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Systematic review: State-of-the-art in sensor-based abnormality respiration classification approaches

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ABSTRACT

Respiration-related disease refers to a wide range of conditions, including influenza, pneumonia, asthma, sudden infant death syndrome (SIDS) and the latest outbreak, coronavirus disease 2019 (COVID-19), and many other respiration issues. However, real-time monitoring for the detection of respiratory disorders is currently lacking and needs to be improved. Real-time respiratory measures are necessary since unsupervised treatment of respiratory problems is the main contributor to the rising death rate. Thus, this paper reviewed the classification of the respiratory signal using two different approaches for real-time monitoring applications. This research explores machine learning and deep learning approaches to forecasting respiration conditions. Every consumption of these approaches has been discussed and reviewed. In addition, the current study is reviewed to identify critical directions for developing respiration real-time applications.

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1. INTRODUCTION

All living things engage in respiration, which is a fundamental activity. It is the method by which cells transform oxygen and nutrients into energy, which is used to carry out numerous cellular processes. For example, the cells use this process to absorb oxygen and expel carbon dioxide as waste. Life cannot exist without respiration, which is vital for maintaining an organism's metabolic processes.

The act of respiration involves moving air into and out of the lungs to enable gas exchange with the internal environment, primarily to expel carbon dioxide and draw in oxygen. The breathing rate, often known as the respiratory rate, is one of the four leading vital indicators measured in respiratory cycles per minute. Under typical circumstances, several homeostatic systems that regulate the partial pressures of carbon dioxide and oxygen in the arterial circulation maintain consistent control over the depth and rate of respiration. Besides, respiration is the most crucial measure of a patient's risk for life-threatening diseases. Therefore, various emergency medicine algorithms say that before pursuing further diagnostic or therapeutic procedures, normal respiration must first be confirmed and ensured [1], [2]. Moreover, the respiratory system is part of the body that delivers oxygen and removes carbon dioxide to tightly regulate the partial pressures of oxygen and carbon dioxide in arterial blood. These roles are partially accomplished by setting the respiratory rate and tidal volume. Normal tidal breathing comprises inspiratory and expiratory phases and occurs with synchronous movements of the thorax and abdomen [3]. Respiratory muscles produce physiological signals known as respiratory signals during inhalation and expiration. The displacement of the chest wall, airflow sensors, and pressure transducers are just a few of the methods that can be used to measure these signals.

Besides, Figure 1 explains the respiratory signal's pattern over time. The amplitude or strength of the signal is shown on the y-axis, and time is shown on the x-axis. The signal usually consists of inhaled and exhaled breaths separated by pauses. As the diaphragm contracts during inhalation, the chest enlarges, drawing air into the lungs. The respiratory signal's amplitude rises because of this. As the diaphragm relaxes and the chest contracts, the air is forced out of the lungs during exhalation. The respiratory signal's amplitude decreases as a result. Numerous aspects of respiration, including the respiratory rate, the depth of each breath, and the variability of the signal over time, can be studied using the respiratory signal. Diagnosing respiratory disorders and gaining insight into how the respiratory system works by analyzing these features is possible.

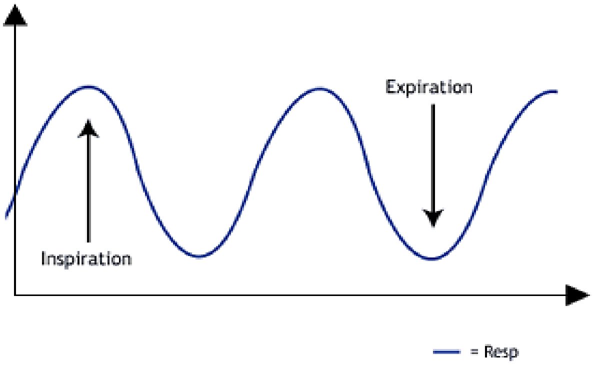

Figure 1. Respiration signal

An indicator of ventilation, or the flow of air into and out of the lungs, the respiration rate, often known as the number of breaths per minute, is a clinical measure. As the body tries to keep the tissues' oxygen supply going, a shift in respiration rate is frequently the first indication of deterioration [4], [5]. For pulmonary disorders, respiration rates and patterns may be used to diagnose and track a person's health concerns. While the average resting respiration rate varies from person to person, it generally ranges from 12 to 20 bpm (breaths per minute). Besides, there are three types of abnormal respiratory rates which are tachypnea (high respiratory rate), bradypnea (low respiratory rate), and apnea (cessation of respiration) [6]. The primary respiratory muscle's diaphragm flattens and contracts typically during inspiration, pulling on the belly and pushing the lower ribs forward and outward [7]. For thousands of years, Eastern civilizations have managed one's breath to improve or restore one's health. For instance, yogic respiration (pranayama) is a well-known, age-old regulated respiration technique frequently used with yoga or meditation because of it is purported spiritual and health-improving benefits.

Pranayama is a type of yoga that focuses on controlling one's breath. There are several forms of pranayama, each with its own set of advantages. Improved respiratory function, less stress and anxiety, increased energy levels, improved focus and attention, enhanced relaxation, and increased self-awareness are some of the benefits of pranayama. A person's respiratory rate is regulated by a variety of factors, including age, exercise level, and body temperature. Although the typical respiration rate varies significantly across individuals, doctors and nurses regard a certain range to be normal. Table 1 presents the type of respiration rate condition according to age from newborn to adult.

