Review Article
Derleme Makale

Bartın University International Journal of Natural and Applied Sciences
JONAS, 5(2): 151-159 e-ISSN: 2667-5048
31 Aralık/December, 2022 DOI: 10.55930/jonas.1200072

COMPARISON OF ARTIFICIAL INTELLIGENCE PERFORMANCES OBTAINED IN DATASET CLASSIFICATIONS USING RESPIRATORY DATA

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Abstract

Diagnosis of disease with respiratory data is very important today as it was in the past. These diagnoses, which are mostly based on human experience, have begun to leave their place to machines with the development of technology. Especially with the emergence of the COVID-19 epidemic, studies on the ability of artificial intelligence to diagnose diseases by using respiratory data have increased. Sharing open-source data has paved the way for studies on this subject.

Artificial intelligence makes important contributions in many fields. In the field of health, significant accuracy results have been obtained in studies on respiratory sounds. In this article, a literat ure review on respiratory sounds and artificial intelligence achievements was made. 34 articles -that were selected from IEEE, Elsevier, Pubmed, and ScienceDirect digital databases and published after 2010- were used for comparisons. As keywords, "breathing sounds and", "respiratory sound classification", together with "artificial intelligence" and "machine learning" were chosen.

In this study, artificial intelligence methods used in 34 publications selected by literature review were compared in terms of the performances obtained in the training.

Key Words: Artificial intelligence, machine learning, respiratory sounds

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Geliş (Received) : 06.11.2022
Kabul (Accepted) : 16.12.2022
Basım (Published) : 31.12.2022

1. Introduction

Different devices (Stethoscope, EKG (Electrocardiography), EMG (electromyography), etc.) and methods (such as machine learning, deep learning methods) have been developed for years to diagnose disorders affecting human health. Among these devices, the most used device for many years is the stethoscope. A stethoscope is used to listen to body sounds. Listening to body sounds is one of the most basic methods used to have information about the body. It provides a lot of information about the respiratory organ and the symptoms of the diseases that affect it (Basu & Rana, 2020). In the history of medicine, it has been tried to make analyzes from body sounds for centuries. At first, body sounds have listened directly, then listening was performed with the help of a pipe and the foundations of the invention of the stethoscope were laid. With the invention of the stethoscope, body sounds began to be analyzed better. Mechanical stethoscopes that can filter better according to the materials used have been created and this technology continues to be used today. These technological developments have also supported the development of electronic stethoscopes. The received audio signals are transferred to digital media by passing through filters applied in electronic circuits. In this way, great convenience has been provided in the storage and analysis of data. The stored data has started to be used in the creation of artificial intelligence models to be used in studies in this field. Today, many different datasets and training models have been created from breathing sounds.

Breath sounds are classified as normal or abnormal. Normal breath sounds are non -musical sounds. Abnormal breathing sounds are the sounds created by abnormal sounds superimposed on normal breathing sounds (Rocha et al., 2021). Artificial intelligence methods have generally achieved successful results in distinguishing between normal and abnormal respiratory sounds. More specifically, studies have been carried out to distinguish sounds such as wheezing, whispering, and coughing from abnormal respiratory sounds (Bardou et al., 2018; Jakovljevi´c & Lonˇcar-Turukalo, 2018; Hassan et al., 2020). The artificial intelligence method has an active role in respiratory diseases such as COPD (Chronic Obstructive Pulmonary Disease) and asthma.

The abundance and accessibility of respiratory sound data have paved the way for many successful studies. The fast processing power of the machines, combined with artificial intelligence technology, brought along detailed analysis and successful results. There are many different studies in the literature. In this article, research and examinations on the studies in the literature were made and the studies in which the best models were created were discussed. Although different datasets have been used in many studies, there are also studies that have examined the same datasets.

2. Methodology

The subject covered under the name of artificial intelligence achievements used in classifications made using respiratory data generally includes information transmission and compilation. It is challenging to reach and work with datasets while conducting scientific studies. In this study, studies that achieved accuracy by using artificial intelligence methods with a dataset are included. For this purpose, first of all, articles containing the subject; Selected from IEEE, Elsevier, Pubmed, and ScienceDirect digital databases.

