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An FMCW Radar-Based Intelligent System for Non-Contact Detection and Monitoring of Pneumonia Symptoms

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ABSTRACT

Pneumonia is one of the most common contagious respiratory diseases, and one of its symptoms is shortness of breath. This symptom underscores the need for non-contact monitoring methods, which our paper addresses by proposing a strategy that uses Frequency-Modulated Continuous Wave (FMCW) radar to extract breathing waveforms and then classifies them with an eXtreme Gradient Boosting (XGBoost) model. The model performs well on our dataset, using stratified k-fold cross-validation and Mel-Frequency Cepstral Coefficients (MFCC) feature extraction. This intelligent system can correctly identify deep and deep-quick breathing patterns with 98% and 87.5% recall scores, respectively. Integrating FMCW and XGBoost offers a promising solution for early detection and real-time monitoring of pneumonia.

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1. INTRODUCTION

Pneumonia is a respiratory infection that causes inflammation of the lung tissue and poses a significant threat to public health (de Benedictis et al., 2020). Fever, cough, and shortness of breath are some of its symptoms, which highlight the need for effective monitoring and early detection (Mani, 2018). Among these symptoms, increased respiratory rates are especially important indicators (Htun et al., 2019). However, traditional methods for monitoring vital signs often rely on contact-based devices, which can be intrusive and uncomfortable for patients (Lee et al., 2018; Naranjo-Hernández et al., 2018).

Radar technology has emerged as a promising solution for non-contact monitoring in the medical field (Singh et al., 2021; Lv et al., 2021). Frequency-Modulated Continuous Wave (FMCW) radar, in particular, can capture detailed respiratory waveforms without direct physical contact (Alizadeh et al., 2019; Wang et al., 2021). This non-invasive approach meets the need for patient-friendly monitoring systems, especially for individuals at risk of respiratory illnesses like pneumonia.

Radar-based monitoring involves collecting and analyzing large and complex data sets, which require intelligent systems to process and interpret the signals. An intelligent agent is essential for classifying and analyzing breathing patterns effectively, contributing to the early detection of pneumonia symptoms. The classification covers various breath types, such as deep breaths, deep-quick breaths, quick breaths, hold breaths, and normal breaths. Previous studies have used different approaches for human vital sign processing, such as deep learning (Yoo et al., 2021), CNN (Kim & Han, 2019), Random Forest Classifier (Zhuang et al., 2022), and others. It has also been highlighted that real-time radar sensing and symptom detection depend heavily on data acquisition, feature extraction, and classification algorithms (Le Kernec et al., 2019).

This article focuses on the integration of eXtreme Gradient Boosting (XGBoost) into the classification process. XGBoost is a powerful machine learning algorithm that is well-suited for this task, as it can handle large data sets and complex relationships within the data (Wu et al., 2021). It excels in classifying patterns and has shown success in various applications, making it a suitable choice for the nuanced task of distinguishing between different breathing waveforms. Moreover, this algorithm has been used with imbalanced data sets, similar to the case in this experiment (Zhang et al., 2022).

Figure 1 shows the overview of the system, which uses an FMCW radar to monitor the patient in real-time, extract and classify breathing classes. The subsequent sections will explore the methodology of using FMCW radar for non-contact respiratory monitoring, the intricacies of breathing waveform classification, and the advantages of XGBoost for this innovative approach. The ultimate goal is to contribute to the development of intelligent systems that play a pivotal role in early pneumonia detection and proactive healthcare monitoring.

Our work only uses a lightweight XGBoost algorithm for the classification process, while previous works used more complex and computationally intensive algorithms, such as stacked ensemble learning (Purnomo et al., 2022) or Transformer architecture (Avian et al., 2023). XGBoost is an ML algorithm that is based on decision trees and has advantages in terms of speed, efficiency, and performance (Purnomo et al., 2022; Ikeda & Fujimoto, 2023). Considering that our device is used for real time measurement, we try to use a classification algorithm that is light but still produces good results.

