the resulting respiratory volume (RV) signal, measures of both respiratory rate and tidal volume can be made. This has prompted an interest in the use of such cameras for providing these physiological parameters[7].

2.11.5 Inertial Measurement Units (IMUs)

An IMU is a sensor package that typically includes an accelerometer, gyroscope, and magnetometer. These sensors can be used to measure acceleration, rotation, and orientation of a subject's body, which can be used to estimate physical activity.In the paper the author used an IMU to measure acceleration of the subject's leg during physical activity, which is then used to estimate step count. The authors achieved an accuracy of 93.2percentage in step count estimation using this method[7].
Some other methods in use were Acoustic methods, Microwave methods,Optical Methods.

2.12 Classification using Machine Learning

In order to classify the breathing patterns in both single and multi-person scenarios, we employed several machine-learning algorithms and assessed the performance of the platform based on training time, accuracy, and prediction speed[13].Utilizing the classification feature in MATLAB, we implemented K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Tree algorithms to identify abnormalities in breathing patterns.Each algorithm demonstrated significant classification capabilities. We measured the accuracies, prediction speeds, and training times associated with each algorithm to evaluate their effectiveness in the classification task.

These algorithms are interpreted below:

2.12.1 SVM

The Support Vector Machine (SVM) algorithm is a powerful tool for classification tasks in machine learning. It works by drawing a line or boundary to separate different categories of data points, such as apples and oranges.The goal is to find the best line that maximizes the distance between the two classes, creating a clear separation. To achieve this, SVM uses mathematical tricks to transform the data into a higher-dimensional space, making it easier to draw the separating line. Once the line is determined, SVM can classify new data points by assigning them to one of the categories based on which side of the line they fall on. SVM is widely used in various fields and has proven to be effective in solving classification problems and successful perception.

2.12.2 KNN

The K-Nearest Neighbors (KNN) algorithm is a simple yet effective machine-learning technique used for classification tasks. It works by comparing a new data point to its closest neighbors in the training data. Imagine you have a set of labeled data points, and you want to classify a new point. KNN finds the "k" closest data points to the new point and looks at their labels. The new point is then assigned the label that appears most frequently among its nearest neighbors. KNN is easy to understand and implement, making it a valuable algorithm for research on classification problems.

2.12.3 Tree

It works like a flowchart, where each node represents a question or decision based on a feature of the data. Imagine you have a dataset of different fruits, and you want to classify them. The Decision Tree algorithm starts at the root node and asks a question about a feature, depending on the answer, it follows a specific branch to the next node and asks another question. This process continues until it reaches a leaf node, which contains the final classification decision. Decision Trees are easy to interpret and can handle both numerical and categorical features.

2.12.4 LDA

The Linear Discriminant Analysis (LDA) algorithm is a machine learning technique that aims to find a linear combination of features that maximally separates different classes in the data. LDA analyzes the data to determine the best linear equation that can distinguish one type of data from another. It achieves this by calculating the mean and variance of each feature for each class and using this information to estimate the likelihood of new data belonging to a specific class. By finding the optimal linear discriminant, LDA can effectively classify new data based on their measurements. The simplicity and interpretability of LDA make it it an accurate classification tool in various domains.

Figures 4.17, 4.18, and 4.19 show the classification of single-person scenarios using the SVM, KNN, and Linear discriminant algorithms respectively. Figures 4.31 and 4.32 show the classification of two-person breathing scenarios using SVM and Tree algorithm respectively. In a three-person scenario figures 4.40 and 4.41. show the classification using SVM and Tree algorithm respectively. To evaluate the performance of each machine learning algorithm, we used a confusion matrix that consisted of eight predicted and true classes. In this matrix, the diagonal entries represent the cases where the predicted class matched the actual class correctly.These entries indicate accurate predictions made by the algorithms.However, the other cell values outside the diagonal entries highlight instances where the machine-learning algorithms performed poorly.These values indicate situations where the algorithms made incorrect predictions, thus revealing areas of weakness or errors in classification. The confusion matrix allowed us to assess and compare the performance of each algorithm based on its ability to correctly classify the different classes[16]. By conducting these evaluations, we gained valuable insights into the performance and efficiency of each algorithm in accurately identifying breathing abnormalities.

Chapter 3

Proposed Methodology

The wireless communication system is utilized to sense human body movements by CSI information gathered by passing electromagnetic waves from the body. It is done by transmitting and receiving the signal through multi-paths and then reviving them with multi-path superposition. RF sensing adds environmental attributes like proximity, strength, human movements, and other environmental influences to the dissemination of signal is realized for clear understanding. Whenever there is a human present in the environment where a signal is propagating there is an addition of path to the signal due to human movements thus coming up with wireless communication[9][21][12]. Figure 3.1 shows the methodology block diagram which comprises of four major blocks: wireless signal sensing followed by signal preprocessing after which there is breathing monitoring, and lastly there is a breathing classification block. Each block's description and block diagram are provided below:

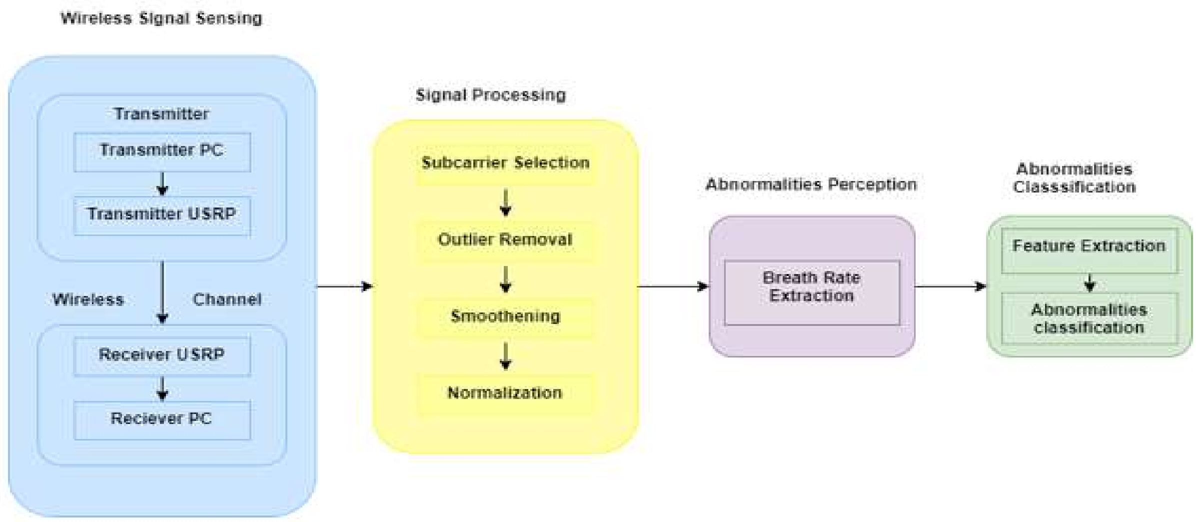


Figure 3.1

3.1 Wireless Signal Sensing

It is done using two steps:

3.1.1 Breathing Data Collection

Breathing data is collected using an experimental setup consisting of two PCs connected with their respective USRP kits. Both USRP kits are equipped with an omnidirectional antenna that observes the breathing of a person in both line-of-sight and non-line-of-sight frameworks. A transmitting PC generates an OFDM subcarrier signal while the receiving PC preprocesses and classifies the received raw data. Placement of USRP's is in such a way that they are parallel to the person's abdomens.The setup for the data collection is established on an observation where the best results are seen.

The data set collection consisted of mainly two scenarios: single and multiple persons.Further in the multi-person, there was a two and three-person scenario. The activity duration was set to 30 seconds and ten sets of data were gathered for every breathing sample.In a single-person scenario, ten participants were requested to execute the breathing activity at fast, slow, and normal breathing rates while in a two-person scenario, six cases were formed when both executed the breathing activity at fast, slow, and normal breathing rates. Extensive experiments were conducted to achieve high accuracy. The Table below shows each participant's specifications:

S/N.	**Age(Yrs.)**	**Height(cm)**	**Weight(kg)**	**Gender**	**BMI**
1.	22	160	43	Female	16.79
2.	22	171	54	Male	18.46
3.	22	172	51	Male	17.2
4.	23	160	45	Female	17.5

Table 3.1

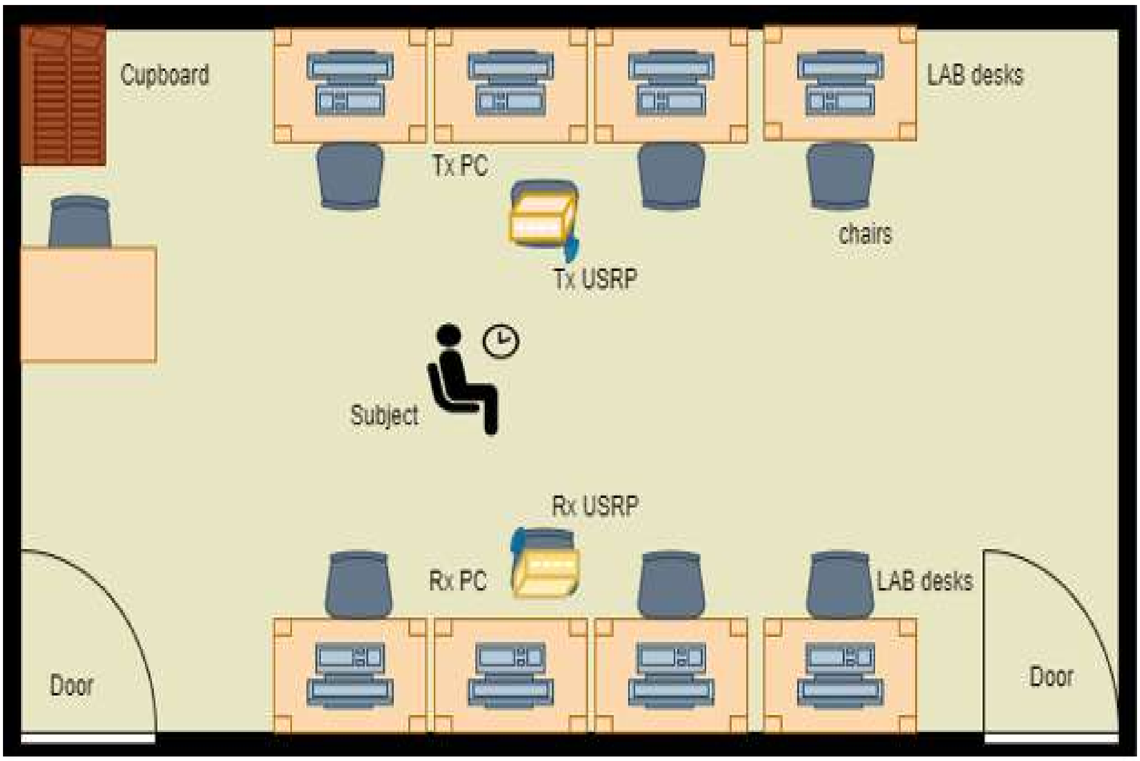


Figure 3.2

3.1.2 Breathing Data Extraction

Breathing data extraction includes three subsegments: Transmitter, a wireless channel, and a receiver. Each segment is described below:

Transmitter

This segment has a transmitter PC with a transmitter USRP connected using an Ethernet cable. The transmitting PC generates random bits and converts them to symbols using (Quadrature Amplitude Modulation) QAM. These symbols are converted into parallel streams.Nulls, DC symbols, and cyclic prefixes are added in each frame. Then for the channel estimation at the receiver reference symbols are added.Afterward, the IFFT is applied to convert the signal into the time domain. The host PC generated data is then handed over to the USRP kit in which the signal undergoes operations such as Digital up-conversion(DUC) and digital-to-analog conversion(DAC). Then the signal goes through a low pass filter. The evolved signal is mixed with a specified carrier frequency and amplified using a transmitter amplifier(TA)and transmitted through the omnidirectional antenna.

