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Enhancing Respiratory Disease Diagnosis through FMCW Radar and Machine Learning Techniques

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ABSTRAK

Penyakit pernapasan membutuhkan diagnosis dini dan pemantauan secara terus-menerus, dimana metode yang ada melibatkan kontak fisik yang berisiko. Studi ini mengusulkan sistem baru yang menggunakan radar FMCW dan pembelajaran mesin untuk memantau pernapasan tanpa kontak dengan pasien. Radar FMCW dapat mendeteksi gerakan pernapasan secara real-time, sementara pembelajaran mesin dapat mengklasifikasikan gelombang pernapasan. Studi ini mengevaluasi sistem dengan validasi silang Shuffle Split, K-fold, dan Stratified K-fold. Hasilnya menunjukkan bahwa Random Forest memiliki akurasi tertinggi 94,6% dan Naïve Bayes memiliki waktu terpendek 0,055 detik. Shuffle Split berkinerja terbaik secara keseluruhan. Studi ini menunjukkan bahwa sistem memiliki kelayakan dan potensi untuk deteksi, dan pelacakan penyakit pernapasan dalam kegawatdaruratan.

Kata Kunci:

Deteksi Pernapasan; Klasifikasi; Pembelajaran Mesin; Radar FMCW

***Keywords* :**

Classification, FMCW Radar, Machine Learning, Respiratory Detection.

ABSTRACT

Respiratory diseases require early diagnosis and continuous monitoring, but existing methods involve risky physical contact. This study proposes a new system that uses FMCW radar and machine learning to monitor breathing without contact. FMCW radar can detect respiratory movements in real-time, while machine learning can classify respiratory waveforms. This study evaluates the system with cross-validation Shuffle Split, K-fold, and Stratified K-fold. The results show that Random Forest has the highest accuracy of 94.6% and Naïve Bayes has the shortest time of 0.055 seconds. Shuffle Split performs best overall. This study shows the feasibility and potential of the system for the detection, response, and tracking of respiratory diseases in emergencies.

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INTRODUCTION

Respiratory diseases pose a substantial global health burden, demanding innovative solutions for early detection and monitoring (Halpin et al., 2021). These diseases encompass a range of conditions, including acute respiratory infection, chronic obstructive pulmonary disease (COPD), asthma, and pulmonary fibrosis, which collectively affect millions worldwide. As technology advances, the urgent need for real-time respiratory signal monitoring becomes increasingly evident, enabling the swift detection of symptoms and enhancing the management of patients with these debilitating diseases.

Infectious diseases have heightened the demand for non-contact medical devices that enable healthcare practitioners to monitor patients remotely (Lee et al., 2021). This shift towards non-invasive and contactless solutions has proven crucial for patients infected with the virus and healthcare workers at an increased risk of exposure of up to 67% (Romero Starke et al., 2021). In this context, radar-based systems, with their capability to monitor vital signs such as respiratory signals, have emerged as a promising technology for remote patient assessment (Wang et al., 2021).

Radar systems, notably FMCW radar, have exhibited remarkable potential in detecting human respiratory signals. These systems are adept at capturing and isolating the subtle movements associated with breathing and heart rate, making them an ideal tool for non-contact vital sign monitoring (Ahmad et al., 2018). The utilization of these technologies can reduce the impracticality of using contact-based monitoring devices that need large capacity batteries, are impractical to use with burn victims or infants, may detach, and are possibly invasive (Khan et al., 2020; Turppa et al., 2020).

Beyond merely detecting the presence of a respiratory signal, the ability to analyze different breathing patterns is paramount for early diagnosis of dysfunctional breathing (Baker et al., 2020). Variations in breathing types have served as valuable indicators for the presence of respiratory diseases such as asthma, tracheoesophageal and esophageal diseases, and chronic pain syndromes (Newson & Elias, 2020). In addition to its application in disease analysis, this classification system can also identify subcategories within asthma related to distinctive breathing patterns, including hyperventilation, rapid and shallow breaths, deep sighing, and various irregular respiratory behaviors (Connett & Thomas, 2018).Hence, a comprehensive analysis of these patterns can aid in early detection of symptoms and monitoring of disease progression.

Machine learning techniques have been leveraged to classify these signals accurately to harness the full potential of radar-based respiratory signal monitoring (Purnomo et al., 2021), (Purnomo et al., 2022). Machine learning algorithms, including Decision Trees, Random Forest, Naïve Bayes, Gradient Boosting, and Support Vector Machine (SVM), have demonstrated their prowess in differentiating vital signals (Kavsaoğlu & Sehirli, 2023). These algorithms are instrumental in turning raw radar data into actionable insights for healthcare professionals.