The keywords used in the literature review are “breath sounds and”, “respiratory sound classification”, together with “artificial intelligence” and “machine learning”. The selection criteria are primarily to consider the publications after 2010. For ease of analysis, only English and Turkish articles were considered.

3. Literature Review

When the studies in the literature are examined, besides the open datasets, there are also studies on private datasets and their comparison. In many studies, the International Conference on Biomedical and Health Informatics (ICBHI) dataset has been used and successful results have been obtained. When we look at the studies with the ICBHI dataset, Liu et al. used a dataset consisting of 222 subjects and 508 records in addition to the ICBHI dataset. When these datasets trained with the Convolutional Neural Network (CNN) model are used as mixed, 61.02% accuracy was achieved. The highest performance was obtained in the ICBHI dataset with 81.62% (Liu et al., 2019). Srivastava et al., in their study on the ICBHI dataset, performed feature extraction with Mel-frequency cepstral coefficients (MFCC) and trained this data with the CNN model. 93% accuracy was achieved in the study (Srivastava et al., 2021). Chen et al. used Optimized S-transform on this dataset and trained with deep residual networks. 98.79% accuracy was achieved (Chen et al., 2019a). Acharya and Basu used (Visual Geometry Group-

16) VGG16, MobileNet, Hybrid CNN-Recurrent neural network (RNN) methods in their study. The highest performance was obtained in Hybrid CNN-RNN with 71.81% (Acharya & Basu, 2020). The model in which Basu and Rana used Neural Network showed 96% accuracy (Basu & Rana, 2020). Rocha et al. used Linear Discriminant Analysis (LDA), Radial Fundamental Function Support Vec tor Machines (SVMrbf), Random Undersampling (SVMrbf), Random Undersampling, Augmented Trees (RUSboost), and Convolutional Neural Networks (CNNs) methods in this dataset. While on the 3 Class task with fixed durations, the best classifier achieved an accuracy of 96.9%, the same classifier reached an accuracy of 81.8% on the more realistic 3 Class task with variable durations (Rocha et al., 2021). Paraschiv and Rotaru used MFCC features in the CNN model and achieved 90.21% accuracy (Paraschiv & Rotaru, 2020).