Wireless Channel

To monitor human breathing activities a wireless channel in real-time was taken which includes valuable information regarding the environment yet there are many different techniques to extract this information but we are manipulating CFR which is computed through equation:

$$H(k) = \frac{Y(k)}{X(k)} \tag{3.1}$$

Here, the transmitted and received frequency domain signals are represented by X(k) and Y(k), respectively, and the CFR is denoted by H(k). Given that H(k) is a complex number, following equation could be used to get the amplitude response:

$$H(k) = \sqrt{H_{Re}^2 + H_{im}^2} \tag{3.2}$$

Here HRe and Him are the real and imaginary parts of CFR respectively. We can determine the CFR amplitude data acquired in time history utilizing multiple frames for a single experimental observation E by using equation:

$$|H(k)|_E = \begin{bmatrix} |H(k)|_{1,1} & |H(k)|_{1,2} & \cdots & |H(k)|_{1,F} \\ |H(k)|_{2,1} & |H(k)|_{2,2} & \cdots & |H(k)|_{2,F} \\ \vdots & \vdots & & \vdots \\ |H(k)|_{K,1} & |H(k)|_{K,2} & \cdots & |H(k)|_{K,F} \end{bmatrix} \tag{3.3}$$

Where K is total OFDM subcarriers, F is total OFDM frames obtained during single experiment observation E.

Receiver

The omnidirectional antenna of receiver USRP receives the signal which then passes through amplifiers such as LNA and DA; low noise and drive amplifiers respectively. From the signal received a baseband complex signal is acquired using a mixer and digital Conversion Receiver(DCR). Afterward, low pass filter(LPF) is applied to signal and is then down-converted using Digital Down Convertor (DDC). Then it is converted to a digital signal using a Digital to Analogue Convertor(DAC) before being sent via an Ethernet cable to the host PC. Next, the frequency domain signal is acquired by applying FFT. Thereafter the reference symbols, Nulls, and DC are removed. These reference symbols were added for channel estimation which helped in getting the equalized data and is then demodulated using QAM demodulation that converts the symbols into bit stream.

3.2 Breathing Data Processing

It involves a number of steps, each of which is described in greater detail below:

3.2.1 Subcarrier Selection

The first step in processing is subcarrier selection in which the most sensitive subcarriers for breathing activity are selected[8]. It is done by measuring the variance with the data. As seen in figure 3.4, those with little variance under 0.001 are eradicated.

3.2.2 Outlier Removal

Succeeding the subcarrier selection, wavelet filtering is applied to remove outliers. It not only remove outliers but also preserves sharp transitions[8].

3.2.3 Smoothening

A moving average filter was used to smoothen data and eliminate high-pitched noise that was not caused by breathing activity. Through this, we can easily detect breathing patterns. Results are shown in figure 3.5.

3.2.4 Normalization

The last step in processing is normalizing breathing data between 1 and -1[8]. It is done using the equation:

$$Y'[n] = \frac{Y[n] - offset}{scale} \tag{3.4}$$

Where y'[n] is normalized data, y[n] is input data. This normalized data is obtained by regulating the offset values and scaling them as shown in figure 3.7.

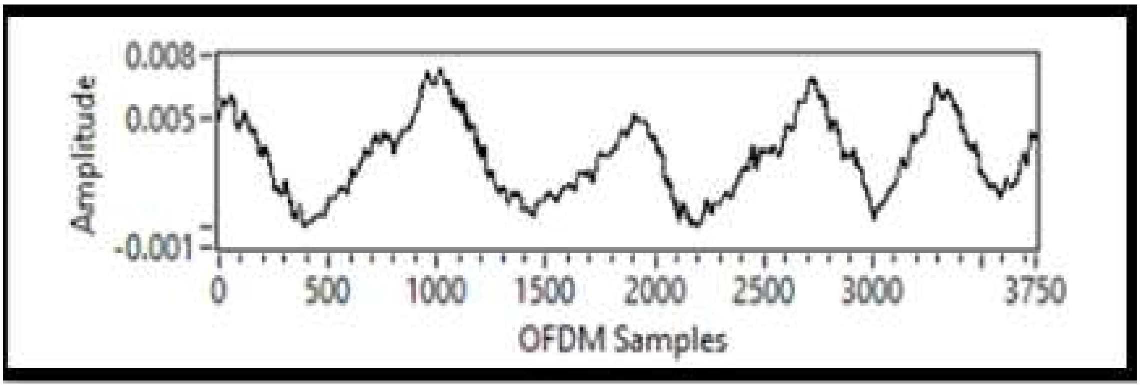


Figure 3.3

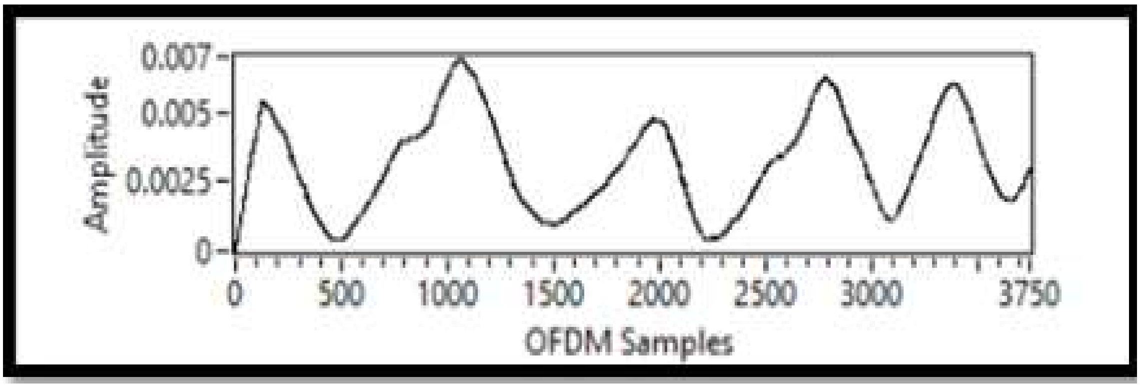


Figure 3.4

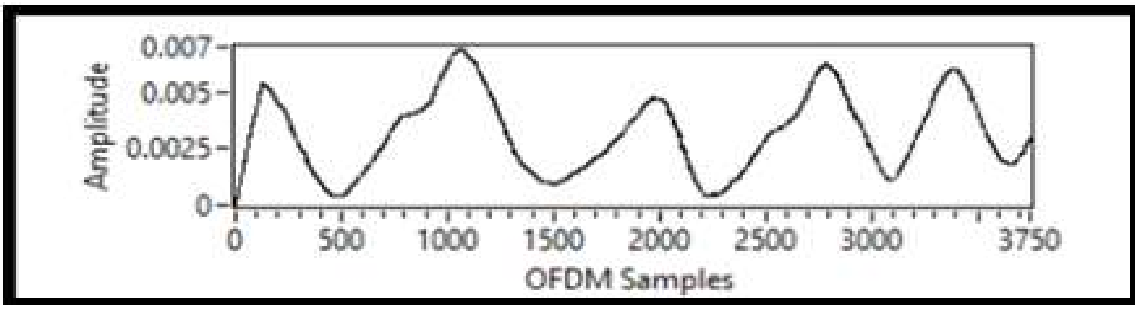
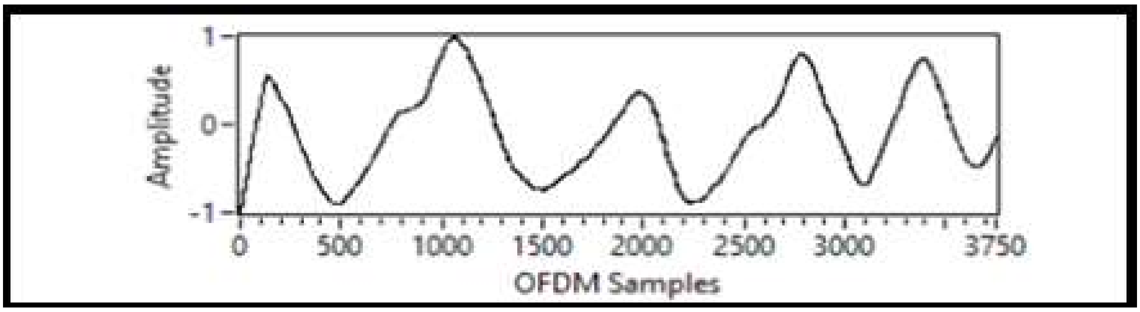


Figure 3.5



3.3 Breathing Abnormality Perception

3.3.1 Breath Rate Extraction

Breathing abnormalities are perceived through breathing rate extraction in both the multi and the single-person scenarios. It is done by transforming the CSI amplitude information stored in time history into the frequency domain. By doing so a frequency peak is detected which represents the breathing rate. It is computed as:

Where s is the total time for breathing activity and fmax represents the maximum frequency peak. The number of peaks shows the how many persons were involved in breathing activity. So if one peak is observed then it is for a single person and if more than one peak is obtained then it is for a multi-person scenario. It can be observed in Figure 3.

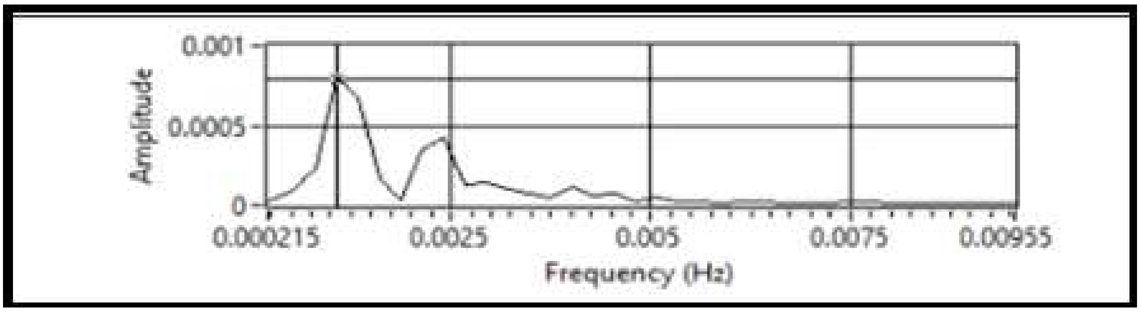


Figure 3.6

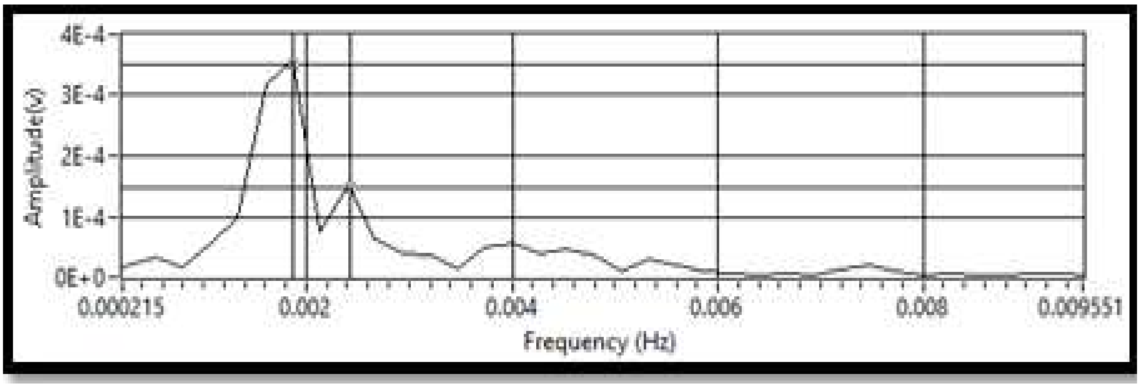


Figure 3.7

3.4 Breathing Abnormality Classification

It is the final step in methodology Firstly, it extracts the features from breathing data and then classifies the abnormalities in them using ML models. These ML models work for both scenarios single and the multi-person. These steps are given in detail beneath:

3.4.1 Breathing Feature Extraction

It is demanding and takes a longer time to come up with a classification system with high dimensionality so to overcome this, only effective features are extracted to enhance the model performance[8]. Abundant features were selected for the classification; also similar features were removed. Moreover, it helps in improving prediction efficiency. The list of the features and their details are given in table below:

3.4.2 Abnormalities Classification

For the purpose of classifying abnormalities in breathing patterns, various ML algorithms are utilized. Each algorithm's training time, prediction speed, and accuracy are estimated. Initially, these algorithms were evaluated without a feature selection method then it was re-evaluated with feature selection and is done for both the single-person and multi-person scenario.