However, tachypnea is the earliest observable clinical symptom and the patient's means of compensating for the restricted lung capacity caused by restrictive lung disease. The activation of auxiliary muscles results in further compensation. Patients with restricted illness may occasionally take larger-than-tidal sighs to attract collapsing units. Infected lungs' compensatory mechanisms also work to improve gas exchange [8]. Thus, each pattern is clinically essential and valuable in evaluating patients [9]. In medicine, respiration measurement is a crucial marker for the early identification of major human disorders. Reportedly, data on respiration can be used to predict pneumonia, cardiopulmonary arrest, and chronic heart failure. However, it has been discovered that the breath rate (BR) can distinguish between stable and unstable individuals more effectively than the heart rate (HR). Monitoring the respiratory signal may be used to identify and treat respiratory problems, including chronic obstructive pulmonary disease, one of the most prevalent long-term conditions, and to forecast cardiac arrest and diagnose hypoxemia or hypercarbia.

Table 1. Type of respiration rate condition

Type of respiration condition		Breath per minute							
		Gender		Age (year)					
		Male	Female	Newborn (Birth-1 y)	Infant (1-3 y)	Toddler (3-6 y)	Child (6 y and older)	Adult	30 y and above
Normal respiration		12-16	14-18	30-50	20-40	20-30	18-24	12-16	Respiratory rate remains constant
Abnormal respiration	*Tachypnea* (high respiratory rate)	>20		>60	>40		>30		>20
	Bradypnea (low respiratory rate)	<8-10			<16				<8-10
	Apnea (cessation of respiration)					>20			

Due to many cases of abnormal respiration occurring, many researchers study the use of technology in managing respiratory diseases. Generally, respiratory system technology has two different types of approach: contact and non-contact respiratory diseases. Generally, respiratory system technology has two types of approaches: contact and non-contact respiration measurement. Conventionally, contact-based measurement has been used widely, such as wearable sensors which can be installed within clothing [10], belts [11], [12], directly attached to the skin [13], [14], or used in other ways as wearable sensors for respiratory monitoring. There are many different approaches to creating wearable technology, and some of them are covered individually in the following sections according to the primary sensor type. The sensor, or the measured component, must be in contact with the subject's body when using contact-based measurement procedures [15]. Table 2 shows the advantage and limitations of the method of respiration measurement wearable contact based.

Table 2. The advantage and limitation of wearable contact-based respiration measurement

Type of contact-based	Advantages	Limitations
EMFit	Less invasive, and it was effective in detecting respiratory rate	The sensor was only effective for patients who were stationary or only moderately active since body motions influence the accuracy of the measurement [12].
Spirometry	Can be used to screen for respiratory disease in some high-risk scenarios. It helpful in separating cardiac disease from respiratory disease [16].	The result will be poor, and the interpretation will be tough when patient not follow the instruction while using the spirometry.
Smartphone’s microphone	For nasal respiration noises recorded by a smartphone's microphone, the accurate respiration rate can be calculated as the estimation errors [17], [18].	As background noise gets louder, accuracy began to decrease progressively the further users were from the source of the respiration sound.
Impedance pneumography	Accurate assessment of several respiratory parameters. This portable, affordable device could help with healthcare [19].	Analyses are difficult to complete and require specialized equipment.

Due to the inconvenient limitation of contact-based, more research introduces non-contact respiration measurement. The non-contact measurement of respiratory motion is an innovative method of evaluating respiratory function. Briefly, non-contact measurements are more comfortable for the patient, especially when performing contact measurements is particularly challenging regarding the specialized equipment and complicated setup process [20]. Therefore, several techniques that do not require touch sensors to be connected to the patient have been developed to reduce patient pain and increase the accessibility of respiratory data, including thermal imaging, microwave-based, and radar-based techniques. For instance, these are a few examples that are frequently used in a clinical setting which are doppler radar [21], depth sensors [22], laser vibrometry [23], and RGB cameras [24], [25]. However, the practical use of these techniques is constrained by the requirement for rather large periods and assumptions regarding the regularity of respiration rate [26]. Table 3 displays the advantage and limitation of the type of non-contact method reviewed.

Non-contact techniques for measuring respiration have drawn more attention in recent years. Thus, the creation of new technologies and the rising demand for non-invasive and remote monitoring solutions in healthcare and wellness applications. Compared to contact methods, non-contact techniques for measuring respiration have a few benefits. They are non-invasive, which means the user can use them more easily and comfortably because no sensors or electrodes need to be affixed to the body. They also eliminate the potential for skin infections or rashes that contact sensors may bring on. Non-contact techniques can also be used when it is impractical to use contact techniques, such as when the user is sleeping or moving around. In the current coronavirus disease 2019 (COVID-19) pandemic context, where there is an increasing need for telemedicine solutions, they can also be used for remote monitoring. The ability to analyze non-contact signals, such as those obtained from cameras or microphones, and extract valuable data about respiration, such as the respiratory rate, depth, and variability, has been made possible by advances in computer vision and machine learning. As a result, new opportunities for tracking changes in respiration patterns over time and monitoring and diagnosing respiratory disorders using non-contact techniques have come to light. In the climax, the advantages of non-contact methods for measuring respiration over contact methods, the development of new technologies, and the rising need for non-invasive and remote monitoring solutions in healthcare and wellness applications all contribute to the growing interest in these methods.