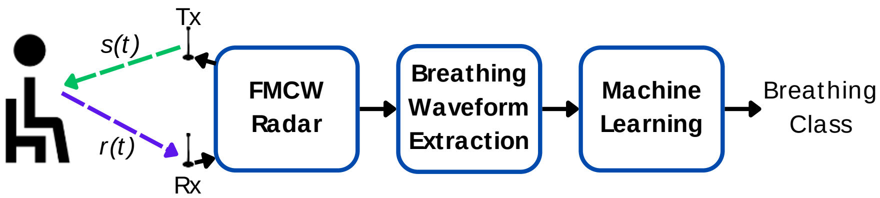

Figure 1. Main modules of the proposed system.

This article presents a system that integrates FMCW radar technology with machine learning algorithms, illustrated in Figure 1. The radar detects breathing waves from the patient through its transmitter Tx and receiver Rx. Then, the signal from the antennas is processed to extract breathing waveforms, which are processed by the selected machine-learning model. The system aims to classify breathing waveforms accurately from a list of common breathing classes, thereby providing valuable information for assessing an individual's health status. This will enable hospitals to continuously monitor the respiratory signs of a patient unsupervised by healthcare workers, improving the typical approach of manual data collection and assistance (Da Costa et al., 2018).

This article is structured as follows: the introduction overviews the importance of non-contact medical devices and radar-based respiratory analysis. The subsequent sections will delve into the method for breathing waveform extraction, dataset description, breathing waveform classification by machine learning algorithms, results, and discussion, and conclude by highlighting the potential impact of this integrated system on the healthcare landscape.

RESEARCH METHOD

Breathing Waveform Extraction

Frequency-Modulated Continuous Wave (FMCW) radar processes the received FMCW signal through a number of phases in order to extract a respiratory signal. This section explains the basic ideas of FMCW radar and how it records and processes signals for obtaining breathing waveforms.

The basis for FMCW radar's operation is a frequency change that occurs linearly over time. The received signal reveals details about the object's movement, including its breathing patterns, while the frequency of the FMCW radar signal being transmitted at time index 't' changes over time.

Research has verified that radar systems are phase-sensitive and can pick up on even the smallest motions, such as breathing signals. Due to its phase sensitivity, FMCW radar is a useful tool for non-contact respiratory monitoring since it can identify minute vibrations caused by lung activity. As an FMCW radar device, this study utilizes the Texas Instrument IWR1443 board operating in the 77-88 GHz range.

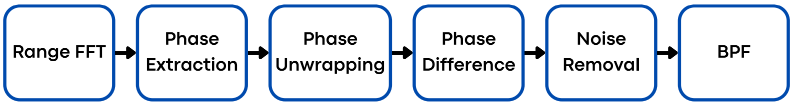

Figure 2. Signal processing steps for breathing waveform extraction

The signal-processing steps for breathing waveform extraction involve a sequence of crucial procedures as shown in Figure 2. First, Range FFT (Fast Fourier Transform) analysis is conducted to identify peaks in the frequency domain corresponding to subtle movements caused by lung activity. Next, Phase Extraction captures the phase information of the received radar signal. Phase Unwrapping rectifies phase values to maintain their continuity across 2π intervals, facilitating accurate analysis. Subsequently, Phase Difference is calculated to quantify variations in phase values, providing insights into respiratory patterns. Noise Removal helps eliminate unwanted interference or artifacts. Lastly, the signal passes through a Band Pass Filter (BPF) to isolate the desired frequency range (0.1 to 0.5 Hz), ultimately yielding the breathing waveform for further analysis. These steps collectively enable extracting crucial respiratory signals from FMCW radar data.

Dataset Description and Format

To measure the breathing waveform, the person must sit still while breathing face-forward to the radar. Figure 3 shows the setup used for collecting the breathing signal dataset.

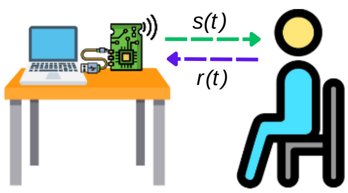

Figure 3. Illustration of the setting when measuring a person's breathing waveform

To create a large dataset, each subject was instructed to breathe according to five different breathing patterns: normal, deep, deep-quick, quick, and hold, each for roughly 5 seconds. One sample dataset contains 85 measurement points throughout the 5 seconds. There are 26,400 records of these different breathing signal data, labeled by either "quick" (2667 data), "normal" (19734 data), "deep" (1066 data), "deep-quick" (800 data), or "hold" (2133 data).