Sr.	Statistical Features	Description	Expression
1	Minimum	Minimum value of data	$\mathrm{Y}_m in = min(y_i)$
2	Maximum	Maximum value of data	$\mathrm{Y}_m ax = max(y_i)$
3	Mean	Mean of data	$Y_m = \frac{1}{N}\sum_{i=1}^{N}(Y_i)$
4	Variance	Degree of data spread	$\mathrm{Y}_{SD} = \sum_{N}^{i=1}(y_i - Y_m)^2$
5	Standard deviation	Square root of variance	$\mathrm{Y}_v = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(y_i - Y_m)^2}$
6	RMS	Root mean square	$\mathrm{Y}_{RMS} = \sqrt{\frac{1}{N}}\sum_{N}^{i=1}(Y_i)^2$
7	Peak-to-peak value	Data fluctuations about the mean	$\mathrm{Y}_p = Y_{max} - Y_{min}(i = 1, 2, \ldots N)$
8	Kurtosis	Measure of tailedness in data	$\mathrm{Y}_k = \frac{1}{k}\frac{\sum_{i=1}^{k}(\lvert Y_i\rvert - Y_m)^4}{Y_{rms}^4}$
9	Skewness	Measure of symmetry in data	$\mathrm{Y}_s = \frac{1}{k}\frac{\sum_{i=1}^{N}(\lvert Y_i\rvert - Y_m)^3}{Y_{rms}^3}$
10	Peak factor	Ratio of maximum value to RMS	$\mathrm{Y}_p = \frac{max(Y_i)}{Y_{RMS}}(i = 1, 2, \ldots N)$
11	Interquartile range	Mid-spread of data	$\mathrm{Y}_{IQ} = Q_3 - Q_1$
12	Waveform factor	Ratio of the RMS value to mean value	$\mathrm{Y}_W = \frac{Y_{RMS}}{Y_M}$
13	FFT	Frequency information about data	$\mathrm{Y}_{FFT} = \sum_{n=-N}^{N} Y(n)e^{\frac{-j2\pi}{N}}nk$
14	Frequency Min	Minimum Frequency component	$\mathrm{Y}_{fmin} = Min(Y_{FFT})$
15	Frequency Max	Maximum Frequency component	$\mathrm{Y}_{fmin} = Max(Y_{FFT})$
16	Spectral Probability	Probability distribution of spectrum	$\mathrm{Y}_{FFT} = \frac{FFT(d)^2}{\sum_{i=-N}^{n} FFT(i)^2}$
17	Signal Energy	Measure of energy component	$\mathrm{Y}_{SE} = \sum_{n=-N}^{N}\lvert Y(d)\rvert^2$
18	Spectrum Entropy	Measure of data irregularity	$\mathrm{Y}_H = \sum_{i=-N}^{N} Y(d)ln(p(d))$

Chapter 4

Results and Discussion

Results are structured into two primary segments.The initial segment is Abnormality sensing which showcases and examines the outcomes obtained from detecting various breathing patterns at slow, fast and normal breaths for the single and multi-person scenario and sense the abnormalities in them. The subsequent segment focuses on the results obtained from the classification of these breathing patterns using diverse machine-learning algorithms for the similar scenarios in the initial segment.

4.1 Block Diagram

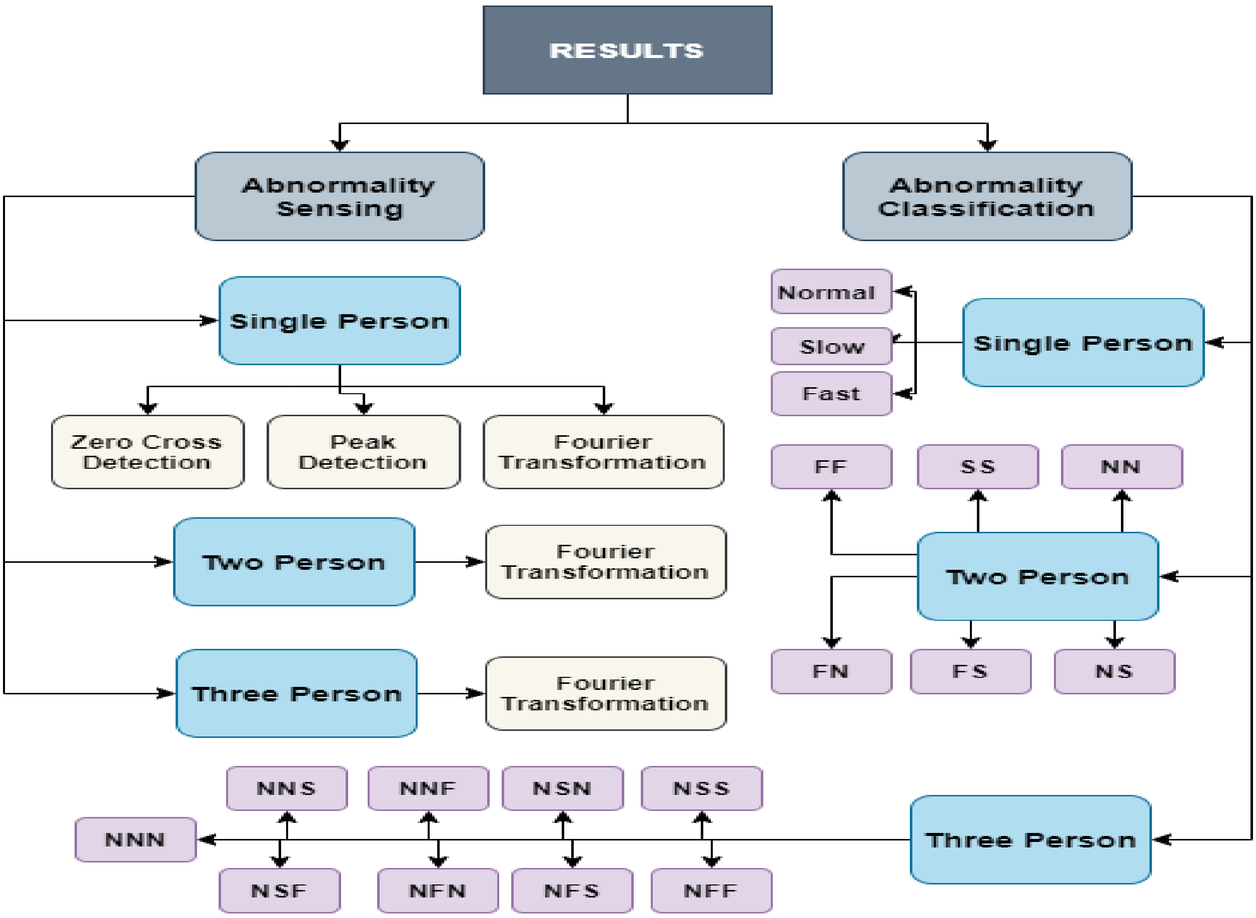


Figure 4.1

According to the block diagram, we can display the results as follows:

4.2 Abnormality Sensing

4.2.1 Single-Person Breathing Analysis

In the single-person scenario, only one subject participated in the breathing activity.

S/N	Subject	Actual Breath			Recorded Breath		
		Normal	Slow	Fast	Normal	Slow	Fast
1.	Subject 1	9	6	13	9	6	14

Table 4.1

Raw Data

In a single-person scenario, raw data has been collected to analyze three different breathing patterns: normal, slow, and fast, as shown in Figure 4.2, 4.3 and 4.4 respectively.

Normal

Normal breath for a healthy person is 12-20 breaths per minute. As we are performing 30 sec breathing activity so the normal breath will be 10 breaths in 30 seconds. Figure 4.2 shows the raw breathing data of the subject at a normal rate containing nine breaths within a duration of 30 seconds. According to raw breath data provided in Figure 4.2, it is observed that there are nine breaths within a duration of 30 seconds. This pattern of breathing falls within the range considered normal.

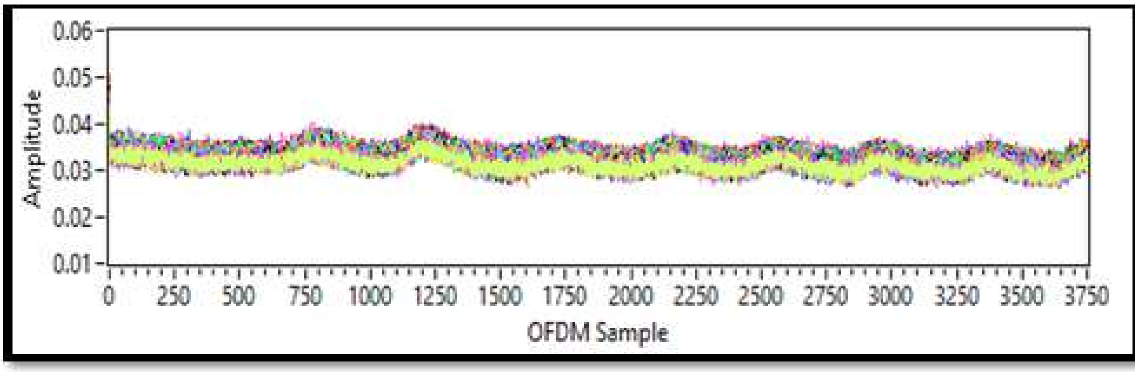


Figure 4.2

Slow

Slow breath consists of under or equal to 12 breaths per minute. As we are performing 30 sec breathing activity so the slow breath will be under or equal to 6 breaths in 30 seconds. Figure 4.3 shows the raw breathing data of the subject at a slow rate containing six breaths within a duration of 30 seconds.