Table 3. The advantage and limitations of non-contact respiration measurement

Type of non-contact method	Advantages	Limitations
RGB video camera system [24], [27], [28]	A simple camera using standard-resolution images can be used. Some methods are easy to use and could be used in the ward or home environment.	Body movement can shift the face from the camera's range of view for long-term (like nighttime) surveillance. A feedback system would be required. The monitoring cannot continue if hands, blankets, or any hide the face.
Doppler radar [21]	It can be used at long distances. Possibility of wireless transfer of respiratory rate data to the central unit.	Movement creates artefacts which alter the respiratory rate signal. Currently expensive and challenging to set up.
Laser vibrometry [29]	The post-processing is primary and uses real-time output. However, it is a significant stand-off distance non-contact displacement measurement as well.	Less accessibility
Ultra-wideband [30], [31]	The ultra-wide band (UWB) radar sensor demonstrated very accurate respiration measurement.	The accuracy could suffer from obstacles between the human body and the sensor.
Thermal imaging [32]	Compared to other techniques for measuring respiratory rate, it could be more impartial and reliable [33]	Successive evaluations of the object's distance from the camera, its variations in movement, temperature, and humidity, as well as the creation of a costly monitor.

Breathing signals are a form of physiological signal used to evaluate respiratory health. It can be used to diagnose respiratory disorders, follow changes in respiratory health over time, and monitor patients with respiratory illnesses. The data review in this research paper is based on both contact and non-contact-based methods. Data classification is the process of labelling a data point. The data classification also can be used to classify respiratory signals as normal or abnormal in the context of breathing signals. There are two approaches to respiration classification: machine learning and deep learning. Knowing the differences between machine and deep learning is better before classification. Table 4 exposes the differences between machine learning and deep learning in general. Deep learning and machine learning are the two suggested methods for respiratory classification, and both are categories of artificial intelligence.

Figure 2 shows the critical difference between artificial intelligence (AI) and machine learning. In a nutshell, machine learning is AI that can automatically adapt with little human help. Hence, there are four categories of machine learning algorithms: supervised, semi-supervised, unsupervised and reinforcement learning.

In supervised learning, the computer uses guidance to infer a function from the data, and it is divided into three main types: classification, regression and forecasting. The typical algorithm is k-nearest neighbor (KNN), naive Bayes (NB), decision trees (DT), linear regression (LR), support vector machines (SVM) and neural networks. Besides, semi-supervised learning uses labelled and unlabeled data comparable to supervised learning. Unlabeled data has no meaningful tags, whereas labelled data has them, so the algorithm can interpret them. Machine learning systems can learn to categorize unlabeled data using this combination. Whereas in unsupervised learning, the computer finds a pattern on its own. Clustering and association rule learning algorithms are the two primary categories of unsupervised learning algorithms. The typical algorithm used is k-means clustering and association rules. Other than that, the Reinforcement Learning approach uses observations from interacting with the environment to adopt behaviors that maximize the reward or minimize the risk. The agent, a reinforcement learning algorithm, iteratively continually learns from the environment. The agent gradually gains knowledge from encounters with the environment until it has investigated every state. Machine learning, which includes reinforcement learning, is a subset of artificial intelligence. It enables software agents and machines to automatically decide the best course of action within a particular situation to maximize performance. The reinforcement signal, or simple reward feedback, is necessary for the agent to learn its behavior. Thus, the standard algorithm consists of Q-learning, temporal difference (TD) and deep adversarial network.

Table 4. Comparison between machine learning and deep learning

Parameter	Machine learning	Deep learning
Execution time	While testing a model with a machine learning algorithm takes longer, it takes less time to train the model than deep learning.	Deep learning requires much processing time during model training but less during model testing.
Hardware dependency	Machine learning models can be used on low-end machines because they do not require much data.	A high-end system with graphics processing unit (GPUs) is required because the deep learning model requires a large amount of data to operate effectively.
Data dependency	Even though machine learning requires a large quantity of data, it can function with less data.	For deep learning algorithms to perform well, users must feed them with much data because they rely heavily on it.
Feature engineering	Before moving forward, machine learning models require feature extraction by a professional.	Since deep learning is an improved form of machine learning, it does not require the creation of a feature extractor for every issue but instead attempts to learn high-level features independently from the data.
Interpretation of result	For a specific problem, the result is simple to interpret. Furthermore, because it can quickly analyze the results when using machine learning, it is clear why a result occurred and how the process worked.	It is exceedingly difficult to interpret the results for a specific problem. For example, while using a deep learning model, it is difficult to determine why the specific result that occurred is a better solution than a machine learning model.
Problem solving approach	The standard machine learning methodology divides a problem into smaller components and solves each separately before producing the final answer.	A deep learning model accepts input for a specific problem and produces the solution, which differs from a typical ML model's problem-solving approach. Consequently, it adheres to the end-to-end method.
Type of data	Most often, structured data is needed for machine learning models.	Deep learning models rely on artificial neural network layers and can process structured and unstructured data.
Suitable	A simple or complex problem can be solved using machine learning models.	Deep learning models are appropriate for resolving challenging issues.

