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Using Machine Learning Methods for Contactless Monitoring of Abnormality in Breathing Patterns

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Abstract: *The objective of the present work was to develop and evaluate different methods for measuring and detecting abnormalities in breathing patterns using a pulsed coherent radar sensor. This study represents a crucial initial step toward developing a life-saving hardware product. The contactless monitoring of breathing abnormalities offers significant advantages over traditional methods using contact sensors, particularly in medical scenarios such as post-stroke recovery. Experiments were conducted at three different distances (0.35 − 0.45m, 0.75 − 0.90m, and 1.20 − 1.40m) using a pulsed coherent radar system. Machine learning methods, including kNN (k-Nearest Neighbors) and ANN-MLP (Artificial Neural Networks Multilayer Perceptron), were employed to distinguish whether the monitored individual exhibited normal or abnormal breathing patterns. Our analysis revealed that employing ML models and data signals from the radar sensor holds promise for classifying breathing pattern abnormalities. This paper covers the steps performed to accomplish this: a) Equipment and Data Processing; b) Measurement Trials and Data Collection; c) Study involving k-Nearest Neighbors method and Feed-Forward Neural Networks.*

Keywords: *machine learning; artificial neural networks; k-nearest neighbors; radar-based sensors; noncontact respiratory measurement.*

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1. Introduction

Contactless sensors offer improved mobility and eliminate the need for attaching or cleaning electrodes. They are particularly beneficial for patients with skin irritations, painful skin damage such as lacerations or burns, and those who exhibit anxiety or allergic reactions to contact sensors (Malešević et al., 2020; Piraianu et al., 2023). Additionally, radar-based sensors (Gu, 2016) can monitor heart rates through clothing or other obstacles. Abnormal breathing patterns, such as Cheyne-Stokes breathing, ataxic breathing, apneustic respirations, and central sleep apnea, are common consequences of stroke. The relationship between disordered breathing, including both obstructive and central apnea syndromes, as potential risk factors for and complications of stroke has been extensively discussed in recent literature (Schmutzhard, 2019). Despite this, the mechanisms underlying these respiratory pattern changes remain poorly understood.

Radar technology is suitable for monitoring respiratory diseases, as microwaves and millimetre waves can penetrate clothing, bedding, and other obstructions, allowing radar systems to accurately measure skin movements generated by physiological signals from remote patients without the need for sensors. This study developed a noncontact measurement system using a millimetre-wave array radar to monitor breathing. Previous studies have focused on breath detection and presentation (Kim, 2019), while others have demonstrated breath rate estimation. Respiratory rates obtained using reference respiratory monitoring belts and radar systems have been compared (Islam, Boric-Lubecke & Lubekce, 2020; Xiong et al., 2020; Walterscheid, Biallawons, & Berens, 2019). Respiratory rate is widely used in the triage and diagnosis of coronavirus infections, highlighting the importance of non-contact respiratory rate monitoring (Massaroni et al., 2020). Recently, machine learning (ML) algorithms have shown promise in improving efficiency and accuracy in detecting various abnormalities in the human body (Xu et al., 2023; Almuhammadi et al., 2022; Pati et al., 2023; Altini et al., 2021). To automatically distinguish whether the individual under surveillance is breathing normally or not, machine learning methods, including kNN (k-Nearest Neighbors) (Fix & Hodges, 1989; Cover & Hart, 1967; Aha, Kibler, & Albert, 1991) and ANN-MLP (Artificial Neural Networks Multilayer Perceptron) (Rumelhart, Hinton, & Williams, 1986; Haykin, 1998), were employed. The scripts that analyse the data were created using Google Colaboratory, a free tool developed by Google Research for quickly developing and running prototypes of Python-based machine learning and data analysis models in the browser (Bisong, 2019; Google Colab, n.d.). To assess the predictive generalisation capabilities of trained models, several open-source tools implemented as Python libraries were used, including scikit-learn (Pedregosa et al., 2012), Keras (Keras: Deep Learning for Humans, n.d.), and TensorFlow (Abadi et al., 2015).

2. Equipment and Data Processing

To perform the proposed tests, the A111 (see Fig. 1a) sensor was used, which is a radar system based on pulsed coherent radar (PCR) technology and sets a new benchmark for power consumption and distance accuracy - fully integrated into a small 29 mm2 package. The 60 GHz radar system is optimised for high accuracy and ultra-low power.

The XM122 module (see Figure 1a) can be used for precise distance measurement, tank level, dustbin level, parking space occupancy, and presence detection: high accuracy distance measurement with configurable update rate; measures absolute distance up to 7 m with absolute accuracy in mm; measures relative accuracy in 42 μm (using IQ software RSS service); can recognise the movement of multiple objects.

(a) *(b)*

Figure 1. The hardware components.
(a)The XM122 module with A111 sensor.
(b)The XB122 Acconeer module.

In order to be able to communicate via USB with the XM122 module it is necessary to use the XB122 Acconner module (see Figure 1b) which is specifically designed to communicate with XM122.

Figure 2 shows the minimum configuration required to test the proposed algorithms (PC + sonar sensor).