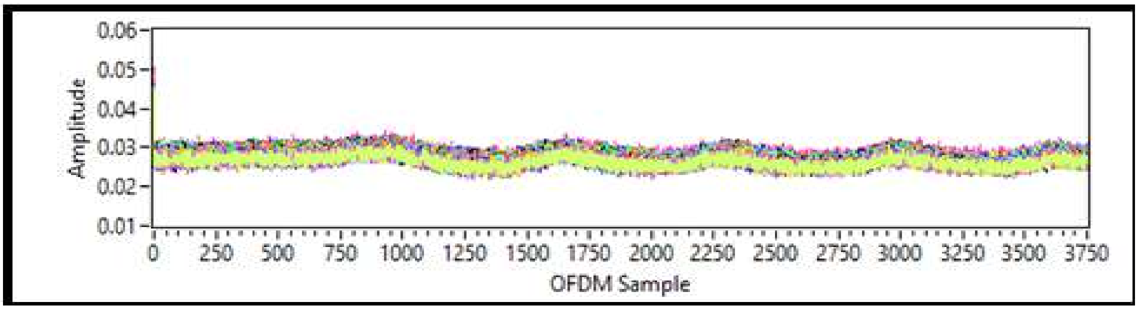


Figure 4.3

Fast

Fast breath has greater than or equal to 20 breaths per minute. As we are performing 30 sec breathing activity so the slow breath will be greater than or equal to 10 breaths in 30 seconds. Figure 4.4 shows the raw breathing data of the subject at a fast rate containing fourteen breaths within 30 seconds.

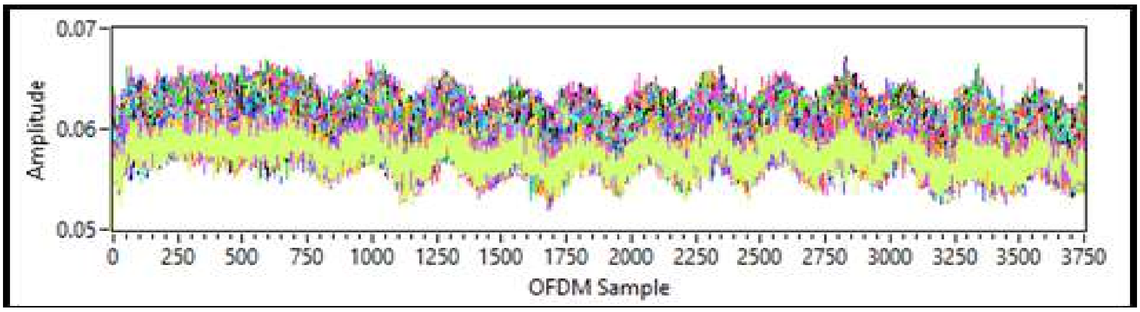


Figure 4.4

Preprocess Data

The raw data is preprocessed in this step after going through various steps of subcarrier selection, outlier removal, smoothening and normalization as discussed in the previous chapter. The raw data is preprocessed as shown in figure 4.5, 4.6, and 4.7 respectively for the same three patterns.

Normal

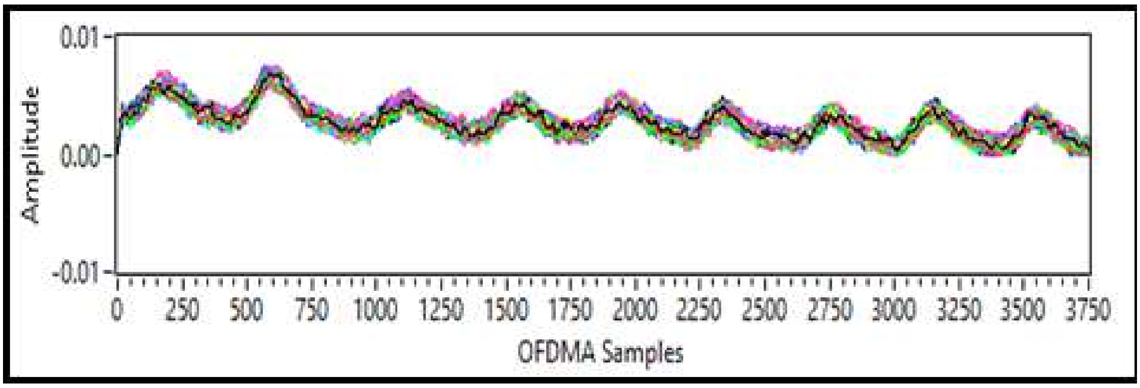


Figure 4.5

Slow

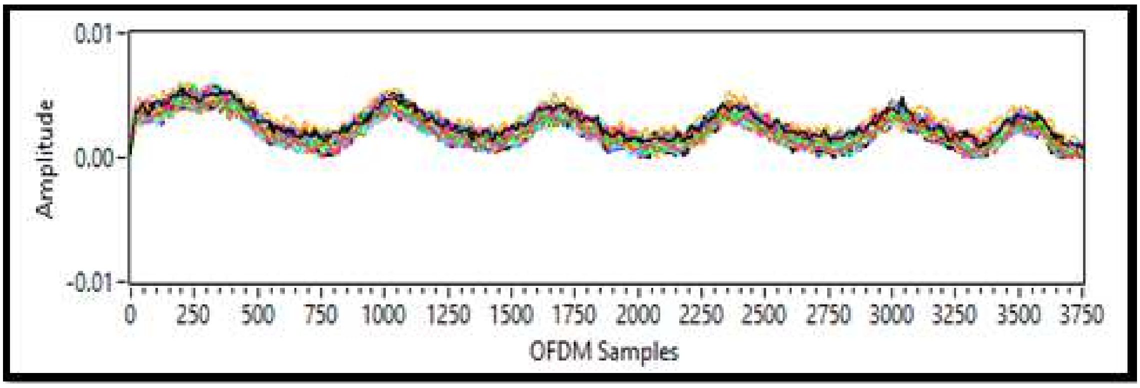


Figure 4.6

Fast

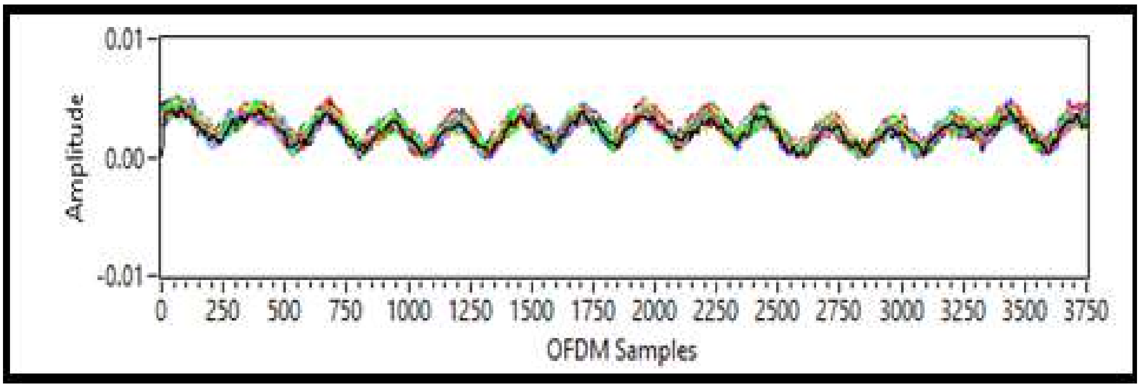


Figure 4.7

After the preprocessing, we apply breath rate extraction methods like zero cross-detection, peak detection, and Fourier transformation for breath rate extraction. As it is directly related to the breathing abnormality sensing.

Zero Cross Detection

The total number of zero crossings ZC are detected for breathing data from which breath rate is calculated using the formula:
Breath rate = ZC/2

Normal

Here in this figure 4.8 there are 18 zero crossings so according to formula we get breath rate of 9 breaths per 30 sec which lies in the normal breath range.

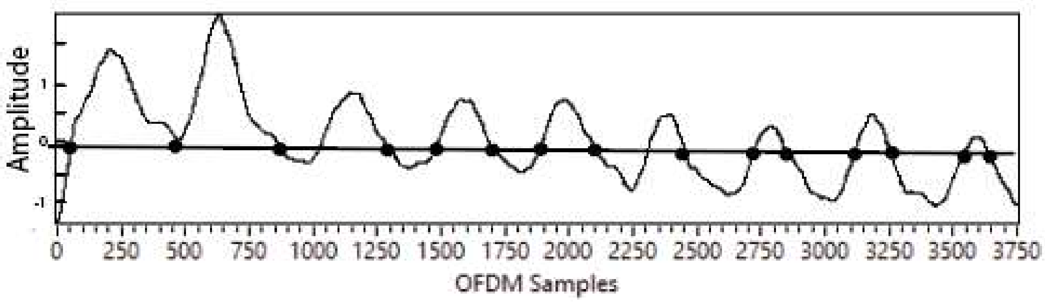


Figure 4.8

Slow

In figure 4.9 there are 12 zero crossings so according to formula we get breath rate of 6 breaths per 30 sec which lies in the range of slow breath.

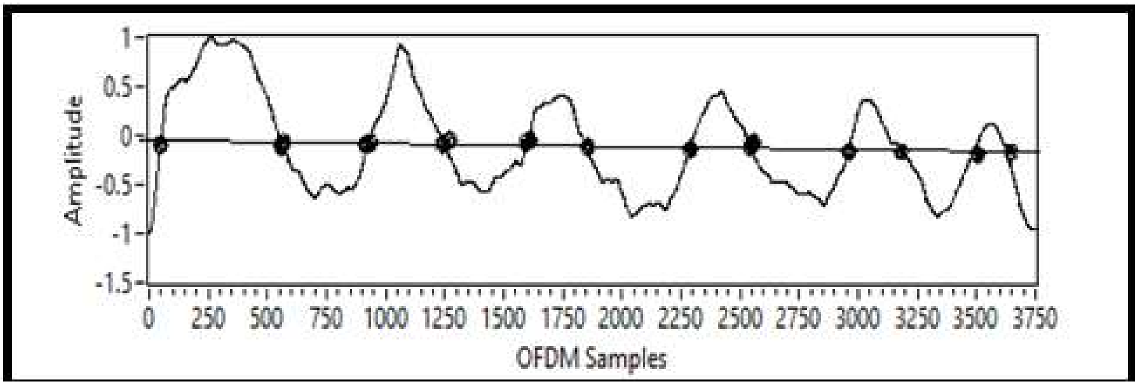


Figure 4.9

Fast

In figure 4.10 there are 27 zero crossings so according to formula we get breath rate of almost 14 breaths per 30 sec which lies in the range of fast breath.

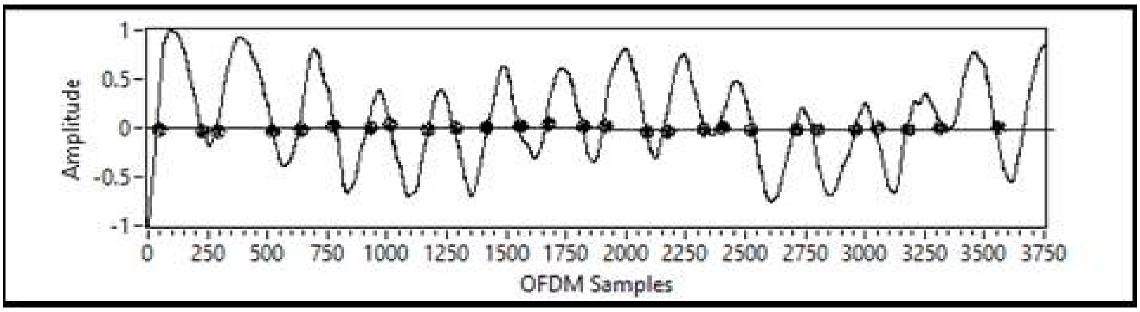


Figure 4.10

Peak Detection

In peak detection peaks are detected and the number of peaks obtained represents the breath rate.