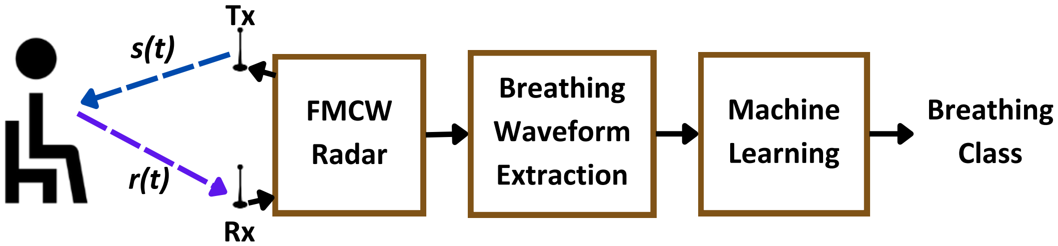

Figure 1. Main modules of the proposed system

In our previous research, we used 10-fold cross validation (CV) (Purnomo et al., 2022) which was somewhat excessive or overkill. In this research, we use stratified k-fold with the consideration that it can overcome the problem of class imbalance and improve the accuracy of the model. Stratified k-fold is a variation of k-fold that preserves the proportion of each class in every fold, unlike k-fold that uses random sampling. This way, we can ensure that the training and testing data represent the original data distribution and reduce the bias or variance of the model.

We consider using a fast and lightweight algorithm because in real-world implementation, we need a real-time detection algorithm and also light to install or apply to hardware so that we hope we do not need a high-spec computer to process our data.

The rest of this paper will be structured into 5 sections. Section 2 explains the process of extracting breathing waveform using the radar. Section 3 provides details about how the dataset was obtained and its contents. Section 4 contains the algorithm used for classification. Section 5 discusses the results, followed by a conclusion of the paper in Section 6.

2. EXTRACTING BREATHING WAVEFORM

The extraction of breathing waveforms through Frequency-Modulated Continuous Wave (FMCW) radar involves a comprehensive process, utilizing various phases to capture and record respiratory signals in detail. This section provides an in-depth exploration of how FMCW radar can be used to safely take human vital signs with its radiated power. Then, continued by explaining the essential concepts and signal processing techniques necessary for obtaining breathing waveforms.

2.1. FMCW Radar Safety

The safety of using Texas Instrument IWR 1443 with Tx power 12dBM for human beings depends on the exposure levels to the radio frequency electromagnetic fields emitted by the radar. The exposure limits for the general public are based on the human body's specific absorption rate (SAR), which measures how much energy is absorbed by the tissues (Texas Instruments, 2024). The SAR depends on the frequency and intensity of the electromagnetic field and the shape, size, and orientation of the human body (Texas Instruments, 2024).

According to the datasheet of the IWR 1443, the Tx power of the radar is 12 dBm, equivalent to 0.016 W (Kamath, 2017). Assuming that the radar is operating at 80 GHz and has a beamwidth of 10 degrees, the maximum SAR at a distance of 1 m from the radar antenna would be about 0.0003 W/kg, which is well below the ICNIRP limits (Texas Instruments, 2024). However, the SAR would increase as the distance decreases or the power increases. Therefore, it is important to maintain a safe distance from the radar and avoid direct exposure to the radar beam for prolonged periods. The safety of this radar also depends on the specific characteristics of the radar system and the environment. Therefore, following the manufacturer's instructions and precautions when using this radar is advisable.

The radiated power of the IWR 1443 radar is the product of the transmitted power and the antenna gain. According to the datasheet of the IWR 1443 (Texas Instruments, 2018), the transmitted power of the radar is 12 dBm, equivalent to 0.016 W (Texas Instruments, 2024). The antenna gain of the radar is 15 dBi, equivalent to 31.6 (Texas Instruments, 2020). Therefore, the radiated power of the IWR 1443 radar is:

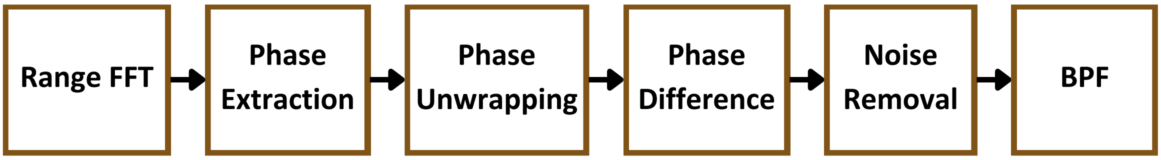

Figure 2. Signal processing steps for breathing waveform extraction.