Apart from the ICBHI dataset, many original datasets were used. Messner et al. used 387 records from 23 people. In this study, in which Multilayer Perceptron (MLP), bidirectional gated recurrent neural network (BiGRNN), and ConvBiGRNN methods were used, 93.1% training accuracy was obtained with BiGRNN (Messner et al. 2020). Rizal et al. obtained 94.95% accuracy using 99 lung sounds and MLP method (Rizal et al. 2017). Balli and Kutlu used a dataset consisting of 103 people and used Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree (DT) methods. ANN also achieved the best test performance with 86% (Balli & Kutlu, 2020). Chauhan et al. created 1381 datasets of real and simulated. MFCC and (Hidden Markov Model) HMM were used and the determinations yielded 95.7% for continuous murmurs, 96.25% for systolic murmurs, and 90% for diastolic murmurs. Aykanat and his friends recorded 17,930 lung sounds from 1630 subjects. Healthy versus pathological classification: CNN 86%, SVM 86% (Aykanat et al., 2017). Sreejyothi 35 bronchial, fine crackle, and coarse crackle, single channeled breath sound signals of the duration of 1.5–3.5 s at a sampling frequency of 44,100 Hz. Classification of data based on supervised machine learning techniques (MLT) (LDA and SVM) using the features of phase portrait was found to be superior to unsupervised classification with 83.3% and 93.3% accuracy, respectively (Sreejyothi et al., 2021). Sen et al., 50 subjects are incorporated in the study, 30 being diagnosed with asthma and 20 with COPD. Classification rates of 100 and 95 percent for asthma and COPD, respectively (Sen et al., 2021). Haider and Behera used 80 asthma, 80 COPD, and 80 healthy Lung Sounds. It achieved the highest performance with DT: 99.3% (Haider & Behera, 2022). Stasiakiewicz et al. dataset comprised 62 healthy (166 recordings) and 58 sick patients (187 recordings). In this study, in which SVM was used, 92.8% accuracy was achieved (Stasiakiewicz et al., 2021). Brown et al, the dataset is composed of 4352 unique users collected from the web app and 2261 unique users collected from the Android app, comprising 4352 and 5634 samples. In the study using SVM, 82% ROC-AUC was obtained. Amoh and Odame used 14 healthy volunteers, consisting of 7 males and 7 females. CNN was used in classification and 87.6% accuracy was achieved (Amoh & Odame, 2016). Mendes et al. obtained 24 records from 12 patients and achieved 98% accuracy (Mendes et al., 2015). Lozano et al. obtained 870 records from 30 people and achieved 94% accuracy with SVM (Lozano et al.., 2016). Chamberlain et al. obtained 500 records from 284 participants and classified them with SVM. Wheeze 86% accuracy, Crackle 73% accuracy (Chamberlain et al., 2016). Hassan et al. used 240 acoustic data. MFCC, LSTM, RNN were used, and the detection performance of cough sound was 97% and breath sound was 98.2% (Hassan et al., 2020). Jord et al. used MFCC and ResNet50 and achieved 98.5% accuracy (Laguarta et al., 2020). Jayalakshmy et al. used 4 different methods in their study. The highest performance was obtained in the CNN model with 96.7% (Jayalakshmy et al.,2020). Ma et al. features were extracted by SFTF and wavelet analysis and classification was performed with a bilinear Resnet network. 69.30% accuracy has been achieved (Ma et al., 2019). In the study of Monaco et al., 85% accuracy was obtained for MLP and 81% for SVM among 4 different classifiers (Monaco et al., 2020). Riella et al. used the ANN method in 28 audio recordings and achieved 85% accuracy (Riella et al., 2009). Pinho et al. used 24 audio files and the multi-annotator gold standard method. Precesion, F1, sensitivity results were examined in the study (Pinho et al., 2015). Gronnesby et al. used 383 audio files and SVM method. Precision, F1, sensitivity results were examined in the study (Gronnesby et al., 2017). Chen et al. extracted MFCC features of 50 lung sounds. trained these features with the SVM method (Chen et al., 2019b). Bhowmik and Most studied 12000 lung data. In the study, 93.4% accuracy was achieved with the STAIN method (Bhowmik & Most, 2022). Meng et al. applied ANN, KNN, SVM methods to 705 breath sounds. 85.43%, 68.51% and 69.50% accuracy were achieved, respectively (Meng et al., 2020). Güler et al. achieved 100% accuracy in KNN and SVM with the voice data they received from 60 people (Güler et al., 2020) These publications and summary findings are shown in Table 1.

Table 1. Publications and summary findings in the literature review

Paper ID	Source	Dataset	Method	Accuracy
1	Liu et al., 2019	ICBHI dataset and pediatric dataset consisting of 508 records from 222 subjects	CNN	ICBHI DatabaseTest Accuracy: %81.62 Pediatric Database Test Accuracy: %69.72 Mixed Database Test Accuracy: %61.02
2	Jayalakshmy et al., 2020	ICBHI dataset	SVM KNN Decision TreeCNN	SVM Train Accuracy: %71.97 K-NN Train Accuracy: %89.56 Decision Tree Train Accuracy: %90.10 CNN Train Accuracy: %96.7
3	Messner et al., 2020	387 records from 23 people	MLP ConvBiGRNN BiGRNN	MLP Train Accuracy: %75.0 BiGRNN Train Accuracy: %93.1 ConvBiGRNN Train Accuracy: %85.9
4	Rizal et al., 2017	99 lung sound	Multilayer Perceptron (MLP)	Accuracy: 94.95%
5	Balli & Kutlu, 2020	103 people from the ICBHI dataset, including 35 healthy, 32 pneumonia and 36 COPD.	ANN, KNN, SVM, DT	ANN Test Acc: 86% KNN Test Acc: 80% SVM Test Acc: 85% DT Test Acc: 76%
6	Chauhan et al., 2008	1381 datasets of real and simulated	MFCC+HMM	Continuous murmurs: 95.7% Systolic murmurs: 96.25% Diastolic murmurs: 90%
7	Aykanat et al., 2017	Recorded 17,930 lung sounds from 1630 subjects.	SVM and CNN	healthy versus pathological classification: CNN %86, SVM %86 rale, rhonchus, and normal sound classification: CNN %76, SVM %75 singular respiratory sound type classification: CNN %80, SVM %80 audio type classification with all sound types: CNN %62, SVM %62