Normal

In figure 4.11, we observed 9 peaks which represent 9 breaths per 30 sec breath rate that is a normal breath rate.

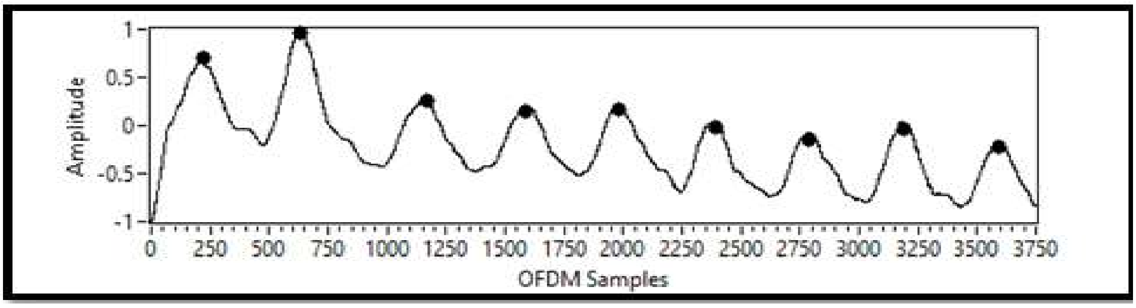


Figure 4.11

Slow

In figure 4.12, we observed 6 peaks which represent 6 breaths/ 30 sec breath rate which is a slow breath rate.

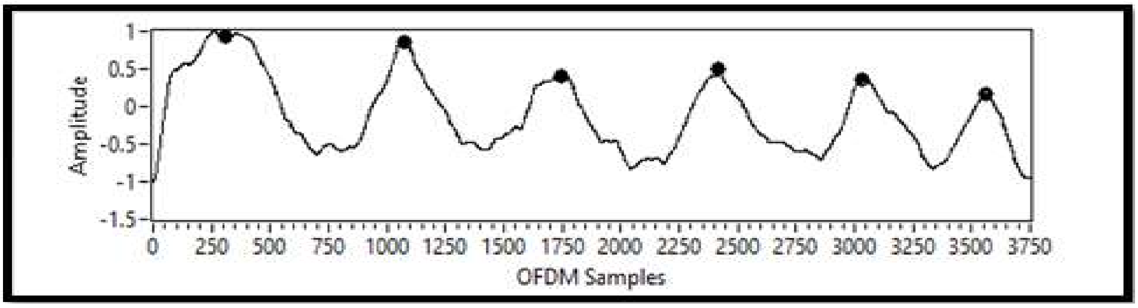


Figure 4.12

Fast

In figure 4.13, we observed 14 peaks which represent 14 breaths/ 30 sec breath rate which lies in a fast breath range.

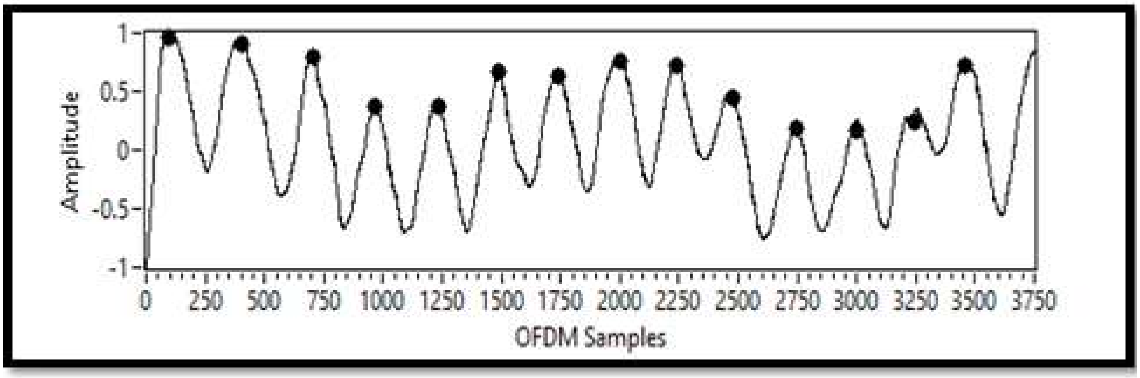


Figure 4.13

Fourier Transformation

Checking the maximum frequency component fmax present in data comes under Fourier transformation step. On the basis of fmax, breath rate is measured using the equation:

Breath Rate = t * fmax

Normal

Figure 4.14 shows Fourier transform of normal breath rate recorded.

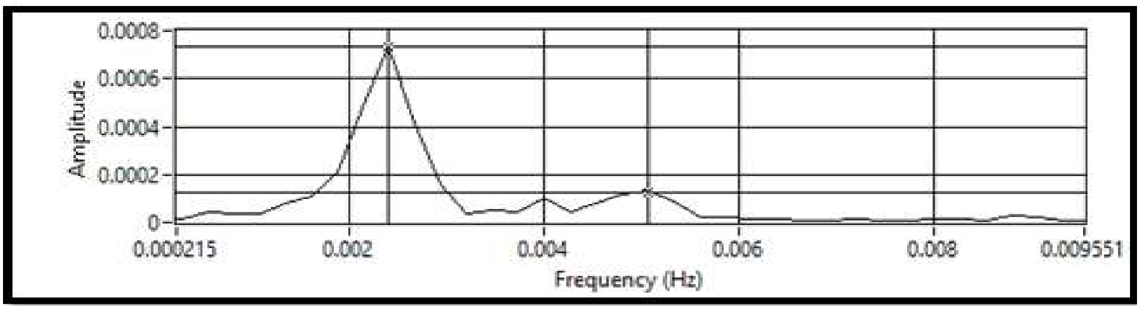


Figure 4.14

Slow

Figure 4.15 below shows Fourier transform of slow breath rate recorded.

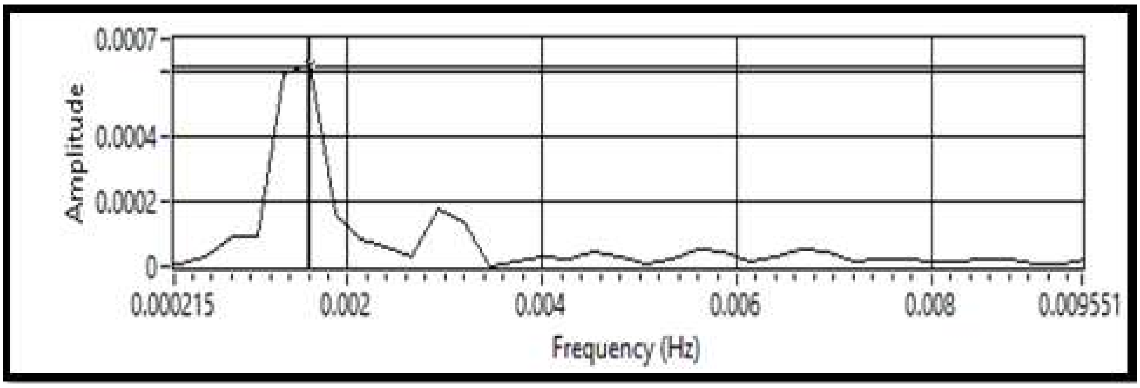


Figure 4.15

Fast

Figure 4.16 below shows Fourier transform of fast breath rate .

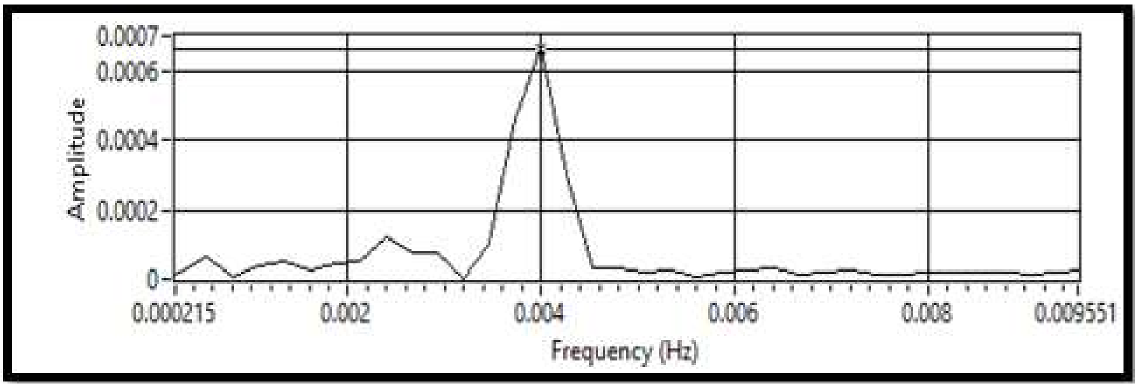


Figure 4.16

4.3 Abnormality Classification

Abnormality classification is performed for a single-person scenario, as shown in figures 4.17,4.18, and 4.19 using SVM, KNN, and linear discriminant machine learning algorithm and all three algorithms show a significant improvement in terms of accuracy, training time, and prediction speed. These are discussed briefly in Chapter 2.

SVM

• Accuracy 85.2• Prediction Speed 12000 obs/sec • Training time 13.35 sec

Figure 4.17

KNN

• Accuracy 95.8• Prediction Speed 8800 obs/sec • Training time 14.78 sec

Figure 4.18

Linear Dicriminant

• Accuracy 99.7• Prediction Speed 12000 obs/sec • Training time 9.2982 sec

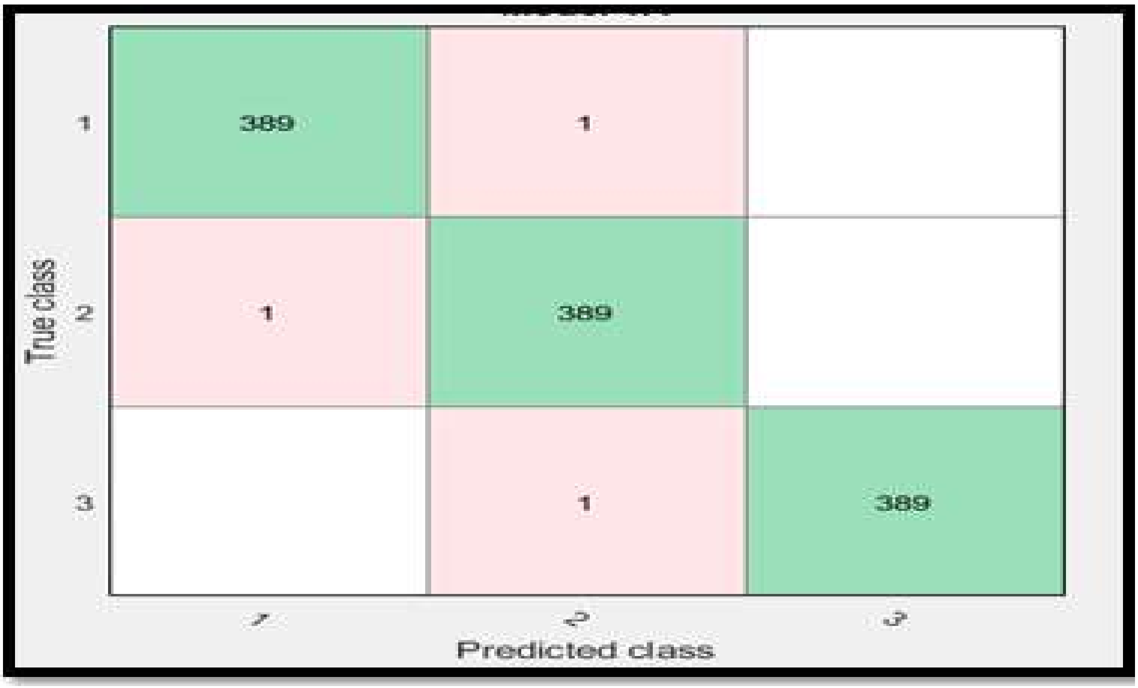


Figure 4.19

4.3.1 Two-Person Breathing Analysis

In the two-person scenario, two subjects participated in the breathing activity. Its particular are:

Subject	Actual Breath			Recorded Breath through FFT		
	F N	N S	N N	F N	N S	N N
Subject 1	13_{fast}	5_{slow}	10_{normal}	14.9_{fast}	6.9_{slow}	10.9_{normal}
Subject 2	7_{normal}	8_{normal}	8_{normal}	6.9_{normal}	9.9_{normal}	7.1_{normal}

Table 4.2

Raw Data

In a two-person scenario, raw data has been collected to analyze six cases of three breathing patterns: normal, slow, and fast; out of which three case results are shown for illustration purposes in Figure 4.20, 4.21 and 4.22 for fast-normal, normal-slow, and normal-normal case respectively.