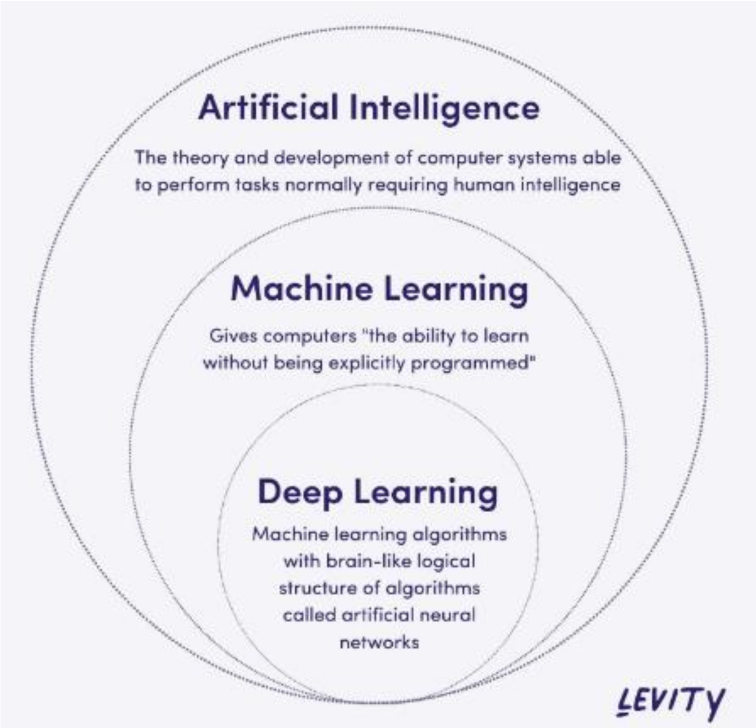

Figure 1. The difference between AI and machine learning [34]

Machine learning algorithms can analyze vast information and uncover complicated patterns that people cannot see. As a result, machine learning algorithms can produce better predictions than traditional statistical methods. Furthermore, machine learning algorithms can analyze data that cannot be simply represented numerically, such as photos, audio, and text. The ability of machine learning algorithms to analyze data that cannot be easily represented numerically has opened up new study avenues. This is particularly true in healthcare, where machine learning algorithms are being utilized to produce new diagnostic tools and therapies.

Deep learning is a kind of machine learning that uses artificial neural networks (ANN) to simulate how the human brain learns. The popularity of deep learning, a branch of machine learning, has grown recently as researchers' access to data has multiplied quickly. These techniques enable the algorithm to automatically find the unique features and transformations necessary for the task in the raw data instead of depending on a researcher's judgement and experience to choose and engineer characteristics [35]. Therefore, deep learning is currently being used to improve speech significantly [36], [37] and picture recognition, respectively. In the field of computer vision and pattern recognition (CVPR), deep learning is one of the most effective and popular methods [35], [36], [38], and could lead to a better understanding of behavior and physiological patterns to an individual's affective moods such as distress, anxiety and any else.

To solve problems involving unstructured data, deep learning networks are the mathematical models used to mimic human brains [39], [40]. Besides, Figure 3 represents the simple neural network. These mathematical models are developed as neural networks, which are made up of neurons. The input layer (initial layer of the neural network), the hidden layer (all the middle layer of the neural network), and the output layer are the three main layers (last layer of the neural network). While self-learning representations are a feature of deep learning algorithms, they also rely on ANNs that simulate how the brain processes information [41]. Algorithms exploit unknown elements in the input distribution throughout the training phase to extract features, classify objects, and identify relevant data patterns. It takes place on several levels, employing the algorithms to create the models, much like training machines to learn for themselves. There are a few lists of deep learning algorithm methods that can be used in this era of globalization to classify the signal of respiration, such as convolutional neural networks (CNNs), long short-term memory networks (LSTMs), recurrent neural networks (RNNs), generative adversarial networks (GANs), radial basis function networks (RBFNs), multilayer perceptrons (MLPs), self-organizing maps (SOMs), deep belief networks (DBNs), restricted Boltzmann machines (RBMs) and autoencoders [41].

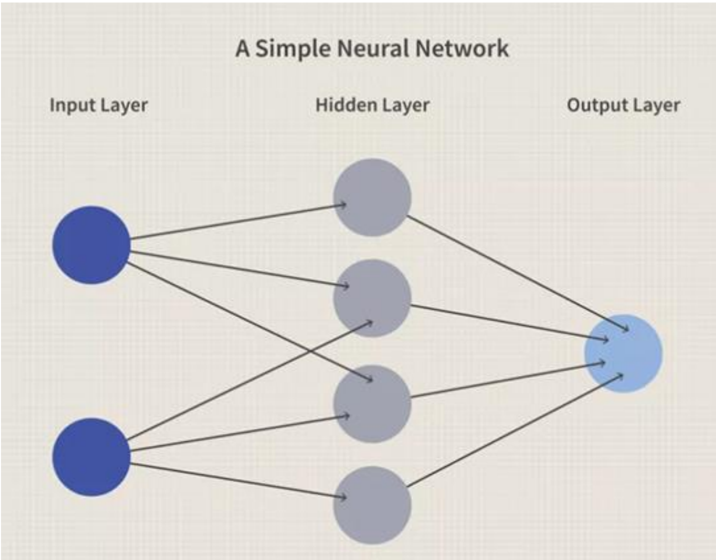

Figure 3. Simple neural network

Depending on the application and the available data, deep learning and machine learning may be effective for classifying respiratory signals. Classifying respiratory signals can be accomplished using either deep learning or machine learning; the chosen approach depends on the task and available data. For example, deep learning will be a good alternative if they want to achieve high accuracy and have a large dataset of raw respiratory signals. On the other hand, if they need more interpretability or have a limited dataset, machine learning may be the better choice.

2. METHOD

In this section, the data classification approaches are reviewed. We used Scopus to do a database search and it is about more than 100 kinds of literature searches on the topic of the data classification of breathing signals. However, not all of the literature searches were included in the final review. Luckily found

66 relevant article papers which are 10 article papers on machine learning classification, 16 article papers on deep learning classification and the remaining article papers about radar sensor-based. The research topic had to employ machine learning or deep learning to categorize breathing signals, use a dataset of breathing signals from healthy controls and patients with respiratory diseases, and describe the classification algorithm's accuracy. At the same time, the research topic was excluded because the research paper was not in English and did not report the classification algorithm's accuracy. The advantages, the limitations, and the main applications of the methods were described along with their technical classification by their algorithm use in the review.