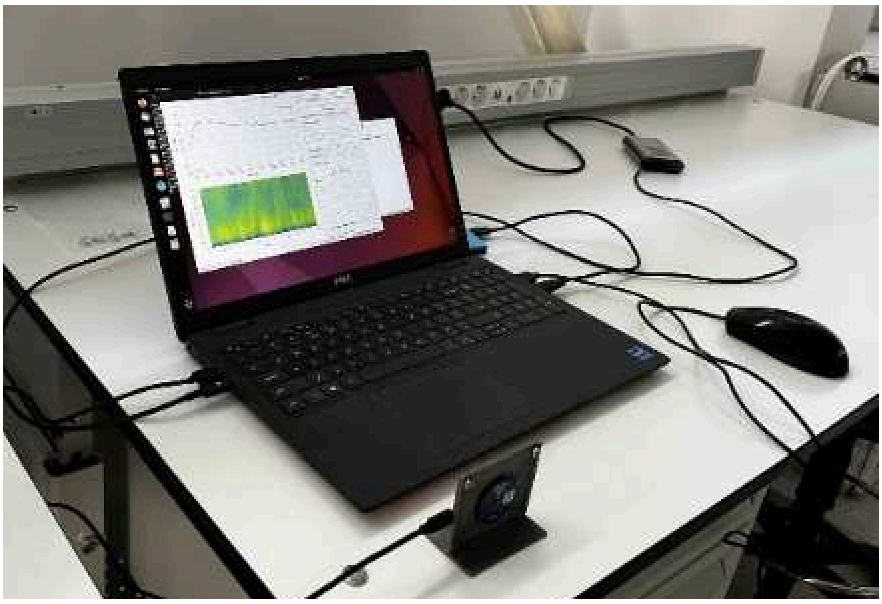


Figure 2. The minimum hardware configuration required to test

In radar technology, distance measurements can be subject to various sources of error, including sensor drift, noise, and environmental factors (e.g., temperature, humidity, or obstacles). These errors can introduce inaccuracies in the radar signal and the derived distance measurements. To compensate for errors we use Z-Score Normalisation (Standardisation) as a preprocessing technique in the distance measurements by transforming the data to have a mean of 0 and a standard deviation of 1. This helps make the measurements more robust for subsequent analysis, such as classification, regression, or feature extraction.

Z-Score Normalisation helps mitigate some of the error sources by transforming the data into a standardised form. It compensates for errors and inconsistencies in distance measurement in the following ways:

- Correcting for Drift and Sensor Bias
- Radar sensors might have a systematic bias over time, where the distance measurements gradually shift (e.g., the sensor always underestimates or overestimates distances).
- Z-Score Normalisation compensates for this bias by centering the data around a mean of 0. This means that any consistent bias (e.g., an offset of +5 mm) will be "removed" by subtracting the mean of the dataset.

- Handling Variability Due to Environmental Effects
- Environmental factors, such as temperature or humidity, can cause fluctuations in radar signal speed and, in turn, affect distance measurements.
- Standardisation ensures that the variation in measurements, caused by environmental changes, does not distort the analysis. By scaling the data according to the standard deviation, we ensure that any variability is accounted for without distorting the dataset.

- Mitigating Noise
- Noise in radar measurements can cause outliers or small, random deviations in the measured distance.
- Z-Score Normalisation helps handle these deviations by scaling them to a unit standard deviation. Extreme outliers will be pushed away from the central data, ensuring they have less influence on the analysis or subsequent distance-based algorithms (like kNN or clustering).

- Making Data Comparable Across Multiple Sensors
- In radar systems with multiple sensors or measurements from multiple objects (e.g., tracking several moving targets), distance readings from different sensors can vary due to differences in calibration, sensor sensitivity, or position.
- Z-Score normalisation standardises all measurements to have the same scale, allowing data from different sources to be directly comparable and treated equally in analysis.

Z-Score Normalisation, or standardisation, transforms the data so that the mean of the dataset is 0 and the standard deviation is 1. This technique is useful for addressing issues like differing scales in the data and ensuring that features are on the same scale, which is especially important when working with radar-based distance measurements.

Z-Score Formula (1):

$$Z = \frac{(X - \mu)}{\sigma} \qquad (1)$$

Where:

- X is an individual data point (in our case, radar distance measurement),
- μ is the mean of the distance measurements,
- σ is the standard deviation of the distance measurements.

Step-by-Step Process:

Collect Radar Distance Data:
Gather a set of radar distance measurements over a period of time. This data will typically have variability due to environmental factors and noise.

Calculate the Mean and Standard Deviation:
Compute the mean (μ) and standard deviation (σ) of the collected distance measurements. These statistics will serve as the baseline for standardisation (2).

$$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i \qquad (2)$$

Where N is the number of data points, and Xi is the i-th distance measurement.

Apply Z-Score Transformation:

- For each distance measurement Xi, apply the Z-score formula to standardise it (3):

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^2} \qquad (3)$$

This transformation results in a dataset where the mean is 0 and the standard deviation is 1 (3).

$$Z_i = \frac{X_i - \mu}{\sigma} \qquad (4)$$

Use the Normalised Data:

- The standardised data can now be used for further processing (such as machine learning algorithms) or distance comparisons. Since all measurements are scaled, they will be directly comparable.

Z-Score Normalisation (Standardisation) is an effective technique for error compensation in radar distance measurements. It corrects for sensor drift, noise, and environmental variations, ensuring the data is centered and scaled appropriately. This preprocessing step is particularly useful when radar systems are subject to varying conditions or when working with data from multiple sensors. By applying Z-score normalisation, you can enhance the accuracy, comparability, and reliability of distance measurements, making them more suitable for further analysis, such as detection or tracking tasks in radar-based applications.

3. Measurement trials and collect datasets

The first measurements with the radar sensor were made using the Acconeer exploration tool (Acconeer, 2024), which can be found on GitHub. Here it is possible to adjust how the data should be collected. Parameters that can be set here are profile, HWAAS (Hardware Accelerated Average Samples), sweeps per frame, rate, start point, number of points, and step length. Tests/experiments were carried out at 3 different distances. The first tests were performed at a distance of 0.35 - 0.45m, at a frequency of 30Hz and 10, 000 values were acquired. The second set of experiments was performed at a distance of 0.75 -0.90m and the third set of experiments at a distance of 1.20 - 1.40m.

One set of experimental data was performed on a person with normal breathing (normal data set). Another data set was performed on the same person who was not moving/not breathing for a period of time or had abnormal breathing - fast or slow or moving beyond the set range = (abnormal data).

In order to use the data in the files, they were converted from .h54 format to .csv format using the converttocsv.py software (Acconeer, 2024).

Data was recorded by radar for a person with normal breathing (Figure 3a) and a person with abnormal breathing (Figure 3b).