$$\begin{aligned} P_r &= P_t \times G_a \\ &= 0.016 \times 31.6 \\ &= 0.5056\,W \end{aligned}$$

This means that the IWR 1443 radar emits about 0.5 W of power in the direction of its beam. However, the radiated power decreases as the distance from the radar increases, according to the inverse square law. Therefore, the radiated power at a certain distance from the radar can be calculated as Equation 1:

$$P_r(d) = \frac{P_r}{4\pi d^2} \qquad (1)$$

where d is the distance from the radar in meters.

For example, at a distance of 1 m from the radar, the radiated power would be:

$$\begin{aligned} P_r(1) &= \frac{0.5056}{4\pi \times 1^2} \\ &= 0.0403\ {}^{W}\!/_{m^2} \end{aligned}$$

This is the power density of the radio frequency electromagnetic field at 1 m from the radar. The power density decreases as the distance increases, so the exposure levels to the field also decrease. To ensure the safety of human beings, the exposure levels should be below the ICNIRP guidelines.

2.2. Waveform Extraction with FMCW Radar

At the heart of FMCW radar is a gradual change in frequency over time, forming the basis for its functionality. As the transmitted FMCW radar signal undergoes this temporal frequency change, the received signal at a specific time index 't' reveals intricate details about the object's movement, particularly its respiratory patterns.

Extensive research has confirmed that radar systems are sensitive to phases, enabling them to detect subtle movements like those associated with breathing signals. Capitalizing on this sensitivity, FMCW radar becomes a valuable tool for non-contact respiratory monitoring, capable of identifying small vibrations induced by lung activity. This study uses the Texas Instrument IWR1443 board, operating within the 77-88 GHz range.

Error! Reference source not found. o utlines essential procedures for extracting breathing waveforms from FMCW radar data. The process starts with Range FFT (Fast Fourier Transform) analysis, which identifies peaks in the frequency domain that correspond to subtle movements of the lungs. Next, Phase Extraction captures the phase information of the received radar signal. Phase Unwrapping corrects phase values to ensure continuity across 2π intervals, enabling precise analysis.

Phase Difference calculation measures variations in phase values, revealing the complex patterns of respiratory activity. Noise Removal filters out unwanted interference or artifacts that could affect the accuracy of the signals. Finally, the signal passes through a Band Pass Filter (BPF) to isolate the desired frequency range (0.1 to 0.5 Hz), resulting in the breathing waveform. These steps extract vital respiratory signals, forming the basis for a thorough analysis and interpretation.

3. DATASET DESCRIPTION AND FORMAT

This chapter provides a detailed overview of the dataset used in this study, describing its characteristics and the format of the data. The data was collected by placing the radar in front of a seated person, as shown in **Figure 3**. The radar used was the IWR1443BOOST (Texas Instruments, 2024).

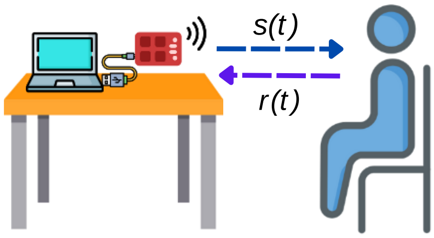

Figure 3. Illustration of recording a person's breathing waveform using the FMCW radar.

Each subject was instructed to perform five breathing patterns: normal breathing, quick breathing, holding their breath, deep breathing, and deep-quick breathing. Each waveform data was measured for five seconds, which was enough to represent one breathing pattern. The setup used to record the subject's breathing pattern can be seen in **Figure 4**. The radar is positioned facing the person at chest level and connected to a computer with a user interface for the radar's data.