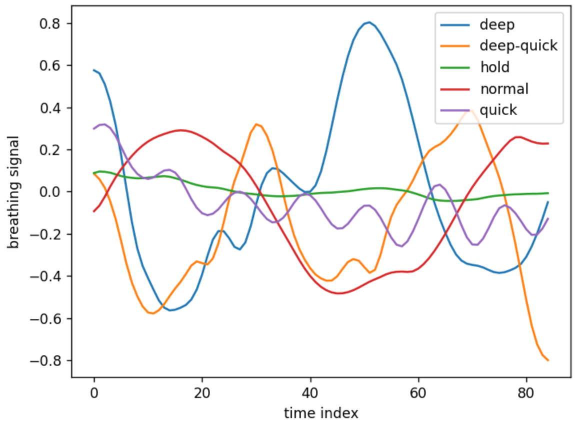

Figure 4. Plots of a sample from each type of breathing waveform data.

A row of data, with 85 data points, is a real number representing the level of breathing signal extracted. Figure 4 illustrates these data if they were to be plotted in an x-y plane of time versus signal. Each type of breathing plot is presented in different colors on the same graph.

Breathing Waveform Classification

The breathing waveform data is classified in three steps: reading and cleaning data, processing by machine learning models, and cross-validation. Figure 5 contains the visualization of these steps.

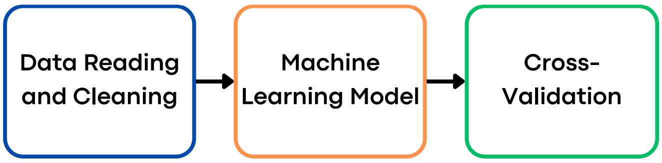

Figure 5. Block diagram of the breathing waveform classification steps.

Reading Data and Cleaning

The data are about breathing waveforms obtained from different people from various backgrounds, as discussed in Section 3. They are obtained using IWR1443BOOST by Texas Instruments, using software. The feature consists of 85 data points.

Table 1. Samples of the Breathing Waveform Dataset.

0	1	…	83	84	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 1 shows the sample of results from the data cleaning and merging. Columns 0 through 84 contain the data points of the breath signal, while the last column contains the labels of the breathing waveform type.

Machine learning classification model

We employ well-established machine learning techniques. These algorithms, integrated with the preprocessed data, serve as the engine for the classification task. Here, we compare five different models for classification to see their performance in predicting breathing waveforms. The models are Decision Tree, Random Forest, Naïve Bayes, Gradient Boosting, and Support Vector Machine (SVM).

Decision Tree

Decision trees are supervised machine learning models that hierarchically structure decisions based on input features. In the specific application of breathing waveform classification, decision trees parse through the extracted features of the respiratory signals, making decisions at each node to iteratively narrow down the possibilities. The decision-making process involves assessing the importance of different features, such as signal frequency and amplitude variations, to differentiate between various breathing patterns. This hierarchical approach makes decision trees particularly adept at capturing complex relationships within the data, enabling them to discern distinctive characteristics associated with different respiratory behaviors. The transparency of decision trees also facilitates interpretability, as the branching structure allows for a clear understanding of the criteria influencing each classification decision. Despite their effectiveness, it's essential to note that decision trees may be susceptible to overfitting, emphasizing the importance of proper tuning and validation to ensure robust performance across various datasets and scenarios.

Random Forest

Random Forest is a popular machine learning algorithm for classification and regression tasks. In the domain of respiratory signal classification, the application of random forest algorithms presents a powerful and effective approach. A random forest is an ensemble learning method that constructs multiple decision trees during the training phase and combines their outputs to enhance overall performance. In the specific context of breathing waveform signals, a random forest analyzes the diverse features extracted from respiratory data, collectively leveraging the insights gleaned from numerous decision trees. This ensemble approach is particularly advantageous for capturing intricate patterns and subtle variations within breathing waveforms, contributing to a robust and accurate classification system. Random forests inherently address the risk of overfitting associated with individual decision trees, providing a more generalized model. Each decision tree within the random forest is trained on a different subset of the data, and the final classification is determined by a majority vote across the ensemble. The versatility of random forests makes them well-suited for discerning complex relationships within respiratory data, ultimately enhancing the precision of classifying distinct breathing patterns.