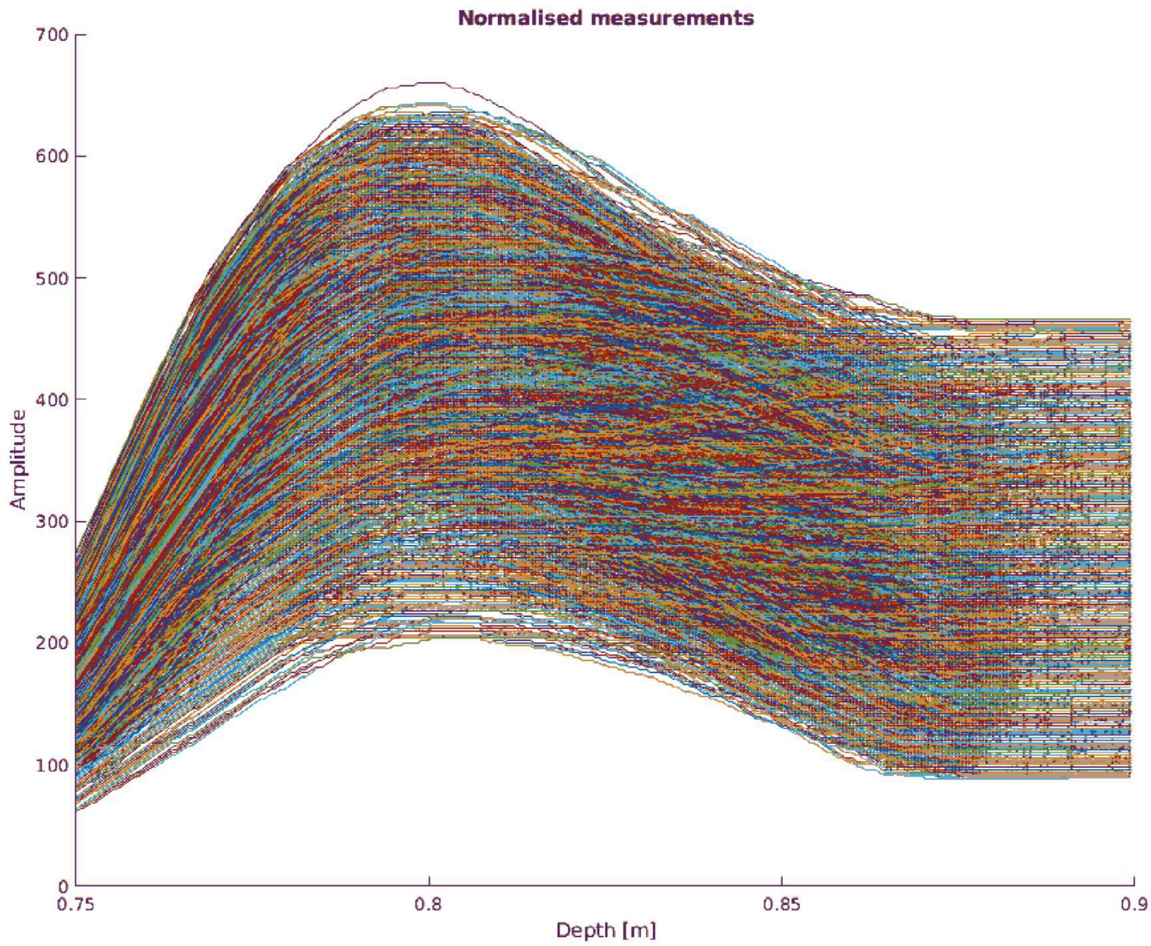


Figure 3. Measurements from A111 radar
(a) Measurements from A111 radar - normal breathing

After data conversion, the .csv files were filtered (using a Kalman filter - see Figure 4), visualised, and converted into a new .cvs file (using a 200 sample window) needed to train the neural network.

The following figures show some examples of the data needed to train the neural networks acquired by the radar sensor.

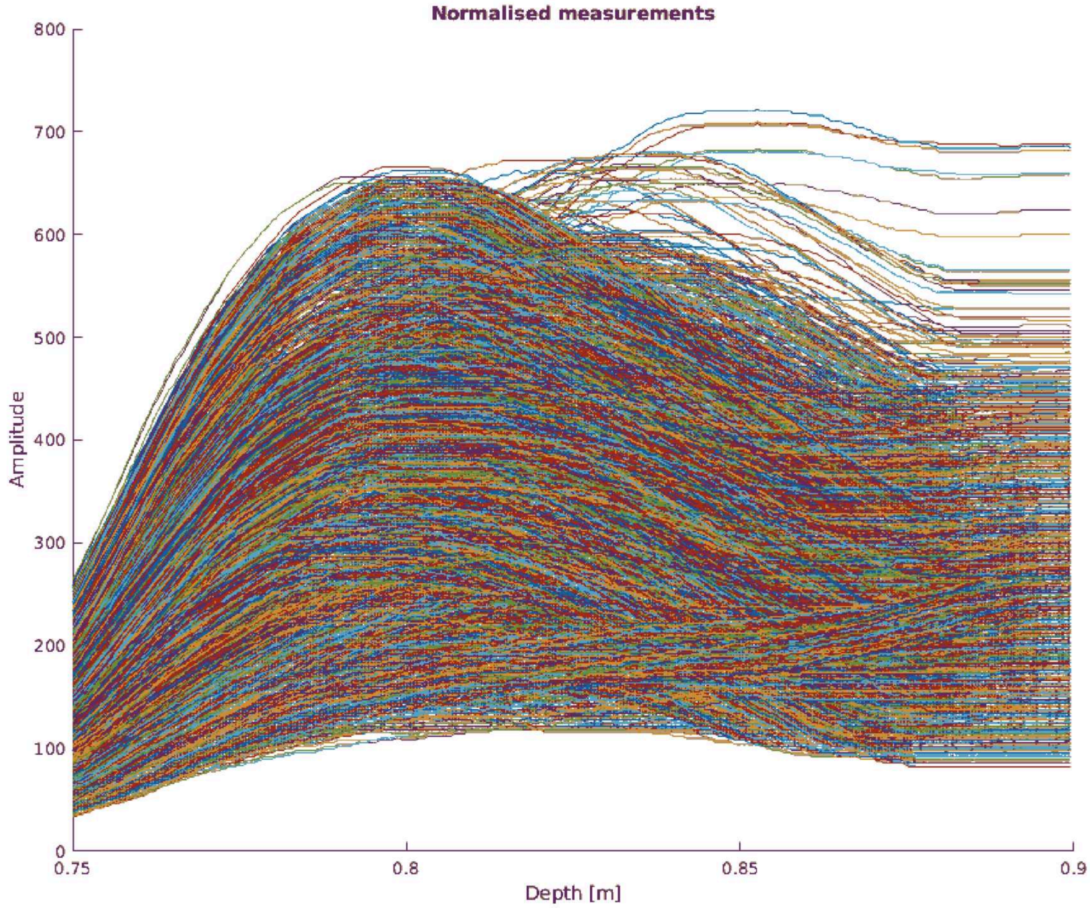


Figure 3. Measurements from A111 radar
(b) Measurements from A111 radar - abnormal breathing