Fast - Normal

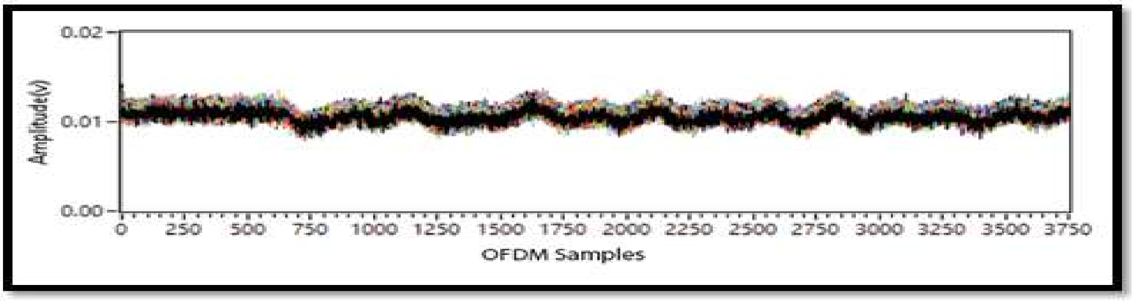


Figure 4.20

Normal - Slow

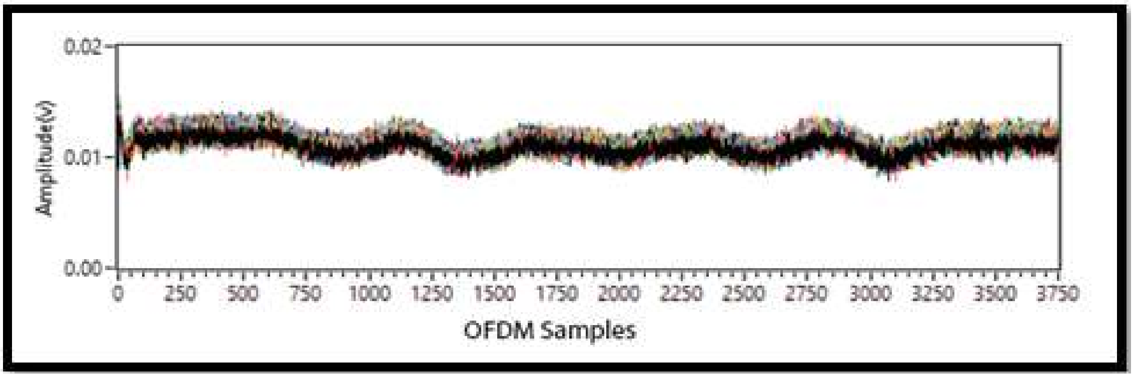


Figure 4.21

Normal - Normal

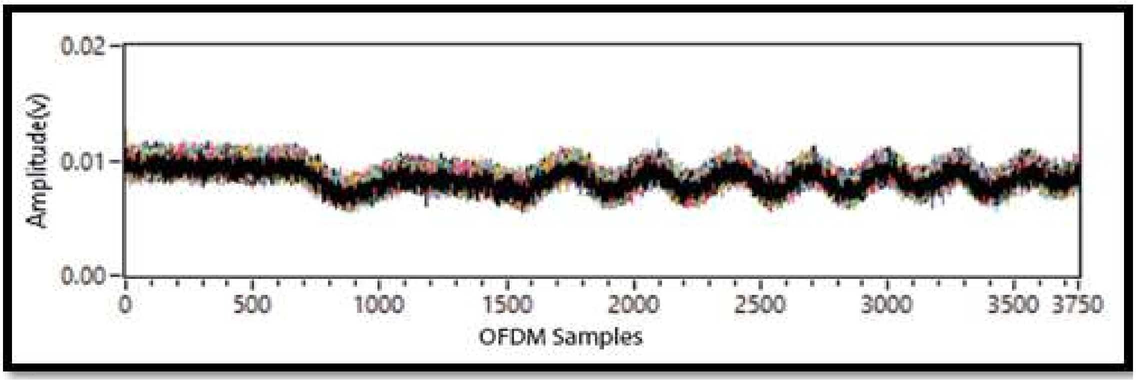


Figure 4.22

Preprocess Data

The preprocess data of raw data of the two-person scenario is represented below in fig. 4.23, 4.24, and 4.25 for the cases for fast-normal, normal-slow, and normal-normal breathing activities respectively.

Fast - Normal

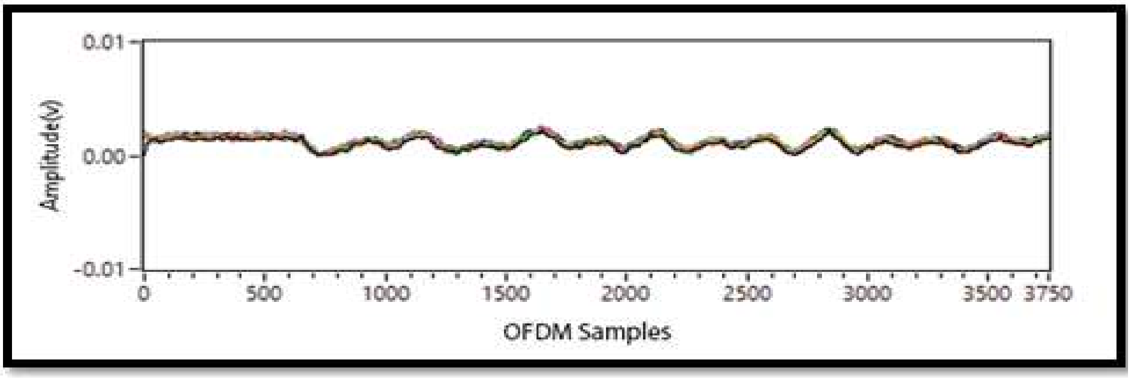


Figure 4.23

Normal - Slow

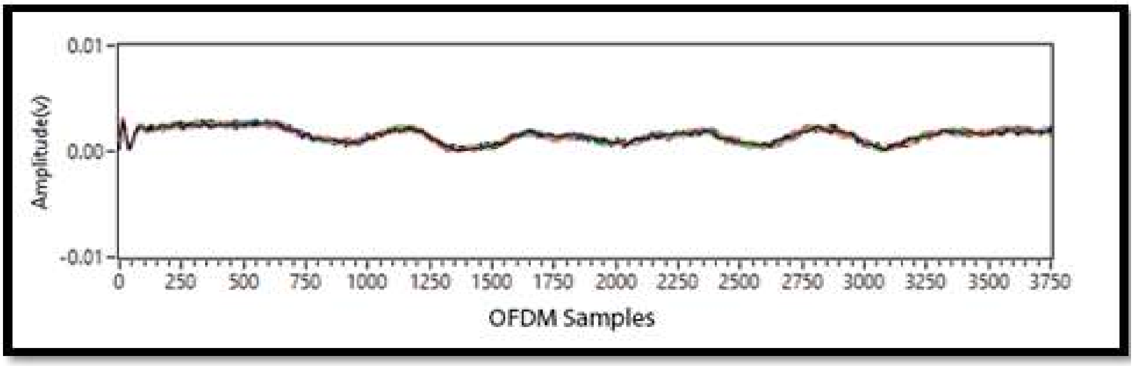


Figure 4.24

Normal - Normal

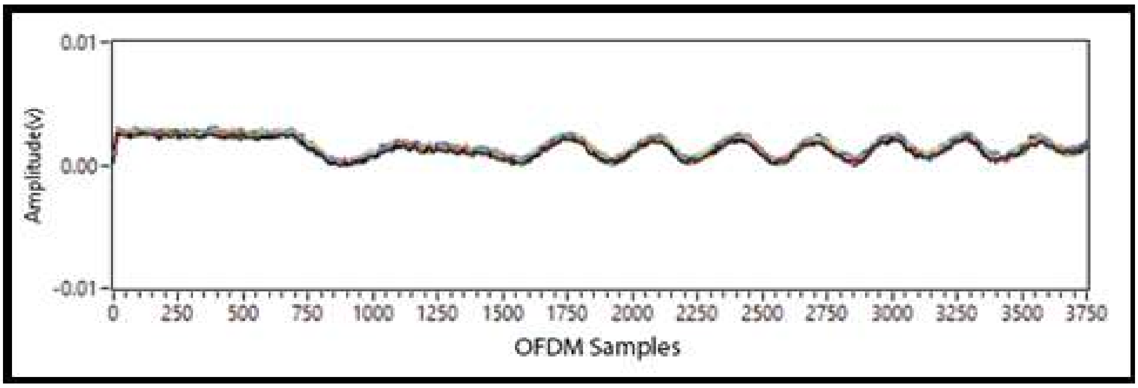


Figure 4.25

Fourier Transformation

To detect abnormalities in similar cases, the Fourier transforms of the breath data from two individuals are extracted. The presence of two distinct peaks in the results displayed in figures 4.26, 4.27, and 4.28 indicates that each subject is engaging in breathing activity independently. These peaks in the Fourier transform represent the characteristic frequencies or patterns associated with individual breathing patterns, allowing for the identification and differentiation of the subjects.