2.1. Classification of respiration using machine learning

For the classification of respiration patterns for both real-time and simulated respiration data, various machine learning techniques were used. Nevertheless, in this paper, supervised learning is a suitable algorithm for respiration classification. Furthermore, it has been demonstrated that using simulated data for training purposes increases accuracy. The article suggests a framework for enhancing machine learning datasets to increase the precision of classifiers. Using a supervised learning methodology, Rehman *et al.* [42] evaluate several machine learning algorithms, such as DT, SVM, and ANN. The dataset is made up of respiratory signals that were captured from 35 patients, including healthy people and those who had different respiratory conditions. The authors divided the dataset into training and testing sets before using data augmentation methods like random cropping and rotation to produce more training data. Then, using metrics like accuracy, precision, recall, and F1 score, the authors trained several machine learning classifiers on the improved dataset. They discovered that adding augmented data increased the classifiers' accuracy, with ANNs producing the best outcomes.

The KNN algorithm categorizes the test data based on the majority class of the KNN after identifying the KNN in the training data. The SVM algorithm divides the data into various classes using hyperplanes and maximizes the distance between the hyperplanes to achieve the best classification. Then, the random forest (RF) algorithm builds multiple decision trees and combines the classification [43]. The authors used accuracy, sensitivity, and specificity metrics to assess the performance of the three algorithms. According to the results, the KNN algorithm had the highest accuracy (97.2%), followed by the SVM algorithm (94.6% accuracy) and the RF algorithm (92.9% accuracy).

The comparison with different machine learning methods was included in this. The system consists of three components: data preparation, disease prediction, and user interface development. Other than that, the dependability of machine learning algorithms is significantly impacted by these discrepancies in variable input coding, and the algorithm's external validity is constrained by the variation in input variables among institutions [44]. Like subject population variations, machine learning model generalizability is constrained.

Then another one of the simplest machine learning methods to comprehend is the KNN classification technique [45]. This review [46] recognized pulmonary acoustic signals from 10 healthy volunteers and 95 patients with respiratory illnesses. They took 20 features out of the signals and trained and tested the SVM and KNN classifiers with them. The study's findings demonstrated that, in terms of accuracy, sensitivity, and specificity, the SVM outperformed the KNN method. Furthermore, the SVM and KNN were employed as two separate classifiers, and it shows that the KNN classifier is better than the SVM classifier. Thus, the classification accuracy results were satisfactory despite the small amount of data utilized to train and test the classifiers.

The study combines patient demographic and medical information with respiratory rate to achieve robust performance. Several machine learning classifiers are used by the authors [47], including NB, SVM, RF, KNN, AdaBoost, and two deep-learning models a CNN and an LSTM network. The proposed approach performs well when additional variables are combined with the respiration rate, and a comparison to earlier research attests to its superiority. The findings show that, with 93% accuracy, the LSTM model beats all other models used. Also, the performance of the suggested approach is contrasted with that of previous studies, demonstrating the proposed approaches superior performance.

The author developed an "Ensemble of regression trees" a computer vision method, to automatically follow the nostrils in the presence of significant head movement and object occlusion [48]. Also, they created a revolutionary "Breath detection algorithm" (BDA) that distinguishes between normal and abnormal breaths based on predetermined thresholds and calculates breaths per minute automatically. The proposed algorithm's accuracy, sensitivity, spurious cycle rate, and missing cycle rate metrics were tested on 80 respiration waveforms under various conditions. To categorize the human volunteer as having normal or abnormal respiration or experiencing Bradypnea or Tachypnea, the parameters obtained from the proposed BDA were then input to a 10-fold cross-validation KNN classifier. Therefore, Table 5 [42]–[44], [46], [48]–[51] summarizes the advantages and disadvantages of using a machine learning algorithm.