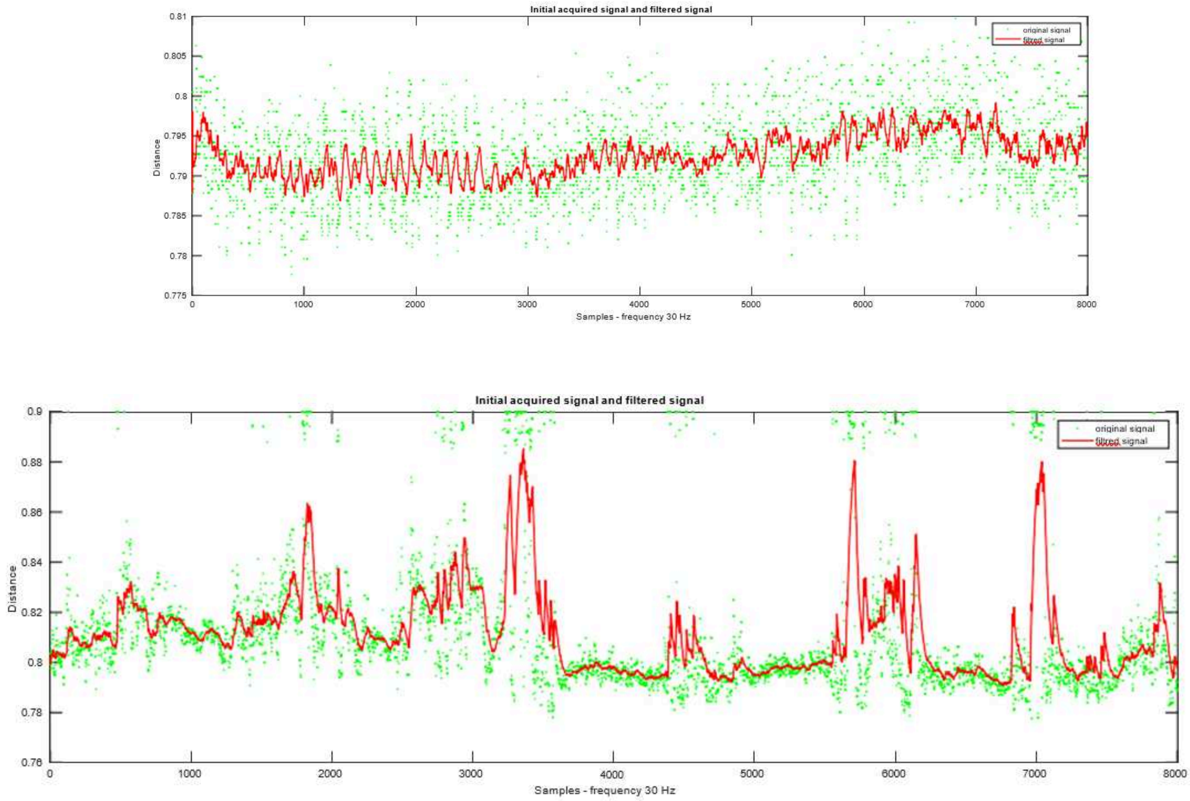


Figure 4. Initial acquired signal and filtered signal - frequency 30 Hz
(a) Measurement performed when a person is breathing normally
(b) Measurement performed when a person is breathing abnormally

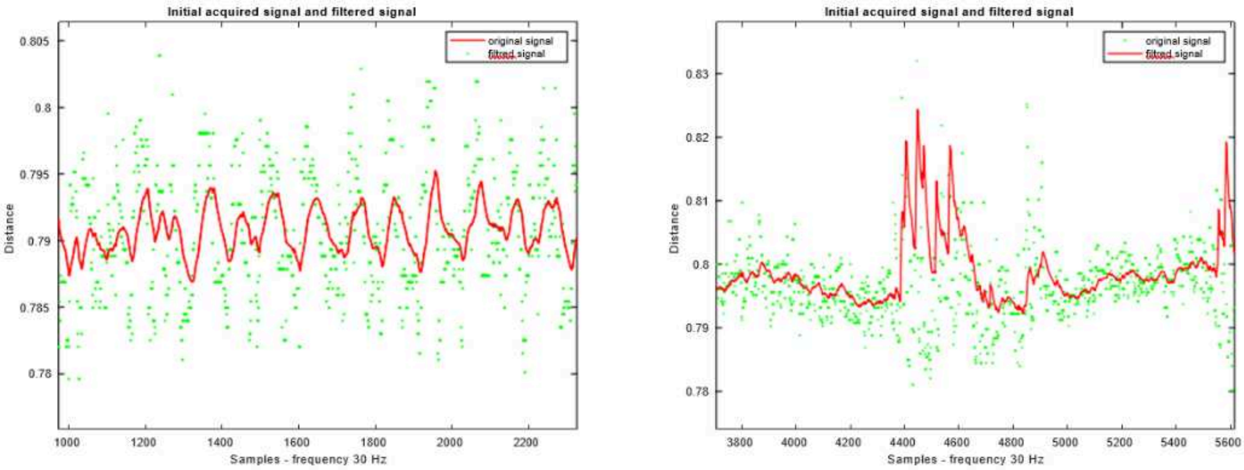


Figure 5. Initial acquired signal and filtered signal
(a) Measurement performed when a person is breathing normally
(b) Measurement performed when a person is breathing abnormally

4. Study involving kNN method and feed-forward neural networks

4.1. kNN

In the initial stage, using kNN, a preliminary data analysis was conducted to assess whether they have predictive power or not.

Classifiers using the k-nearest neighbors method predict the class of unlabeled examples by assigning the class of the most similar labeled examples, based on a metric (e.g., Euclidean distance). This approach is useful when objects from similar classes tend to be quite homogeneous and can be recognised when seen/observed. Therefore, this approach is useful in the case of radar signal analysis to identify situations in which the observed person is breathing normally or not.

Selecting the correct value for k, which represents the number of neighbors, is rather a challenging task. In real-world scenarios, the optimal value depends on the complexity of the problem being examined, the representativeness of the target classes, and the size of the training dataset (i.e., the number of examples). There are numerous empirical methods based on various heuristics for identifying an appropriate value for the specific problem, but there are also scientific methods based on repeated cross-validation and testing various values of k. In this study ten times ten-fold cross-validation was involved.