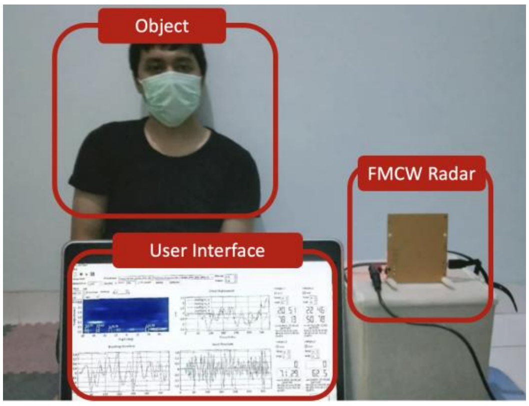

Figure 4. Real-time measurement of breathing waveform using FMCW IWR1443 radar.

The collected dataset contains 26,400 records of labeled data, consisting of 2667 instances of "quick" breathing, 19734 of "normal" breathing, 1066 of "deep" breathing, 800 of "deep-quick" breathing, and 2133 of "hold" breathing. Each record has 85 data points of the breathing signal level for five seconds.

Figure 5 plots one instance of each breathing class. It visualizes how the breathing wave changes over time. Furthermore, these graphs show how the breathing signal does not always oscillate around 0 on the y-axis, especially for quick breathing, indicating the need for a suitable machine-learning model.

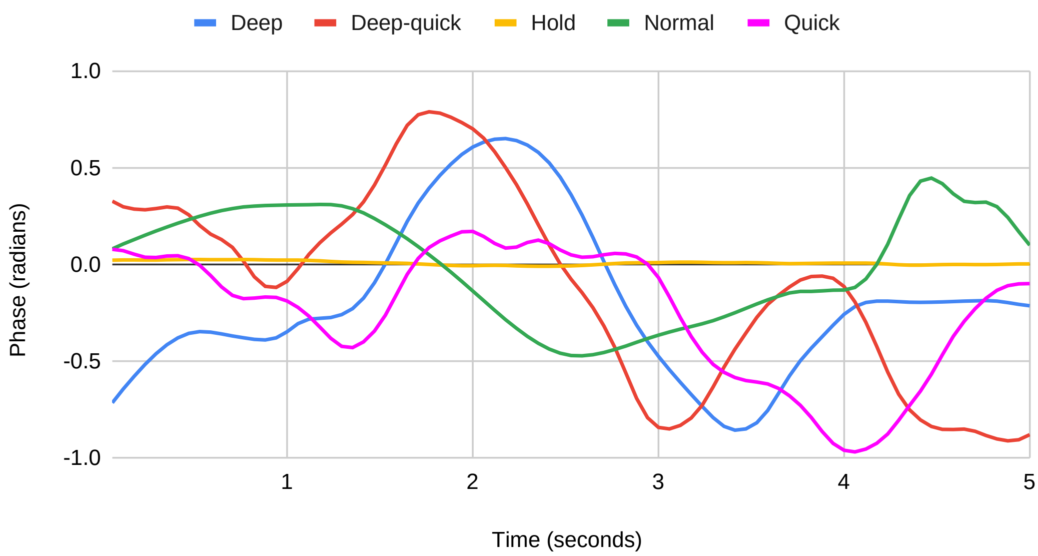

Figure 5. Breathing waveform samples in the time domain (sampling rate of 17 measurements/second).

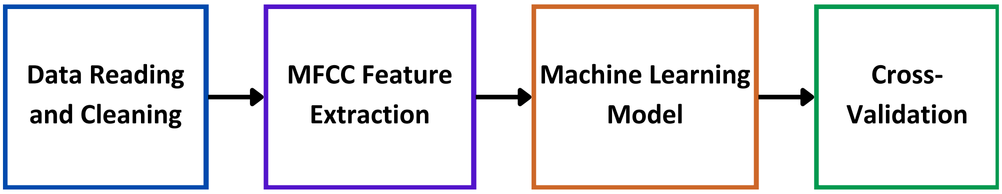

Figure 6. Breathing waveform classification block diagram.

4. BREATHING WAVEFORM CLASSIFICATION

The data undergoes a series of steps to produce an effective classification model using machine learning. **Figure 6** shows the overview of this breathing waveform classification process. The dataset goes through preprocessing, followed by feature extraction, to enhance the quality of the data input into the model.