Table 5. The advantages and disadvantages of using a machine learning algorithm

Algorithm	Data input	Finding	Advantage	Limitation
Cosine KNN, complex tree, ensemble boosted tree and linear SVM [42]	RF-based technologies were used to collect a dataset of respiratory abnormalities. There are eight types of breathing irregularities in the dataset: eupnea, bradypnea, tachypnea, Biot, sighing, Kussmaul, Cheyne-stokes, and central sleep apnea (CSA).	It entails building a high-quality dataset using data augmentation methods and instructed supervised learning classifiers to classify respiration abnormalities precisely.	Classifier accuracy can be increased by using data augmentation techniques, and a supervised learning approach	Improved datasets could still have flaws and biases that reduce classification precision. The generalizability of the algorithms used in this study to more extensive and more varied datasets is unknown
KNN, SVM, and RF [43]	Breathing sounds from persons with respiratory problems were recorded and utilized to generate spectrogram images. The images were then used to train a CNN model, which was capable of reliably classifying various respiratory diseases.	The potential of using lung sounds to accurately classify respiratory lung diseases for the rapid and precise diagnosis of respiratory diseases.	Useful for analyzing respiratory sounds and spotting patterns that might be suggestive of respiratory diseases	Only respiratory sounds were used in the research as the input data for the machine learning algorithms.
SVM, DT, RF, and gradient boosting [44]	When vitals are examined more regularly, an algorithm trained on electronic medical record (EMR) data may learn that a patient is more prone to decompensate.	Using data from electronic health records (EHRs) to predict the onset of acute respiratory failure (ARF) and acute respiratory distress syndrome (ARDS) in hospitalized patients.	It shows the use of ML to anticipate the onset of ARF and ARDS, which can help with early diagnosis and treatment of these illnesses and improve patient outcomes.	The lack of external validation for the machine learning models in the study restricts the generalizability of the findings beyond the study's patient group and EHR system.
KNN and SVM [46]	A dataset of respiratory sounds from the R.A.L.E lung sound database was used as the study's data input. Normal, airway obstruction pathology, and parenchymal pathology are the three classes of pulmonary acoustic signals that are manually classified.	Pulmonary acoustic signals can be used to identify respiratory illnesses accurately	The study emphasizes the significance of feature selection strategies to decrease the dimension of the data and enhance classification accuracy.	It only used a tiny dataset, which might make the findings less generalizable.
KNN [48]	A dataset of thermal camera recordings of human nostrils from healthy adults and babies was used as the study's data input. The breathing rate is labelled on the recordings as normal or abnormal.	The resulting respiration waveform is subsequently processed with the appropriate filtering techniques to increase the signal-to-noise ratio (SNR).	The suggested algorithm can discriminate between fast and slow respiration and between normal and abnormal breaths, which can help diagnose and treat respiratory illnesses.	The research does not mention the performance of the proposed algorithm compared to previous non-contact respiratory monitoring algorithms. Therefore, how the suggested algorithm stacks up against other cutting-edge techniques is unknown without this comparison.
Naïve Bayes [49]	The exhaled airflow collected by the microphone serves as the input data for the real-time contactless respiration monitoring system. The airflow is converted into an electrical signal via the microphone, which is then analyzed using blind source separation (BSS) and the NB classifier.	Employing BSS enables the ICA algorithm to distinguish between respiratory signals.	When used for disease categorization, the Nave Bayes classifier is computationally effective and can produce good results with limited data sets.	External elements like noise and motion artefacts could have an impact on this.
LDA, SVM, FNN, DT, RF, and ANN [50]	A dataset of breathing sounds is used as input for the respiratory pattern classification task. The dataset includes recordings of respiratory sounds from both healthy people and people with respiratory disorders. Some of the recordings in the collection have missing data since they were made in loud environments.	The issue of missing data in respiratory signals can be effectively solved by using various imputation strategies.	Enhancing the classification of respiration patterns is highlighted in the paper.	Utilized a limited dataset, so it is possible that the findings would not apply to a more extensive dataset.
KNN [51]	Seismocardiography (SCG) signals were gathered from both healthy individuals and people with heart conditions. The breathing and lung volume phases of the recordings were noted, and they were saved as digital audio files. Either inspiration or expiration are the phases of respiration.	The dataset contains seismocardiographic signals from ten healthy participants, and independent component analysis (ICA) is used to disentangle the signals into their parts.	The algorithm successfully separated the respiratory and non-respiratory components and correctly classified the signals with high sensitivity and specificity.	The KNN technique differed from other machine learning algorithms in the study, which would have shed light on the relative performance of various approaches.

2.2. Classification of respiration using deep learning

Recently, researchers have demonstrated the effectiveness of CNN based models in a range of issues, from image classification to semantic segmentation, proving that the models can produce better learning performances than earlier deep learning approaches [36], [38], [52]. The CNN-based model predicts respiration signal values from the subject action waveform. The design was first set forward and researched for use in a variety of identification processing applications, including gender recognition, and more recently for the detection of behavior (e.g. depression) [53]. Additional research has been done to clarify how this method models the source and system-related information in the linked signal. This architecture was included in the article under review because the respiration signal can be closely tied to the signal's source. Other than that, this author [54] developed a unique algorithm to categorize abnormal and normal respiration episodes using the signal decomposition method. Additionally, the system performed better in accuracy than the current best practices.

CNN, recurrent neural networks (RNN), or hybrid architectures are the most common deep learning classifiers used today to analyze respiratory sound spectrograms. The architectures used by CNN-based systems range widely, including LeNet6 [55], [56], VGG5 [57], two parallel VGG16s [58], and ResNet50 [59]. A CNN was initially utilized to translate a spectrogram input to a temporal sequence in relation to the hybrid architectures suggested in [58], [60]. Prior to classification using fully-connected layers, sequence structures were first learned using LSTM or gated recurrent unit (GRU) layers.

For instance, Perna and Tagarelli [61] offers a RNN-based system to forecast respiratory abnormalities and illnesses using lung sounds. The analysis of the classification of abnormal respiratory sounds and respiratory illnesses using a LSTM network. The approach comprises three steps: feature extraction, classification, and data pre-processing. The authors employ a digital stethoscope to record the patients' lung sounds during the data preparation stage. The data is then separated into fixed-length segments after pre-processing to reduce noise and artefacts. Next, the authors turn each segment into a spectrogram representation during the feature extraction stage using a time-frequency analysis approach known as the short-time Fourier transform (STFT). A trained RNN is then fed the spectrogram to extract pertinent features from the lung sounds. The retrieved RNN features are used to predict the presence or absence of respiratory abnormalities and illnesses during the classification step. Finally, the authors calculate the probability of each class for each segment using a machine learning algorithm. Then they add the probabilities for all segments to get a final prognosis for the patient. The method is assessed using a dataset of patients with various respiratory diseases. The findings demonstrate that the overall algorithm is highly accurate in identifying respiratory abnormalities and illnesses.