To determine the suitable setup, such as the ideal number of neighbors in kNN, layers, and hidden neurons per layer in ANN-MLP, and to gain insight into the predictive effectiveness of the models generated using these methods, we employed a repeated stratified cross-validation (Hastie, Tibshirani & Friedman, 2009). The cross-validation technique randomly divides the available data set into several subsets, to be used circularly, fold after fold, one of the subsets for testing and the remaining ones for training the predictive model. Stratified cross-validation takes into account the division by the percentage of samples in each class, producing subsets in which the ratio of classes in the subsets is similar to that in the original data set. Repeating the process and shuffling the data before selecting the samples, allows for improving the evaluation of the average performance of the obtained models and making better comparisons between the models, based on the performances, using statistical tests.

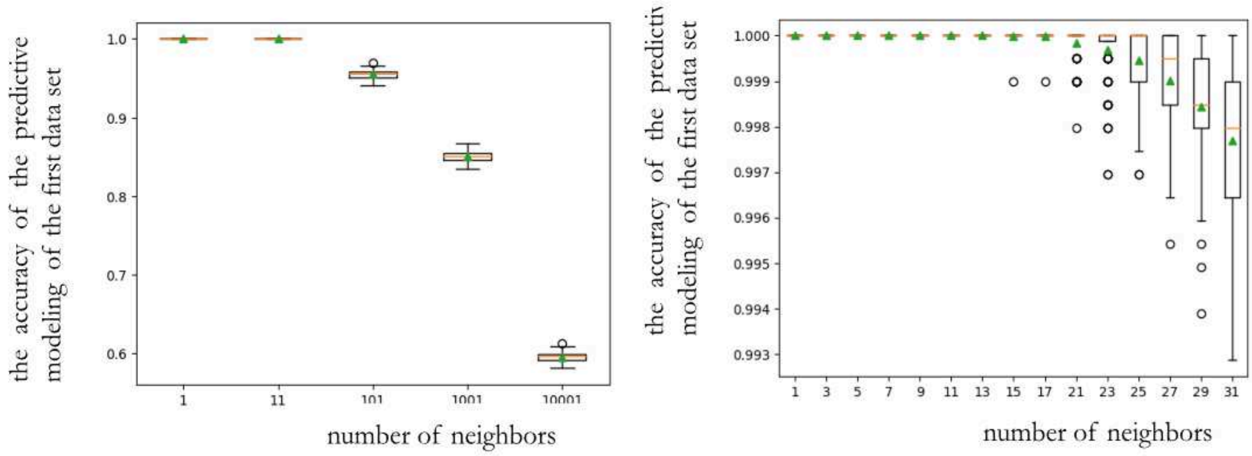
Another important and widely used technique, which we put into practice here, is to bring the values from the training set to a common denominator either by normalisation, bringing the values into the unit interval, [0, 1] by reporting the difference against of the minimum value of an attribute at the length of the interval from which it takes values, or by data standardisation, computing the number of standard deviations above or below the average value of the attribute. Standardisation was chosen (Z-Score Normalisation) because, in addition to the fact that it produces both positive and negative values, it is more appropriate to highlight the outliers and eliminate the need for calibration for the radar sensor.

Finally, with the aim of giving more importance to nearby neighbors in the decision-making process, their influence is weighted inversely proportional to the distance to the new classified example. It has been found in the preliminary experiments that it could result in a slight improvement in accuracy, typically in the range of 1 to 3 percentage points.

Table 1. kNN cross – validates accuracy

Accuracy	Neighbors				
Mean (Stdev)	1	11	101	1001	100001
Dataset 1	100% (0%)	100% (0%)	95.52% (0.49%)	85.07% (0.68%)	59.58% (0.61%)
Dataset 2	100% (0%)	100% (0%)	95.18% (0.56%)	86.07% (0.88%)	79.30% (0.73%)
Dataset 3	100% (0%)	100% (0%)	92.92% (0.54%)	75.85% (0.90%)	60.65% (0.55%)

As can be seen, both in Table 1 and in the boxplots in Figure 6a, where the number of neighbors is shown on the horizontal axis and the accuracy of the predictive modeling of the first data set is represented on the vertical axis, the latter decreases with the increase the number of neighbors taken into account. The situation is very similar in the case of the other data sets, regardless of the distance from which the scan was performed (small 0.20 - 0.40m, medium: 0.75 - 0.90m, or large: 1.20 - 1.40m). A deeper analysis of this behavior is performed for a number of neighbors between 1 and 31, observing an extremely good accuracy for all these values of k (Figure 6b). Therefore, choosing a relatively small number of neighbors proves to be sufficient.

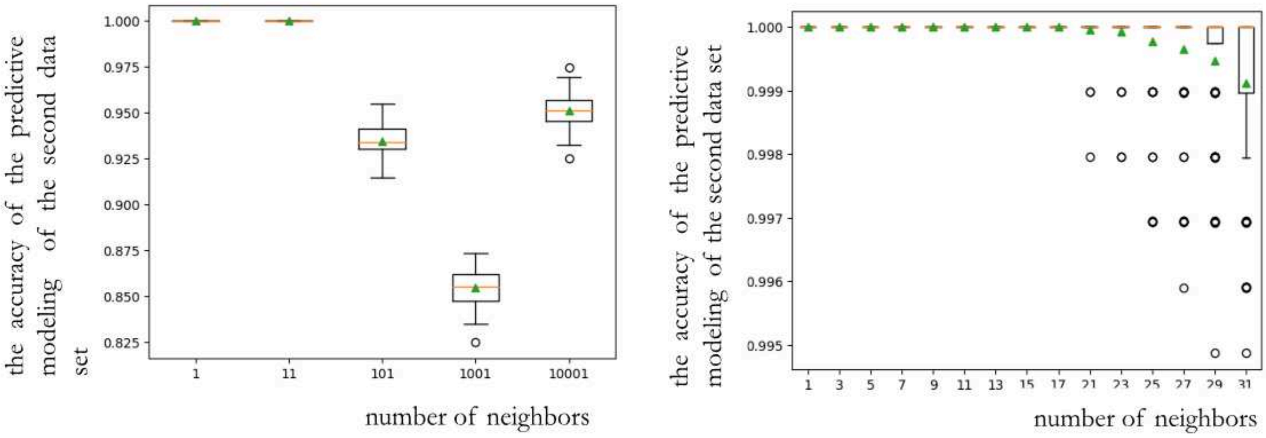


(a) *(b)*
Figure 6. Accuracy vs. neighbors (dataset1)