The processed data is inputted into the machine learning model for training, validation, and testing. These data splits are determined by a cross-validation method to ensure the model's reliability and reduce bias. Hyperparameter tuning is also done to find the best configuration of the XGBoost model. Subchapters 4.1 through 4.5 elaborate on these processes in more detail.

4.1. Data Reading and Cleaning

The data consists of breathing waveforms obtained from different people with different backgrounds (**Table 1**). They are collected using the IWR1443BOOST radar by Texas Instruments, using software developed in MATLAB. The feature has 84 data points. Since the data was taken from different sources, merging them into a single CSV file is needed. Therefore, about 25,725 rows of data in a single file will be used for training and testing the machine learning model.

As mentioned in Section 3, the dataset does not contain evenly spread-out data. Therefore, the training and testing data are equally composed of 840 and 160 rows, respectively, for each class. This training data is split into 5 folds using the cross-validation method in Section 4.4, where 1-fold (128 rows) will be used for validation split and the remaining 4 folds for training split. In total, there are 2560 data used for training, 800 for testing, and 640 for validating. Therefore, the train-test-validation split in percentages is 64-20-16. The actual numbers of data used for each class and split is listed in **Table 2**. After splitting the data, the next method is to extract meaningful features from the data using MFCC feature extraction.

Table 1. Samples of the breathing waveform dataset

Time 0 phase (radians)	Time 1 phase (radians)	…	Time 83 phase (radians)	Time 84 phase (radians)	label
1.137026	1.309561	…	0.402893	1.050250	Normal
-0.489525	-0.336083	…	0.163767	0.022457	Deep-quick
-1.293316	-1.228519	…	-0.484406	-1.460045	Quick
-0.271695	0.130003	…	0.226376	-0.049865	Hold
-0.090600	-0.493776	…	0.601362	0.367818	Deep

Table 2. Samples of the breathing waveform dataset

Class	Training Data		Testing Data
	Train Split	Validation Split	Test Split
Normal	512	128	160
Deep-quick	512	128	160
Quick	512	128	160
Hold	512	128	160
Deep	512	128	160
Total	**2560**	**640**	**800**

4.2. MFCC Feature Extraction

Feature extraction is a process in machine learning where relevant information is extracted from raw data to create a set of features that can be used as input for a model. The goal of feature extraction is to transform raw data into a set of meaningful and relevant features that capture the essential characteristics of the data and can be used to train machine learning models for prediction or classification tasks.

Mel-Frequency Cepstral Coefficients (MFCC) is a feature extraction technique widely used in machine learning for speech recognition and audio classification (Rejaibi et al., 2022). Since heart and breath waveforms are similar to audio signals, MFCC can be applied to classify them. From the 85 features in each data, this process extracts them into a reduced dimension of 13 meaningful features. This simplified and enhanced data can then be passed to the machine learning model.

4.3. Machine Learning Model

The classification of breathing waveforms in this study is orchestrated through the implementation of the XGBoost machine learning algorithm, which represents a pivotal component of the methodology. XGBoost, renowned for its ensemble learning approach, constructs an array of decision trees and amalgamates their outputs to enhance predictive accuracy. Trained on a meticulously curated dataset encompassing diverse breathing patterns, the model exhibits adaptability to a spectrum of respiratory signals. The choice of XGBoost is underpinned by its inherent robustness and versatility.

4.4. Cross Validation

Cross-validation is a procedure that creates partitions of the data, where one part is used for testing while the rest is used for training. It is repeated multiple times with different training and testing parts combinations so that every data partition is used for testing and training. This procedure helps avoid overfitting and obtain more accurate results by taking the average performance from each partition.

Stratified k-fold cross-validation is used, which works similarly to the k-fold method. K-fold cross-validation splits training data into k subsets of roughly equal sizes, and the model is trained on k-1 subsets and evaluated on the remaining subset. This process is repeated k times, with each subset serving as the validation data once. While stratified k-fold is similar to this, it also considers a balanced proportion. It is especially useful when working with imbalanced datasets, where some classes have a much smaller number of samples than others. As mentioned in Section 3, the dataset obtained from the volunteers is highly imbalanced, where the “normal” breathing samples significantly outweigh the others. The cross-validation method is used to make sure this imbalance does not propagate to the ineffectiveness of the machine learning model.