The other paper introduced a novel design called the noise masking RNN [62], which intended to discriminate noise and strange respiratory sounds by utilizing LSTM and GRU cells in an RNN-based network. The approach is divided into four steps: feature extraction, noise masking, classification, and data pre-processing. First, the authors record patient respiration sounds with a digital stethoscope during the data preparation stage. After that, the data is pre-processed to eliminate any noise and artefacts. Next, the authors apply a STFT to turn each segment into a spectrogram representation during the feature extraction stage. Then, to extract pertinent features from the respiratory sounds, the spectrogram is passed to a trained RNN. Next, to increase the robustness of the RNN to fluctuations in respiratory sounds, the scientists add random Gaussian noise to the retrieved features during the noise masking stage. Finally, the features with the additional noise are utilized to predict the presence or absence of respiratory illnesses during the classification stage.

Moreover, Alqudah *et al.* [63] focused on using several deep learning models, as demonstrated by the combination of CNN and LSTM neural networks. The developed models attained high levels of performance. The hybrid CNN-LSTM model yielded the highest accuracy, sensitivity, and specificity results, which pave the path for applying deep learning in clinical contexts at 100%, 100%, and 100%, respectively. This paper reviewed proposed a deep learning model based on a combination of LSTM, CNNs, and both. As classification techniques, various deep learning models like CNN, LSTM, and CNN-LSTM were used, and the results were compared. According to the experimental findings, the hybrid CNN-LSTM classification model performs better than the CNN and LSTM methods frequently used in the literature. Through developing and applying deep learning models in clinical contexts, this research paves the path for doctors to make highly accurate decisions. Therefore, according to the papers that have been reviewed, it is shown that CNNs is the most popular deep learning algorithm used to classify the respiration rate system.

Kim *et al.* [64] suggests using deep learning to classify respiratory sounds such as crackles, wheezes, and rhonchi in the clinical setting. It is found that 1,918 datasets of respiratory sounds captured in a clinical context was divided into categories by the author using deep learning CNN. By fusing a pre-trained picture feature extractor of series, respiratory sound, and CNN classifier, they create a prediction model for respiratory sound classification. The authors state that their work provides good classification accuracy for respiratory sounds, although the categorization excludes pneumonia.

The author classifies the data into several respiration patterns, such as typical respiration, shallow respiration, deep respiration, and rapid respiration, using a deep learning technique, namely a CNN [65]. The study found that the suggested strategy highly accurately classified various respiration patterns using information gathered from wearable sensors. To further highlight the potential for clinical applications, the authors also demonstrated how their technique might be used to detect respiration patterns in real-time. Using a convolutional neural network, [55] suggests classifying respiratory sounds. To achieve this, they created a visual representation of each audio sample that allows identifying resources for classification using the same techniques used to classify images with high precision. They also extracted resources using Mel frequency cepstral coefficients (MFCCs) to classify respiratory diseases. Therefore, Table 6 summarizes the advantages and disadvantages of using a deep learning algorithm.

Table 2. The advantages and disadvantages of using a deep learning algorithm

Algorithm	Data input	Finding	Advantage	Limitation
CNN, RNN and hybrid CNN+RNN [53]	A dataset of speech data is used as the study's data input. The data is gathered from a variety of speakers, including those who are healthy and those who have respiratory conditions.	Suggest a unique method for estimating respiratory parameters from speech recordings using deep learning architectures.	This study shows that the suggested method can estimate respiratory parameters with high accuracy and little error.	The small sample size may affect how generalizable the findings are and the absence of comparisons with established techniques for measuring respiratory parameters.
CNN and ANN [59]	The study's data input is a dataset of digital respiratory sounds. The optimized S-Transform is a signal processing approach for emphasizing the characteristics of wheeze, crackle, and normal noises.	Suggest a novel technique for recognizing wheeze, crackle, and normal respiratory sounds utilizing deep residual networks and optimal S-transform (OST) (ResNets).	In the multi-classification of respiratory sounds, the suggested method using optimal S-transform (OST) and deep residual networks (ResNets) showed good accuracy, sensitivity, and specificity.	The study did not compare the proposed method to other cutting-edge approaches that use various feature extraction and classification strategies, which might have revealed more information about the performance of the suggested method.
RNN [61]	Patients with a range of respiratory diseases contributed to a dataset of respiratory auscultation sound data. To create data features related to respiratory illnesses, the data was pre-processed using state-of-the-art feature extraction methods.	The approach suggested in this paper is well-designed and efficient in using lung sounds to predict respiratory abnormalities and illnesses.	The algorithm has high accuracy in identifying respiratory abnormalities and disorders, making it a reliable tool for respiratory categorization.	The algorithm can only categorize respiratory abnormalities and diseases based on lung sounds.
Noise masking recurrent neural network (NMRNN) [62]	A dataset of lung sound data was used as the study's data input. Data is gathered from patients suffering from various respiratory disorders.	The algorithm attempts to isolate only critical respiratory-like frames free of extraneous noise and classifies lung sounds into four groups: normal, containing wheezes, containing crackles, and containing both wheezes and crackles.	The computational cost and time needed for feature extraction are decreased by the NMRNN algorithm, which effectively extracts pertinent features from lung sounds using a pre-trained RNN.	The NMRNN algorithm, like many deep learning algorithms, is tricky to interpret, making it challenging to comprehend how it generates its predictions.
CNN-LTSM [63]	A dataset of raw lung auscultation sounds was used as the study's data input. Data is gathered from patients suffering from various respiratory disorders.	This study focuses on applying deep learning models for detecting respiratory diseases utilizing raw lung auscultation sounds. It emphasizes the significance of choosing suitable deep learning models for this task.	Evaluating various deep learning models on both augmented and non-augmented datasets offers a thorough analysis of various methods for diagnosing respiratory diseases.	The study is constrained by the comparatively small dataset size, which can affect how broadly the findings can be applied.
CNN [65]	The study's data input is a dataset comprising accelerometer and gyroscopic data. The information was gathered from 100 healthy individuals who simulated various breathing episodes.	The wearable sensors and deep learning are combined to present a novel approach for classifying and detecting respiration patterns.	The use of wearable sensors to collect data on respiration patterns, the deep CNN used for classification, and the high level of accuracy attained while classifying various respiration patterns.	Using a limited sample size could affect how generalizable the findings are.
CNNs [66]	The study's data input is a dataset of respiratory sound data. The information is gathered from patients suffering from various respiratory disorders. Fourier analysis is a mathematical approach for separating a signal's constituent frequencies. This can be used to visualize a signal's spectrum, which can then be used to distinguish different sorts of sounds.	This study proposed to create an augmented dataset. The authors first add synthetic noise to the original respiratory sounds. The sounds are then divided into four groups using a deep CNN: normal, wheezing, crackles, and both.	The deep CNN model performed better due to the application of artificial noise augmentation, highlighting the value of augmented data in enhancing the robustness of deep learning models.	The study needs to analyze the deep CNN model's interpretability in detail, which may limit its clinical use.