Table 2. kNN cross-validated precision

Accuracy	Neighbors				
Mean (Stdev)	1	11	101	1001	100001
Dataset 1	100% (0%)	100% (0%)	97.77% (0.52%)	85.45% (0.94%)	100% (0%)
Dataset 2	100% (0%)	100% (0%)	93.46% (0.78%)	85.47% (0.98%)	95.10% (0.87%)
Dataset 3	100% (0%)	100% (0%)	98.72% (0.49%)	89.72% (1.40%)	100% (0%)

In addition to global accuracy, an assessment of precision can also be made, i.e. of the ratio between correctly predicted positive cases and the total number of positive predictions made by the model, considering the positive class the one that describes abnormal breathing ("1" class) because we are interested in identifying the moments when the patient experiences breathing difficulties or changes his position. In a similar scenario (see Table 2 and Figure 7), precision diminishes as the number of neighbors under consideration increases. Nonetheless, there are situations where predictive models exhibit variability in their ability to fully identify the positive class (Figure 7a).



(a) *(b)*

Figure 7. Precision vs. neighbors (dataset2)

To conclude, comparing the accuracy and precision of the identification of the positive classes in the three data sets, it is immediately noticeable that the value of the precision is slightly higher, even if not statistically significant, than that of the accuracy, for the same value of k, indicating that the models are able to better identify these positive cases (normal breathing) than the negative ones (abnormal breathing).

Regarding the model limitation we need to consider that breathing data often contains noise, such as movement artifacts, environmental interference, or sensor errors. kNN relies on the similarity between a test sample and its neighbors in the feature space, and noise can dramatically affect these distances, leading to poor classification or detection results. In real-world environments, where breathing signals can be affected by external factors (e.g., motion), the accuracy of kNN can suffer if noise or motion detection is not effectively managed. In the case of using multiple sensors or a number of features increases, the distance between data points becomes less distinct in high-dimensional spaces. This phenomenon, known as the curse of dimensionality, can lead to poor performance for kNN since the algorithm relies on distance metrics. In breathing detection, if multiple variables (e.g., respiratory rate, tidal volume, heart rate, etc.) are used, kNN may not perform well unless dimensionality reduction techniques are applied, complicating the pipeline. From the computational complexity point of view, kNN requires calculating distances between the test sample and every training example during prediction. As the number of training samples increases, this process becomes computationally expensive and slow resulting in a struggle with latency and scalability for real-time breathing detection, where rapid and continuous prediction is necessary.

4.2. ANN

After the initial analysis of the data sets using the nearest neighbor method, the experiments continued with a study involving Feed-Forward Neural Networks (Multilayer Perceptron).

Artificial Neural Networks (ANN) are known to have good results in supervised learning problems, both in classification and regression, being able to discover complex patterns and relationships in data. ANN models are inspired by the structure and function of biological neural networks in the human brain and consist of interconnected artificial neurons organised into layers, typically comprising an input layer, one or more hidden layers, and an output layer.

In this study, the activation functions employed include the hyperbolic tangent for the hidden layers and the sigmoid for the output layer, the recommended selection for classification problems. Several architectures are tested in which the number of hidden layers and the number of neurons in each layer vary. The same technique of repeated stratified cross-validation is used to perform a comparison regarding the predictive accuracy of the model. The number of layers was successively increased while the number of neurons was halved with each new layer, forcing the network to focus on the essential information captured in the previous layers.

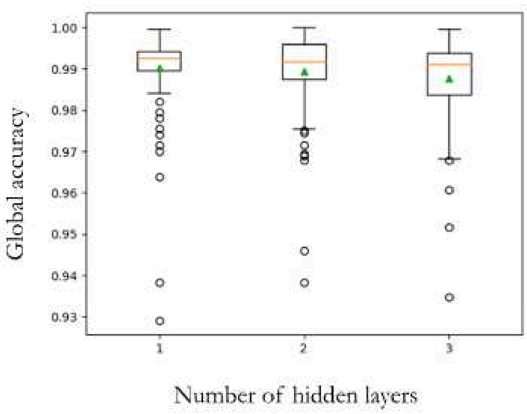
Table 3. ANN accuracy

Accuracy	Network topology		
Mean (Stdev)	1 hidden layer 200in->[200]->1 out	2 hidden layer 200in->[200->100]->1 out	3 hidden layer 200in->[200->100->50]->1 out
Dataset 1	99.02% (1.01%)	98.95% (1.01%)	98.78% (1.01%)
Dataset 2	94.97% (0.90%)	95.30% (1.01%)	95.67% (1.01%)
Dataset 3	96.69% (0.90%)	97.89% (1.01%)	97.73% (1.01%)

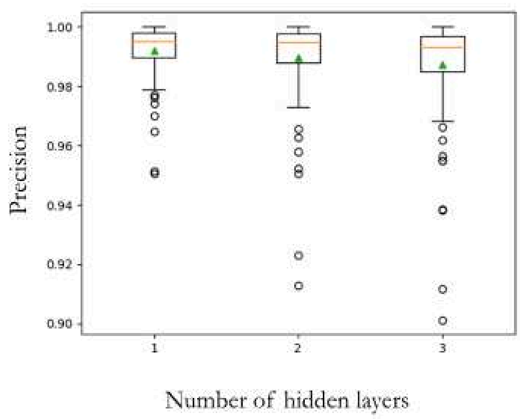
Table 4. ANN precision

Accuracy	Network topology		
Mean (Stdev)	1 hidden layer 200in->[200]->1 out	2 hidden layer 200in->[200->100]->1 out	3 hidden layer 200in->[200->100->50]->1 out
Dataset 1	99.20% (0.91%)	98.97% (1.42%)	98.73% (1.7%)
Dataset 2	96.48% (2.60%)	97.23% (1.88%)	97.34% (1.73%)
Dataset 3	96.35% (1.79%)	97.80% (1.28%)	97.71% (1.14%)

As depicted in Tables 3 and 4 and visually represented through boxplots in Figure 8, it is evident that in both global accuracy and precision for dataset 1 hidden layers, when classifying positive examples (corresponding to less normal breathing), neural networks achieve comparable average scores across all three topologies after training. Also, the dispersions show similar values among these topologies.