4.5. Hyperparameter Tuning

Every machine learning model has parameters. For example, in XGBoost, the parameters are “max_depth”, “learning_rate”, “n_estimators”, etc. Before running the evaluation, choosing the best parameter is needed to ensure that the output is optimized. It can be done using a loop; however, this method might be too complex when finding multiple parameters. Hyperparameter tuning is a handy tool for overcoming this problem. Grid Search is one of the hyperparameter tuning methods that evaluate every combination of parameters. It tests all combinations of the hyperparameters in a grid and outputs their most optimal combination.

5. RESULTS AND DISCUSSION

The multiclass XGBoost classifier was evaluated on its performance in categorizing breathing waveforms into five classes: "Deep", "Deep-quick", "Hold", "Normal", and "Quick". The model was evaluated using four different metrics: precision, recall, F1-score, and support.

Precision shows the proportion of correct identifications. It is calculated using the number of true positives (TP) and false positives (FP) in Equation 2 (Ali et al., 2021).

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall explains how many of the actual positives are captured correctly. It is mathematically defined using the number of true positives (TP) and false negatives (FN) in Equation 3 (Ali et al., 2021).

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

The F1 score is used to see the harmonic mean between precision and recall, delving into how many of the overall predictions are correct. It is evaluated using Equation 4 where P and R are precision and recall scores (Ali et al., 2021).

$$F1\ score = 2 \times \frac{P \times R}{P + R} \tag{4}$$

Lastly, support serves as a functionality to see how many occurrences a class has within a dataset. Different support values between classes suggest that the data is imbalanced and affects the model’s performance.

Table 3. XGBoost breathing pattern classifier evaluation results.

Evaluation	Precision	Recall	F1 score	Support
Deep	0.84409	0.98125	0.90751	160
Deep-quick	0.88608	0.87500	0.88050	160
Hold	0.95238	1.00000	0.97561	160
Normal	0.80690	0.73125	0.76721	160
Quick	0.87413	0.78125	0.82508	160
Accuracy			0.87375	800
Macro avg	0.87271	0.87375	0.87118	800
Weighted avg	0.87271	0.87375	0.87118	800

Table 3 displays the recorded values of each class's performance on all evaluation parameters. The breakdown of these results is explained with each breathing category:

1. Deep

This class achieved a high precision (0.844), F1-score (0.908), and impressive recall (0.913) compared to the Hold class. This suggests that the Deep class is good at correctly identifying instances (precision) and balancing precision and recall (F1-score), as well as capturing true cases (recall).

2. Deep-quick

This class had a slightly higher precision (0.886) than the Deep class but had a lower recall (0.875) and F1-score (0.881). This suggests that the Deep-quick class is good at precision but not as good as the Deep class at capturing true instances (recall).

3. Hold

This class achieved the highest recall (1.000), precision (0.952), and F1-score (0.976) compared to the Deep and Deep-quick classes. This suggests that the Hold class is very good at capturing all true instances (recall) but may also classify some instances from other classes as Hold (precision).

4. Normal

This class had the lowest precision (0.807), recall (0.731), and F1-score (0.767) among all classes. This suggests that the Normal class is not very good at distinguishing itself from other classes.

5. Quick

This class had a precision (0.874) and F1-score (0.825) similar to the Deep-quick class but had a lower recall (0.781). This suggests that the Quick class is similar to the Deep-quick class in terms of precision and F1-score but not as good at capturing true instances (recall).

The results show that the Deep and Deep-quick classes performed well in terms of precision, recall, and F1-score, suggesting that they are well-defined and distinguishable by the XGBoost model. The Hold class also performed well in terms of recall but had lower precision, indicating some overlap with other classes. The Normal and Quick classes did not perform as well as the others, suggesting that they may be less clearly defined or may share characteristics with other classes.