Fast - Normal

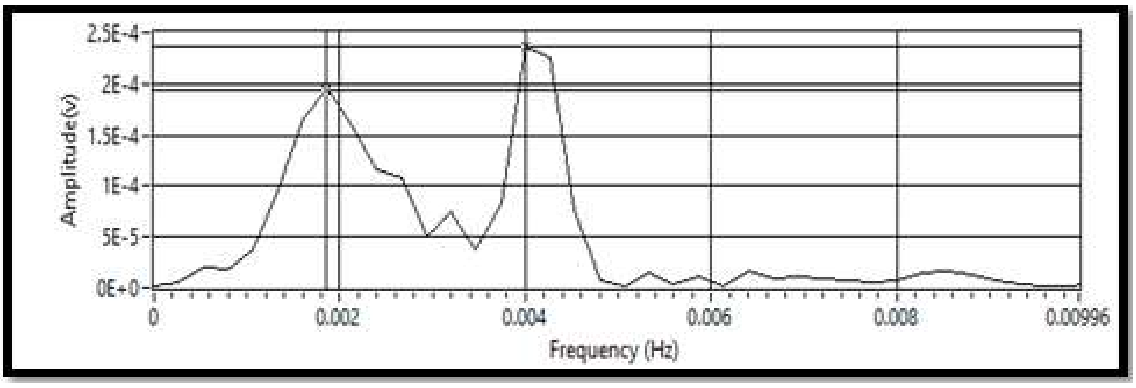


Figure 4.26

Normal - Slow

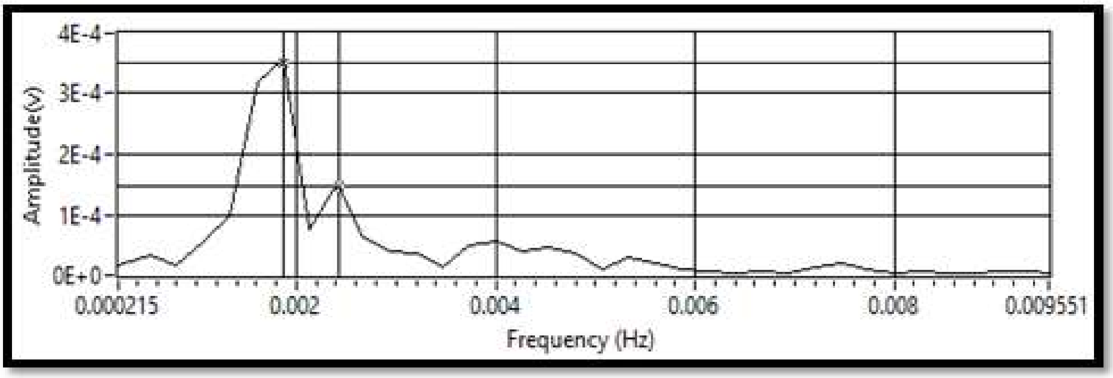


Figure 4.27

Normal - Normal

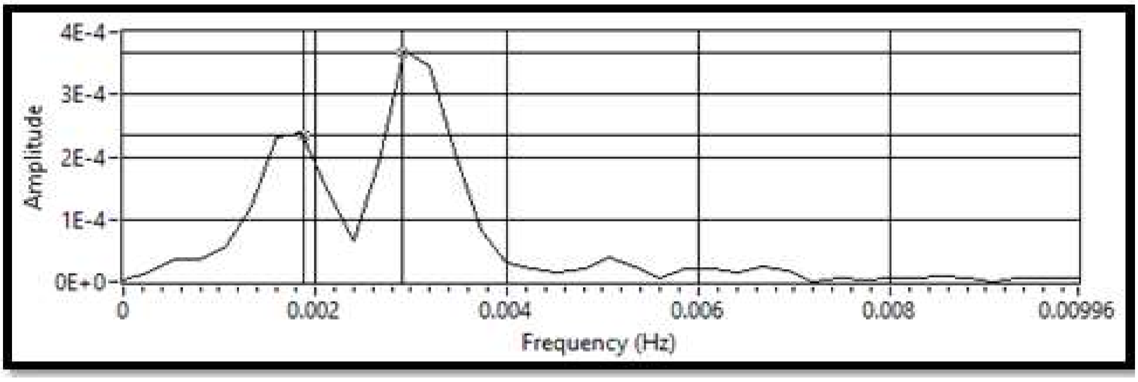


Figure 4.28

4.4 Abnormality Classification

The utilization of SVM and tree-based machine learning algorithms is showcased in figures 4.29, 4.30, and 4.31 for the purpose of classifying abnormalities in a two-person scenario. The outcomes derived from these algorithms reveal a significant improvement in accuracy, training time, and prediction speed when compared to previous methods.

SVM • Accuracy 97.3• Prediction speed 4500 obs/sec • Training time 13.492 sec

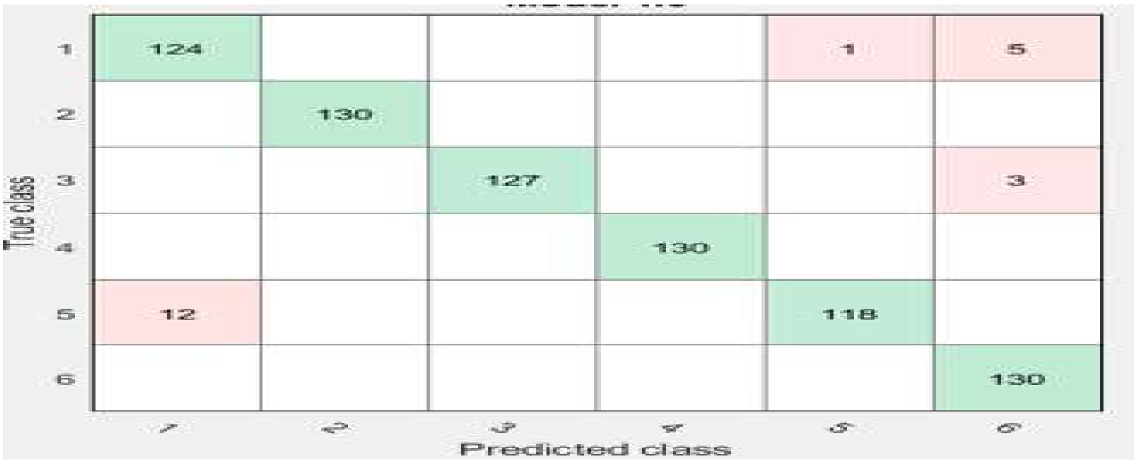


Figure 4.29

Tree
• Accuracy 79.5• Prediction speed 38000 obs/sec • Training time 8.3361 sec

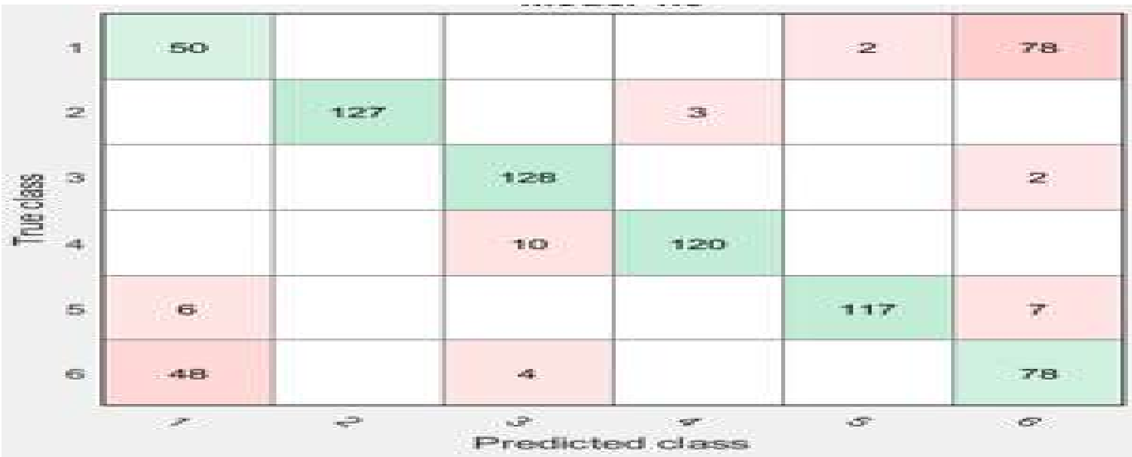


Figure 4.30

4.4.1 Three-Person Breathing Analysis

In the three-person scenario, two subjects participated in the breathing activity. Its particular are:

S/N	Subject	Actual Breath		Recorded Breath through FFT	
		FSN	NSS	FSN	NSS
1.	Subject 1	8_{normal}	5_{slow}	10_{normal}	6_{slow}
2.	Subject 2	5_{slow}	10_{normal}	5.9_{slow}	10.75_{normal}
3.	Subject 3	14_{fast}	6_{slow}	17_{fast}	7_{slow}

Table 4.3

Raw Data

Raw data has been collected from a three-person scenario to analyze nine instances of three breathing patterns: normal, slow, and fast. Two cases have been chosen as examples, showcased in Figure 4.31, 4.32, to provide a visual representation of the fast-slow-normal and normal-slow-slow scenarios, respectively, highlighting the different breathing patterns observed in the data.

Fast - Normal - Slow

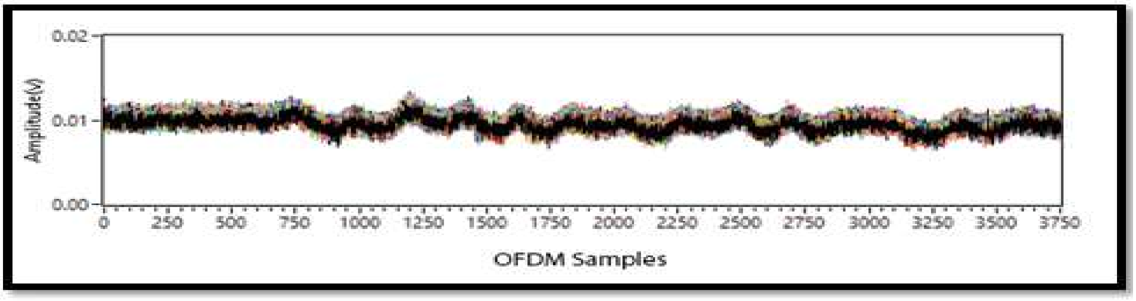


Figure 4.31

Normal - Slow - Slow

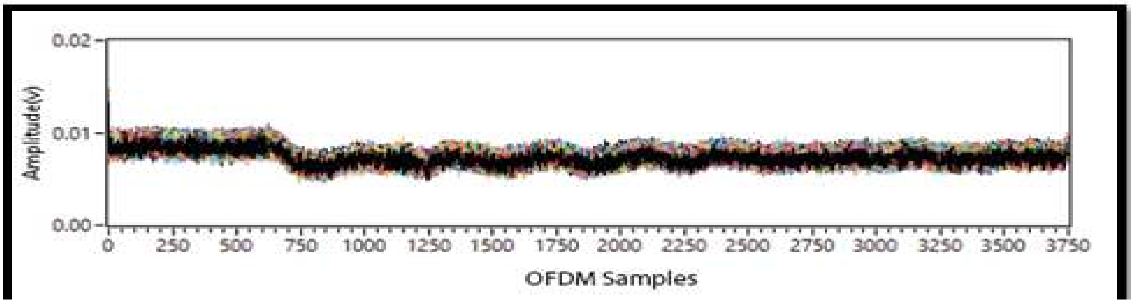


Figure 4.32

Preprocess Data

Figures 4.33 and 4.34 present the preprocessed data of the three-person scenario, focusing on the similar cases discussed earlier and depicted in the raw data shown above.