Naïve Bayes

When it comes to figuring out different ways people breathe, the Naïve Bayes algorithm takes a unique approach. It is like a smart method that uses probabilities to understand breathing patterns, assuming that the features it looks at are independent, even if they might be connected. For example, when we want to tell apart patterns like deep, quick, normal, and hold breathing, Naïve Bayes calculates the chance of each pattern based on what it sees in the breathing signal. Even though it simplifies things by assuming features are unrelated, Naïve Bayes is great for quickly figuring out breathing patterns because it is straightforward and fast in training and making predictions. In the world of breathing signals, Naïve Bayes looks at how likely certain characteristics are for each breathing style, helping in making decisions based on probabilities.

Gradient Boosting

Gradient Boosting is a smart way of teaching a computer to recognize different breathing patterns, like deep, quick, normal, and hold breathing. It does this by creating a series of learning steps, often using decision trees, where each step corrects the mistakes of the previous one. This method is great for picking up on the details and nuances in the data about how people breathe. It pays extra attention to places where it made mistakes before, getting better each time. In the world of classifying breathing patterns, Gradient Boosting is like a detective, considering all the little details to tell the patterns apart. The best part is that it's good at learning without getting too fixated on specific details, making it a reliable and adaptable tool

Support Vector Machine

Support Vector Machines (SVM) provide a robust and effective method, particularly in discerning patterns associated with deep, quick, deep and quick, normal, and hold breathing. SVM is a powerful machine learning algorithm that strives to find an optimal hyperplane to separate different classes within the input data. When applied to respiratory signal classification, SVM evaluates the intricate features and variations inherent in breathing waveforms. SVM aims to identify a hyperplane that maximizes the margin between different breathing classes, enabling precise discrimination. The algorithm's ability to handle complex datasets with high-dimensional feature spaces aligns well with the multifaceted nature of respiratory signals. SVM's versatility allows it to effectively capture the distinctions in breathing patterns, contributing to accurate classification.

Cross-Validation Comparison

A critical step in splitting the dataset into training and testing sets, cross-validation is essential for evaluating the effectiveness and generalizability of the machine learning model. To guarantee reliable model evaluation, we discussed and contrasted a number of cross-validation techniques in this section.

K-Fold Cross-Validation

In the classification of breathing waveform signals encompassing deep, quick, deep and quick, normal, and hold breathing patterns, K-fold cross-validation serves as a vital technique for assessing the robustness and generalization ability of the classification models. K-fold cross-validation involves partitioning the dataset into K equally-sized folds and iteratively using K-1 folds for training and the remaining fold for validation. This process is repeated K times, each time using a different fold as the validation set. By applying K-fold cross-validation, the classification model is evaluated on various subsets of the data, providing a more comprehensive understanding of its performance across different scenarios. In the context of breathing waveform classification, K-fold cross-validation ensures that the model's accuracy is not overly reliant on a specific subset of the data, mitigating the risk of overfitting. The averaged performance metrics across multiple folds provide a more reliable estimate of the model's effectiveness in distinguishing between different breathing patterns. This rigorous evaluation methodology enhances the credibility and generalization capacity of the classification system, making it well-suited for real-world applications in respiratory disease detection and continuous monitoring.

Stratified K-Fold Cross-Validation

Similar to the conventional K-Fold approach, stratified K-Fold cross-validation considers class balance. It guarantees that the class distribution in each fold remains consistent with that of the original dataset. This method is especially helpful when working with imbalanced datasets—where some classes have much fewer samples than others.

Shuffle Split Cross-Validation

Train-test splitting and K-fold cross-validation features are combined in Shuffle Split Cross-Validation. Like K-Fold cross-validation, this method divides the dataset into training and test subsets at random several times. The randomization contributes to a reliable assessment of the model's performance by ensuring that distinct subsets are used for testing and training.

Each one of these cross-validation techniques has benefits of its own and works well in different scenarios.

RESULTS AND DISSCUSSION

In this study, the accuracy of breathing type classification serves as a pivotal indicator of the machine learning models' successes. To evaluate this metric, the accuracy formula is presented in Equation 1 (Grandini et al., 2020).

$$score = \frac{\sum_{i=1}^{N} \mathbb{1}\left(y_{pred_i} = y_{true_i}\right)}{N} \quad (1)$$

In formula (1), N is the total number of predictions, $\mathbb{1}(\cdot)$ is an indicator function that evaluates to 1 if the condition inside is true and 0 otherwise, y_{pred_i} is element i in the prediction set, and y_{true_i} is element i in the test set. Another evaluation metric of the models is the time needed to execute training and testing. Their results are discussed in the following subsections, where we performed 80-20 train-test data split and various cross-validation methods to be compared.