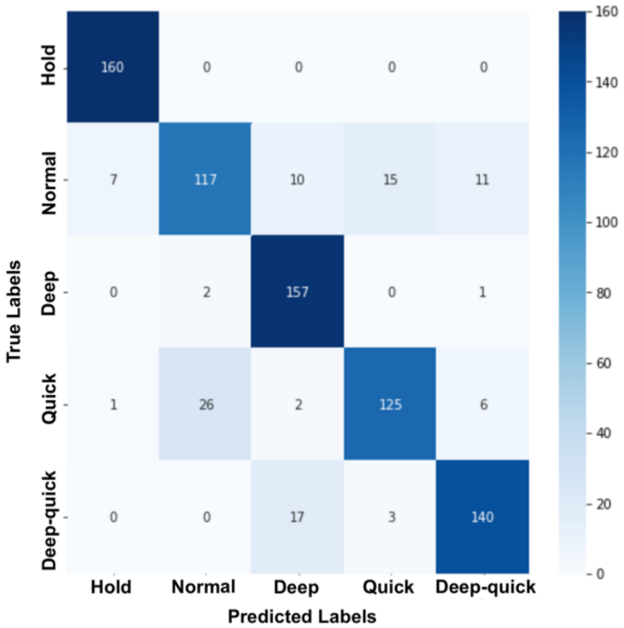

Figure 7. Confusion matrix of performance by the XGBoost breathing pattern classifier

To visualize the algorithm's performance, **Figure 7** presents a confusion matrix. The horizontal axis shows the predicted breathing classes, and the vertical axis shows the true classes. The "Hold" class is perfectly identified every time, followed by the two other best-performing classes, "Deep" and "Deep-quick." Accurate detection of these latter classes is crucial to prevent missed diagnoses. Finally, the "Normal" class is the most ambiguous and is often detected as other classes. However, this is more tolerable because the consequence is not as severe as a missed diagnosis.

In the context of using this multiclass classifier for health, the choice of the most important evaluation parameter depends on the specific application and its associated risks. However, considering the potential negative consequences of missing true pneumonia cases (false negatives), recall becomes a crucial metric. Therefore, the Deep and Deep-quick classes, with their high recall and reasonable precision and F1-score, show this model as a promising candidate for applications where identifying true instances of specific breathing patterns related to pneumonia, such as deep and heavy breaths, is pivotal. It emerges as a potential tool for detecting and monitoring symptoms of respiratory disease.

6. CONCLUSION

This research has successfully explored the integration of FMCW radar and XGBoost for breathing waveform classification, opening doors for a new era of intelligent non-contact monitoring devices. The chosen machine learning algorithm, XGBoost, demonstrated remarkable multiclass classification capabilities, with classes like "Deep" and "Deep-quick" exhibiting high precision and F1 scores, indicating clear differentiation and accurate identification. Most importantly, the "Deep-quick" class, characterized by its exceptional recall, provides a strong foundation for applications were capturing true instances of specific breathing patterns, potentially indicative of early pneumonia, is pivotal.

Beyond the impressive classification performance, the seamless integration of FMCW radar technology with XGBoost holds immense promise for the development of intelligent non-contact monitoring devices. This technology has the potential to revolutionize respiratory healthcare.

6.1. Future Works

In this research, we have demonstrated the feasibility and effectiveness of using FMCW radar and XGBoost for breathing waveform classification, which can be applied for non-contact monitoring of pneumonia symptoms. However, there are still some limitations and challenges that need to be addressed in future works, such as:

1. Evaluating the performance of the system in different scenarios, such as different distances, angles, or environments. This can help assess the robustness and reliability of the system in various conditions and challenges.
2. Incorporating other physiological signals, such as heart rate, blood pressure, or oxygen saturation, into the system. This can help provide a more comprehensive and holistic picture of the patients' respiratory health and status.
3. Improving feature extraction and selection methods for breathing waveform data. This can help reduce the data's dimensionality and noise and enhance the discriminative power and interpretability of the features.
4. Applying other data augmentation and balancing techniques for the

imbalanced dataset. This can help increase the diversity and quantity of the data and mitigate the model's bias and overfitting.

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