Fast - Normal - Slow

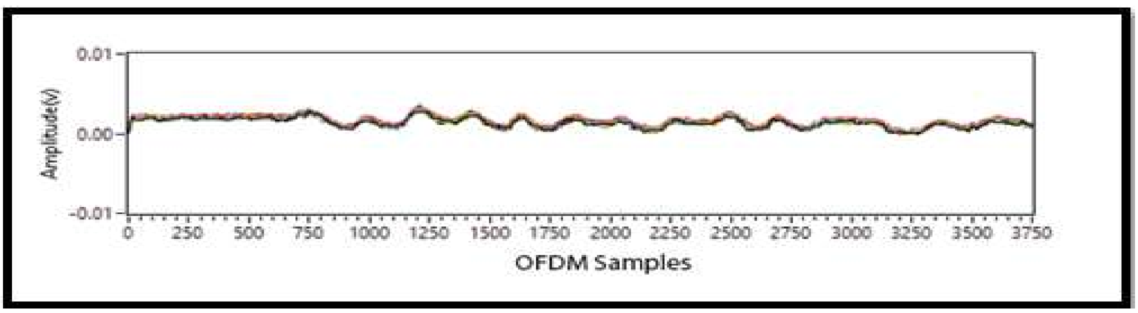


Figure 4.33

Normal - Slow - Slow

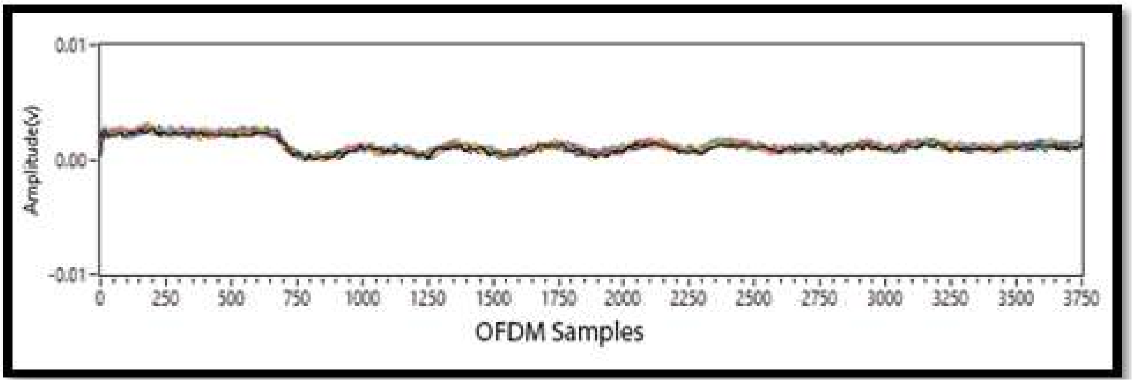


Figure 4.34

Fourier Transformation

To identify abnormalities in similar cases, the breath data from three individuals is subjected to Fourier transform analysis. In figures 4.35 and 4.36, the resulting spectra exhibit three distinct peaks, signifying that each person is involved in independent breathing activity. This analysis was performed specifically for the similar cases mentioned earlier, serving as an illustrative example.

Normal - Slow - Slow

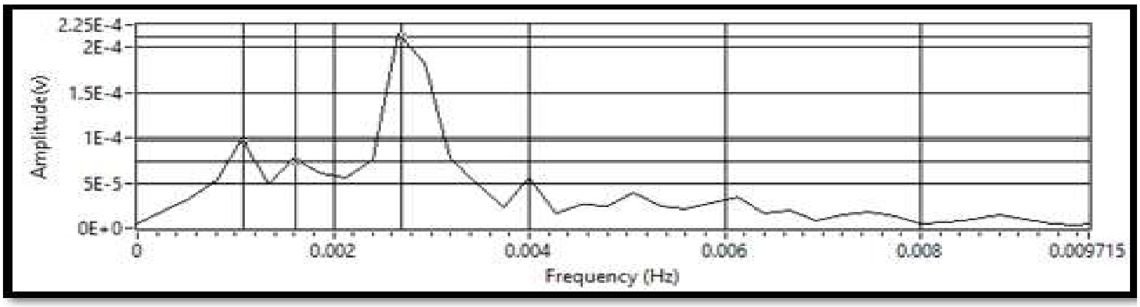


Figure 4.35

Fast - Normal - Slow

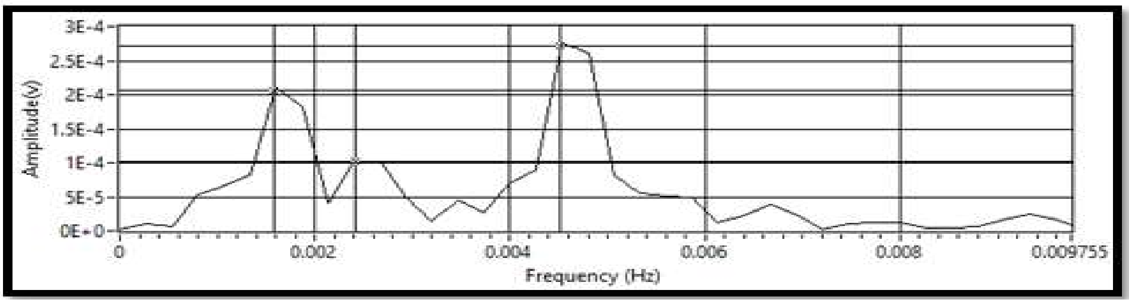


Figure 4.36

4.5 Abnormality Classification

Figures 4.37 and 4.38 demonstrate the SVM and tree-based machine learning algorithms for the classification of abnormalities in a three-person scenario with respect to the accuracy, prediction speed, and training time as classifying parameters.

SVM

• Accuracy 93.3 • Prediction speed 5300 obs/sec • Training time 18.864

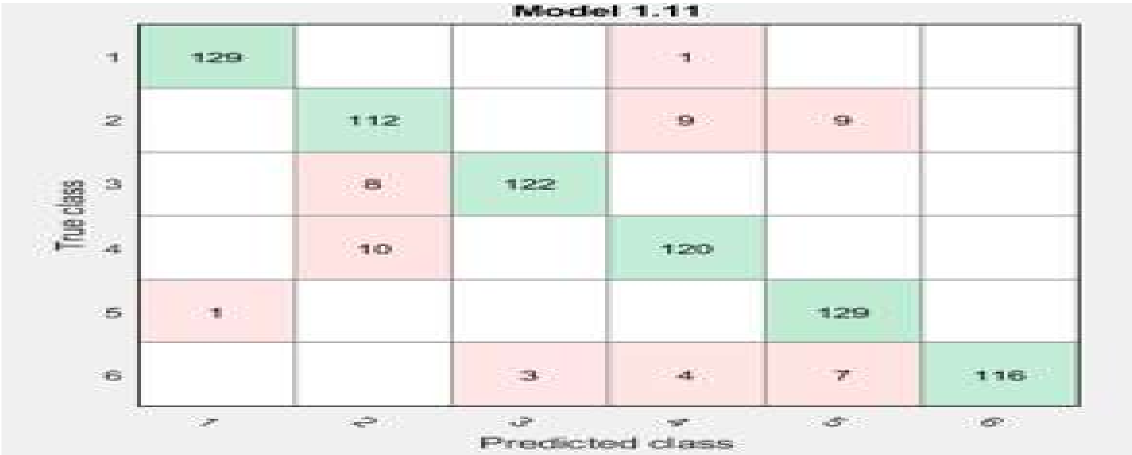


Figure 4.37

Tree

• Accuracy 95.3• Prediction speed 7700 obs/sec • Training time 8.3648 sec

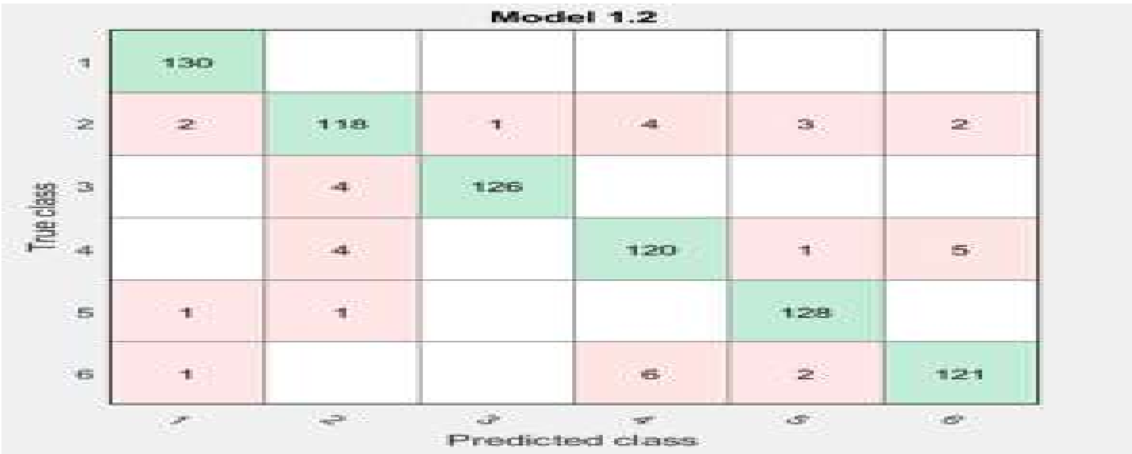


Figure 4.38

Chapter 5

Conclusion and Future Work

5.1 Conclusion

Wireless communication technologies, in addition to voice, text, video, and multimedia, have valuable applications in healthcare monitoring and detecting abnormalities. The purpose of this study was to show how to use a software-defined radio (SDR) platform for non-invasive detection of breathing abnormalities. The following are the key findings:

- The OFDM technology and USRP device capture detailed wireless channel state information (WCSI) about human body movements.
- Channel frequency response (CFR) analysis was performed using ideal, AWGN, fading, and TFD channels via simulations on the software-designed platform.
- The simulation results showed that CFR accurately represents WCSI, taking into account channel noise, time, and frequency dispersion.
- To synchronise OFDM frames, the Van-de-Beek technique was used, which proved extremely useful for detecting small-scale movements that are more sensitive to channel conditions.
- The developed platform successfully detects subtle body movements such as breathing through real-time experiments.
- The system performs admirably in both single and multi-person scenarios.
- Using the ensemble bagged tree algorithm, the platform detects and classifies nine breathing abnormalities in a single-person scenario with a maximum accuracy of 99.7perc.
- In two- and three-person scenarios, the ensemble bagged tree algorithm detects and classifies three breathing abnormalities with maximum accuracies of 93.3perc and 88.4perc, respectively.
- Several feature selection methods were used, which resulted in improved system performance for both single and multi-person scenarios.
- The creation of a simulated breathing abnormalities dataset addresses data collection challenges and results in noticeable improvements in system performance.
- The dataset was collected from a maximum of ten participants, ensuring a manageable size. Participants also received disciplined training for experiment performance.

- Several experiments show that the SDR-based platform is scalable, portable, dependable, and flexible, with multifunction capabilities.

5.2 Future Work

While this study successfully monitors breathing abnormalities and aids in the early detection of various health disorders, it does have some limitations. In a multi-person scenario, the system was tested for a maximum of three-person cases, taking into account only three breathing abnormalities. Furthermore, no actual COVID patients were used in the data collection. Future extensions of this research could include cutting-edge machine learning (ML) and deep learning (DL) algorithms that can be modified without changing the hardware, allowing for a wide range of applications. The following suggestions are made to improve the performance of the developed platform:

- Extend the system's development and testing to include more than three-person cases, a broader range of breathing abnormalities, and actual patients.
- Research optimal parameter settings such as antenna gain, transmit power, sampling rate, operating frequency, and modulation scheme/order further to improve the system's ability to detect human body movements.
- Look into using the testbed for post-surgery monitoring, heart problems, sleep disorders, and other healthcare applications. Enhance and investigate its potential in emergency and catastrophic situations such as earthquakes and wars.

  In conclusion, wireless communication technologies hold promise beyond traditional applications, including healthcare monitoring and abnormality detection. The findings of the study highlight the efficacy of an SDR-based platform in detecting breathing abnormalities, and future improvements and applications can improve its performance and contribute to the early detection and monitoring of various health conditions.

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