(a)



(b)

Figure 8. Predictive performance vs. ANN topology (number of hidden layers)

Regarding the model limitation for the ANN technology we need to consider that when the model memorises the training data rather than learning to generalise, it leads to poor performance on unseen data and occurs overfitting. ANNs, especially deep neural networks, are prone to overfitting when there is insufficient training data or when the model is too complex for the available data. In breathing detection, where the dataset may not be large or diverse enough (e.g., only a small sample of patients), ANNs might overfit and fail to correctly detect breathing patterns in new, unseen cases or when encountering noise. ANNs typically require large amounts of labeled data to perform well and avoid overfitting. Breathing detection data might be limited or hard to acquire, especially for medical applications where privacy and patient consent are issues. A lack of data for training might hinder the model's ability to generalise.

In breathing detection, particularly in medical or critical care settings, clinicians may need explanations for why a certain breath pattern was detected as abnormal or why a breathing event was missed. ANNs' lack of transparency could hinder their adoption in such environments. Neural networks are often considered "black-box" models, meaning their internal workings are not easily interpretable. This can be a significant issue in healthcare or clinical applications, where understanding how a model arrives at its decisions is crucial for trust, validation, and regulatory compliance. Despite their ability to learn complex patterns, ANNs still require careful feature selection or engineering for optimal performance. In breathing detection, extracting meaningful features from sensor signals can be challenging. Poor feature extraction can lead to suboptimal training results, and improper features can lead to reduced performance. In breathing detection, choosing the right set of features (e.g., frequency-domain features, time-domain features, etc.) is critical for good performance.

From a complexity and computational requirements point of view, training an ANN can be computationally expensive. This process requires significant computational resources (e.g., GPUs) and time. For breathing detection, where real-time or near-real-time results are often necessary, training an ANN may not be practical, especially if the system needs to be deployed in resource-constrained environments. While ANNs are powerful, their training and tuning process can be cumbersome and may not be suitable for situations where quick deployment is essential. Additionally, the power consumption and memory requirements for deploying deep networks can be a concern in mobile or wearable applications.

5. Comparative analysis with similar studies

The papers by Malešević et al. (2020), Xiong et al. (2020), and Massaroni et al. (2020) explore different aspects of radar-based and non-contact monitoring of physiological parameters such as heart rate and respiratory rate, with a special focus on their applications in clinical or pandemic settings. Below is a comparative analysis of these studies, highlighting their objectives, methods, findings, and relevance to the field of contactless monitoring.

- Objective

Malešević et al. (2020) aimed to develop a method for contactless heart rate monitoring using radar technology. The focus was on exploring the feasibility of using radar systems to accurately detect heart rate without physical contact with the subject.

- Methodology

- The authors used millimeter-wave radar to detect the micro-movements caused by the heartbeats. The radar signal interacts with the chest, and changes in the reflection pattern due to the heart's pulsations are captured.
- The technique involved sophisticated signal processing algorithms to extract the heart rate from the radar signal.
- Fast Fourier Transform (FFT) was applied for frequency-domain analysis to detect periodic signals corresponding to heartbeats.

- Key Findings

- Radar systems can effectively capture heart rate without direct contact with the person, offering advantages in terms of comfort and hygiene.
- The system was able to detect heart rate even in the presence of body movements, which is often a challenge in traditional sensors.
- The method's accuracy was comparable to conventional heart rate monitoring techniques, such as ECG (electrocardiogram) systems.

- Relevance

- This research is relevant for applications where traditional contact-based heart rate monitoring is impractical, such as for remote monitoring, elderly care, and during medical procedures where contact may be disruptive or infeasible.
- It demonstrates the potential of radar-based contactless health monitoring, which could be expanded into more complex physiological monitoring systems.

- Objective

Xiong et al. (2020) focused on multi-target respiratory monitoring using radar, specifically aiming to monitor the respiration rates of multiple subjects in the same environment simultaneously. This is particularly important for monitoring groups of people in crowded settings, such as hospitals or emergencies.

- Methodology

- The study utilised radar sensors operating in the microwave band, which are capable of detecting slight chest movements associated with breathing.
- The radar system employed multiple target detection algorithms, designed to track and monitor multiple individuals simultaneously. The system was able to distinguish and isolate signals from different people in a shared environment.
- Techniques like frequency-modulated continuous wave (FMCW) radar were used to enhance detection accuracy, and algorithms were applied to filter and interpret the respiratory signals.

- Key Findings

- Radar technology was successful in tracking multiple respiratory signals concurrently, even in the presence of overlapping signals from different individuals.
- The system was able to measure respiratory rate with high accuracy, even in cluttered environments.
- This method offers a significant advantage over traditional methods, such as wearable sensors, by eliminating the need for direct contact and enabling remote monitoring of several people at once.

- Relevance

- Xiong et al.'s work is highly relevant for crowded environments, such as emergency response units, public health monitoring, or pandemic-related settings where it is critical to monitor large numbers of people in real-time without physical interaction.
- This research emphasises the scalability of radar-based systems, making them ideal for multi-target applications where individual tracking would be difficult or cumbersome with conventional sensors.

- Objective

Massaroni et al. (2020) addressed the challenge of non-contact respiratory monitoring in the context of the COVID-19 pandemic. Their focus was on using remote sensing technologies to monitor respiratory parameters, such as the respiratory rate (RR), without physical contact, which became particularly crucial due to the need for social distancing and minimising exposure.

- Methodology

- The authors employed a thermal infrared (IR) imaging system and radar technology to monitor respiratory patterns. The thermal imaging system detected the slight temperature variations caused by breathing, while radar technology captured the chest wall motion associated with respiratory movements.

- The study combined signal processing algorithms with advanced pattern recognition techniques to analyse the data and derive accurate respiratory measurements from the thermal and radar signals.

    - Key Findings
- Both thermal IR and radar-based systems were able to monitor breathing patterns accurately in real-time, with the radar being especially useful in noisy environments or situations where the thermal signal could be obscured (e.g., in low-light conditions).
- The system was successfully applied in a hospital setting, where it allowed continuous monitoring of patients with respiratory issues without the need for direct contact, which is vital for infection control.
- The approach could detect irregularities in breathing, such as signs of respiratory distress, offering an advantage in medical diagnostics.

    - Relevance
- Massaroni et al.'s study is directly relevant to pandemic response strategies, where contactless monitoring of respiratory functions is a critical tool for preventing the spread of infections, especially in hospital or healthcare settings.
- Their findings highlight the importance of developing safe, non-contact monitoring methods in situations where reducing physical contact is crucial, such as in COVID-19 management.