3. DISCUSSION

Both feature engineering and feature visualization are critical strategies for machine learning and deep learning classification for respiratory disorders. The process of changing raw respiratory signal data into features that are more informative and relevant to the classification task is known as feature engineering. Feature visualization is a method for comprehending the features utilized by machine learning classifiers. For respiration-related challenges, feature engineering is more significant in machine learning classification than in deep learning classification. This is because deep learning algorithms can automatically learn features from data. However, feature engineering can still be applied to improve deep learning classifier performance for respiration-related difficulties. Besides, feature visualization is a valuable tool for both machines learning and deep learning classification of respiration-related difficulties. It can assist in identifying the features that are most significant for the classification process as well as identifying any potential problems with the data. However, feature visualization is not as frequent in deep learning classification as it is in machine learning.

In respiration classification, where the characteristics of the signals may differ significantly between individuals and even within the same individual over time, overfitting can be particularly problematic. Due to this variability, developing a machine learning model that generalizes well to novel, unexplored data may be challenging. The requirement for high-quality, labelled data to train the models effectively is another concern related to machine learning for respiration classification. Labelling respiration signals can be challenging, and labelling mistakes can introduce bias and impact how well machine learning models perform. The development and application of machine learning-based systems for respiration classification can be hampered by the time and expense of obtaining high-quality labelled data. In some clinical applications, where it is critical to comprehend how the model makes its predictions, machine learning models can be challenging to interpret. The ability of clinicians to make wise decisions based on the model's outputs may be constrained due to the black-box nature of some machine learning models, which can make it difficult to pinpoint the specific features of the respiration signals driving the model's predictions.

Thus, deep learning is a better approach to classifying the respiration signal. Respiration signal classification can benefit significantly from deep learning, which has several benefits, including learning complex features, achieving high accuracy, scaling effectively, and being versatile. When it comes to respiratory signal classification, where the signals can have complex patterns and structures, deep learning models are especially advantageous because they can automatically learn complex features from raw data without manual feature engineering. When it comes to various tasks, deep learning models can perform at the cutting edge, including the classification of respiratory signals, which is essential for both diagnosis and treatment. Deep learning models are scalable for respiratory signal classification because they are simple to scale up to handle even larger datasets. Deep learning models can also be used for various signal classification tasks, such as the analysis of respiratory sounds, the monitoring of respiration rates, and the diagnosis of sleep apnea. The use of deep learning for respiration classification has some drawbacks. Some respiratory signal classification tasks can be challenging because deep learning models frequently need more data to train effectively. It is true if the data is limited and challenging to obtain. Deep learning model training can be computationally expensive, particularly for large datasets or complex models, and it may also call for specialized hardware or cloud computing resources. In addition, deep learning models can be challenging to understand because of their complicated and opaque internal workings. It can be a drawback in medical applications where it is crucial to comprehend how the model generates its predictions.

4. CONCLUSION

In conclusion, deep learning methods outperform machine learning algorithms for categorizing respiratory signals because they can automatically learn features from data, discover complicated correlations between features, and scale to enormous datasets. Deep learning classifiers, on the other hand, do not require as much feature engineering as machine learning classifiers, can be more accurate for jobs involving complicated interactions, and can be trained on huge amounts of respiratory signal data. The respiration signal is a complex signal that includes a variety of data on respiratory function. The general state of one's respiratory system can be evaluated using simple respiratory activity indicators like respiratory rate, inspiratory time, and expiratory time. Specific respiratory illnesses can be identified using more intricate patterns and structures, like Cheyne-Stokes respiration and Biot's respiration. Healthcare workers can more accurately identify and treat respiratory problems by comprehending these patterns and structures. Deep learning models are created to automatically learn data representations that can capture intricate patterns and structures. CNNs, a popular kind of deep learning model and effective at analyzing signals like respiration signals, are one example. Because the features of interest in respiration classification may be localized to parts of the signal, CNNs are built to detect local patterns in the input data automatically. Compared to machine learning algorithms, deep learning algorithms are more complicated and require more training data.

The advantages of deep learning algorithms, however, outweigh these difficulties. Complex correlations between the features can be learned using deep learning algorithms, which may improve performance. They can also be used to personalize treatment and remotely monitor patients, as well as to diagnose disorders that are challenging to diagnose using conventional techniques. Deep learning algorithms are consequently growing in popularity in the area of medical diagnosis.

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