Model Comparison on 80-20 Train-Test Data Split

Each model was assessed for accuracy using the train-test split methodology, with default parameters applied consistently across all models. All models employed a uniform split of 80% for training and 20% for testing data. The results presented in Table 2 below reveal that the Random Forest classifier achieved the highest accuracy score, attaining a remarkable 94.6%. In contrast, the Decision Tree, Gradient Boosting, and Support Vector Machine (SVM) models demonstrated comparable accuracy scores, hovering around 85%. Notably, the Naïve Bayes classifier yielded the lowest accuracy score at 38%. However, it is noteworthy that this particular model exhibited the shortest processing time, requiring 0.055 seconds. In comparison, the Decision Tree model had a processing time of 2.361 seconds, followed by Random Forest at 13.908 seconds, SVM at 16.565 seconds, and Gradient Boosting, which necessitated 158.589 seconds for classification.

Table 2. Comparative Analysis of Machine Learning Algorithms Using an 80-20 Train-Test Split.

Model	Train-Test (80-20)	
	score	time (s)
Decision Tree	0.862	2.361
Random Forest	0.946	13.908
Naive Bayes	0.38	0.055
Gradient Boosting	0.85	158.589
Support Vector Machine	0.845	16.565

Cross-Validation Comparison Between the Models

Table 3 below shows the mean accuracy scores and time elapsed for every classification model evaluated in three cross-validation methods. For the K-fold cross-validation method, the Gradient Boosting model achieves the highest accuracy score with 0.732, followed closely by the Random Forest model with 0.727. The next is the Support Vector Machine with 0.692, then the Decision Tree with 0.619. Lastly, Naïve Bayes scores the lowest, 0.294.

In stratified K-fold cross-validation, the Random Forest model delivers the highest score with 0.831, while Gradient Boosting comes in second place with 0.812. Support Vector Machine and Decision Tree close with 0.757 and 0.730, respectively. Naïve Bayes scored lowest with 0.363. The validation time, Stratified K-fold cross-validation, is just slightly slower than K-fold.

Finally, in Shuffle Split, Random Forest achieves the highest accuracy score again with 0.943. Decision Tree, Gradient Boosting, and Support Vector Machine achieve comparable scores at 0.858, 0.848, and 0.840, respectively. Naïve Bayes model has the lowest accuracy score again at 0.371. For the time elapsed, the Shuffle split has the quickest evaluation time compared to the other two methods, except for Naïve Bayes and Support Vector Machine, which require a longer time.

Table 3. Cross-validation Comparison Between Machine Learning Algorithms.

Model	K-fold		Stratified K-fold		Shuffle Split	
	score (mean)	time (s)	score (mean)	time (s)	score (mean)	time (s)
Decision Tree	0.619	25.916	0.730	26.707	0.858	23.043
Random Forest	0.727	159.138	0.831	159.081	0.943	137.708
Naive Bayes	0.294	0.385	0.363	0.393	0.371	0.502
Gradient Boosting	0.732	1725.626	0.812	1795.973	0.848	1585.532
Support Vector Machine	0.692	157.117	0.757	154.444	0.84	157.957

CONCLUSION AND RECOMMENDATION

Conclusion

In conclusion, this study presents an innovative system that integrates FMCW radar technology with machine learning algorithms for real-time, non-contact respiratory monitoring. The Texas Instrument IWR1443 board effectively captures subtle respiratory movements

Machine learning models such as Support Vector Machine, Random Forest, Naïve Bayes, Decision Trees, and Gradient Boosting were used for precise classification. With an accuracy of 94.6%, the Random Forest classifier outperformed the other models. The systematic application of cross-validation methods, such as Shuffle Split, K-fold, and Stratified K-fold, in the study's breathing waveform classification significantly influenced the accuracy and validation times of machine learning models. In conclusion, the integrated system presented in this study has the potential to revolutionize the early detection, response, and monitoring of respiratory diseases. By combining the strengths of FMCW radar technology and machine learning algorithms, this system offers an efficient means of continuous respiratory monitoring without the need for physical contact. The study highlights how it is crucial to balance accuracy and processing times when picking the right machine-learning model and cross-validation method for practical use.

Recommendation

There is an opportunity to implement this integrated system in everyday healthcare settings, including hospitals and healthcare centers. Future research can focus on applying this integrated system in healthcare settings and exploring its broader impact on managing respiratory diseases. Efforts should be made to integrate this technology as a routine respiratory monitoring tool, enhancing overall patient monitoring. For further development, research can be conducted regarding the integration of FMCW radar technology and pre-trained machine learning models, as demonstrated in this article. In the context of advanced research, focus can be directed towards the application of this system in specific scenarios, such as monitoring patients with particular respiratory diseases or in different environmental conditions. This research can provide additional insights into the utility and limitations of the system.

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