    - Comparative Analysis (see Table 5)

Table 5. Comparative analysis

Aspect	**Malešević et al. (2020)**	**Xiong et al. (2020)**	**Massaroni et al. (2020)**	**Our paper**
Focus Area	Contactless heart rate monitoring	Multi-target respiratory monitoring	Non-contact respiratory monitoring, especially in pandemic settings	Contactless Monitoring of Abnormality in Breathing Pattern
Technology	Millimeter-wave radar	Microwave radar, FMCW radar	Radar, thermal infrared imaging	Pulsed Coherent Radar
Application	Heart rate monitoring in healthcare, elderly care, medical procedures	Simultaneous respiratory monitoring of multiple individuals in crowded environments	Respiratory monitoring during the COVID-19 pandemic, hospital settings	Detection of abnormality in breathing pattern
Methodology	Signal processing for heart rate extraction using radar	Multi-target detection algorithms, radar-based respiratory rate estimation	Combination of radar and thermal imaging for respiratory monitoring	Machine Learning methods for abnormality detection in breathing pattern
Key Findings	Accurate heart rate detection without contact, robust to body movement	Accurate multi-target respiratory monitoring, scalable for crowded environments	Successful contactless respiratory monitoring for pandemic management, real-time monitoring of respiratory distress	Successful contactless abnormality detection in breathing pattern.
Limitations	Sensitivity to noise, single-target focus	Potential interference in crowded settings, complexity of multi-target tracking	Thermal system limitations in low light, radar signal processing challenges	Real-time monitoring, resource-constrained environments, environments with large-scale sensors.
Relevance	Remote heart rate monitoring, especially in non-invasive scenarios	Public health monitoring, emergency response, real-time tracking	Pandemic settings, hospital infection control, non-contact monitoring	Remote detection of breathing abnormalities, especially in the home and nursing home environment

6. Future research direction

Contactless monitoring of breathing patterns, particularly using technologies such as radar, infrared, ultrasound, or cameras, has garnered significant interest in healthcare and wellness applications. The ability to detect abnormalities in breathing patterns (such as those caused by respiratory diseases, sleep apnea, COPD, or COVID-19) without physical contact can provide numerous advantages in terms of comfort, hygiene, and continuous monitoring. The integration of machine learning methods into such systems offers promising opportunities for improving accuracy, scalability, and real-time decision-making.

Future research directions to explore in the field of contactless monitoring of abnormal breathing patterns using machine learning methods:

Explainable AI (XAI) for Healthcare Applications

Healthcare professionals need not only accurate predictions of abnormal breathing patterns but also **explainable** insights that help understand why a particular abnormality was detected. Traditional machine learning models often function as "black boxes," which hinders their practical use in medical settings.

Research Directions:

- Develop Explainable Models: Investigate explainable AI techniques, such as SHAP values, LIME, and attention mechanisms in neural networks, to provide interpretability to complex machine learning models. These methods could help clinicians understand the features or patterns that triggered a particular prediction.
- Visualisation of Breathing Patterns: Create visualisations (such as heatmaps or saliency maps) to demonstrate which areas or movements in the breathing cycle are associated with abnormalities, enabling practitioners to better diagnose and understand the underlying causes.
- Real-time Feedback: Develop real-time, patient-specific feedback systems that give clinicians actionable insights, helping them monitor changes in breathing patterns over time and make clinical decisions.

Personalised Monitoring Systems

Different individuals have unique baseline breathing patterns, which can vary due to factors such as age, gender, weight, and existing health conditions. Personalised models are needed to account for this individual variability when monitoring for abnormalities.

Research Directions:

- Personalised Machine Learning Models: Develop machine learning algorithms that can learn and adapt to individual patterns. For instance, using a patient's historical data (such as breathing patterns collected over time), models can generate personalised baselines for each individual and detect deviations from their normal patterns.
- Dynamic Adaptation: Investigate online learning techniques where models continuously adapt to changes in the individual's breathing patterns, making them more sensitive to subtle shifts over time.
- Transfer Learning: Explore the use of transfer learning to leverage knowledge from one patient's data to help in monitoring another, especially when large amounts of labeled data for new patients are not available.

Unsupervised and Semi-supervised Learning

Labeled data for abnormal breathing patterns is often limited, especially for rare conditions or in specific populations (e.g., pediatric or geriatric patients). Unsupervised and semi-supervised learning methods can help alleviate the dependency on large labeled datasets.

Research Directions:

- Unsupervised Anomaly Detection: Explore unsupervised learning techniques such as autoencoders or clustering algorithms (e.g., DBSCAN) to detect abnormal breathing patterns without requiring labeled data.
- Semi-supervised Learning: Develop semi-supervised learning techniques that combine a small amount of labeled data with a large amount of unlabeled data, enabling better generalisation to new cases without needing exhaustive labeling of every instance.
- Generative Models: Investigate generative adversarial networks (GANs) to synthesise realistic breathing patterns that can be used to augment training data, especially for rare or underrepresented conditions.

7. Conclusions

To automatically distinguish whether the supervised individual is breathing normally or not, machine learning methods including kNN and ANN-MLP were used.

Despite the promising outcomes and the fact that no time is spent on actual model construction, being equivalent to the training data, the classification of examples takes a relatively long period of time, even with the adoption of more efficient algorithmic search methods, such as BallTree or kD Tree instead of a linear search. Therefore, we opted to conduct a study on the utilisation of Artificial Neural Networks for further analysing the datasets. While the training time is notably longer compared to the kNN search, once the network is trained, it can provide exceptionally swift responses.

While both kNN and ANNs have their merits for breathing detection, their limitations such as sensitivity to noise, computational complexity, overfitting, and data requirements pose challenges, particularly in real-time, resource-constrained, and high-dimensional sensor environments. Overcoming these limitations requires strategies such as data pre-processing, feature selection, dimensionality reduction, and model simplification to ensure accurate and reliable breathing detection.

The integration of machine learning methods in contactless monitoring of abnormal breathing patterns is a promising and evolving area of research, with significant potential to improve early diagnosis and personalised care. The future directions outlined above highlight the importance of developing robust, scalable, and explainable systems while addressing challenges such as limited labeled data, sensor fusion, and real-world validation. As these technologies advance, they could play a critical role in preventive healthcare, chronic disease management, and pandemic surveillance.

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