8	Sreejyothi et al., 2021	35 bronchial, fine crackle, and coarse crackle, single channeled breath sound signals of the duration of 1.5–3.5 s at a sampling frequency of 44,100 Hz	MLT-LDA,SVM	Classification of data based on supervised MLT-LDA and SVM using the features of phase portrait was found to be superior to unsupervised classification (PCA) with 83.3% and 93.3% accuracy, respectively.
9	Ma et al., 2019	ICBHI dataset	Short-time Fourier transform (STFT), Wavelet + Bi-ResNet	Accuracy: 69.30%
10	Sen et al., 2021	Fifty subjects are incorporated in the study, 30 being diagnosed with asthma and 20 with COPD.	Gaussian mixture models (GMM), and SVM	Classification rates of 100and 95 percent for asthmaand COPD, respectively.
11	Srivastava et al., 2021	ICBHI dataset	MFCC+CNN	Accuracy: 93%
12	Haider & Behera, 2022	80 asthma, 80 COPD, and 80 healthy Lung Sounds.	SVM, DT, KNN, DA	Accuracy: DT: 99.3% SVM: 98.6% KNN: 95% DA: 96.3%
13	Chen et al.,2019a	ICBHI dataset	OST and ResNets	Sensitivity:96.27% Specificity:100% Accuracy: 98.79%
14	Stasiakiewicz et al., 2021	Dataset consisting of 62 healthy (166 recordings) and 58 sick patients (187 recordings)	SVM	Sensitivity:94.8% Specificity:90.7% Accuracy: 92.8%
15	Brown et al., 2020	Dataset is composed of 4352 unique users collected from the web app and 2261 unique users collected from the Android app, comprising 4352 and 5634 samples	SVM	COVID-positive / non-COVID: 80% COVID-positive with cough / non-COVID with cough: 82% ROC-AUC COVID-positive with cough / non-COVID asthma cough: 80% ROC-AUC
16	Amoh & Odame, 2016	14 healthy volunteers: 7 males and 7 females.	CNN, RNN	CNN: 87.6% RNN: 79.7%
17	Acharya & Basu, 2020	ICBHI dataset	VGG16, MobileNet, Hybrid CNN-RNN	VGG16: 68.54% MobileNet: 67.60% Hybrid CNN-RNN: 71.81%
18	Basu & Rana, 2020	ICBHI dataset	Neural Network	Accuracy: 95.67%± 0. 77%

19	Monaco et al., 2020	ICBHI dataset	Random Forest (RF), SVM, MLP and (Deep Neural Network) DNN	Accuracy:MLP: 85% SVM: 81%
20	Rocha et al., 2021	ICBHI dataset	Linear discriminant analysis (LDA), radial basis function support vector machines (SVMrbf), random undersampling augmented trees (RUSboost), and convolutional neural networks (CNNs).	While on the *3 Class* task with fixed durations, the best classifier achieved an accuracy of 96.9%, the same classifier reached an accuracy of 81.8% on the more realistic *3 Class* task with variable durations.
21	Riella et al., 2009	28 Record	ANN	Accuracy: 85%; Sensitivity: 86%;
22	Pinho et al., 2015	24 sound files	multi-annotator gold standard	Precision: 95%; Sensitivity: 89%; F1: 92%
23	Mendes et al., 2015	Patients: 12; Recordings: 24;	Matthews correlation coefficient (MCC)	Accuracy: 98%; Sensitivity: 91%; Specificity: 99%; MCC: 93%
24	Lozano etal., 2016	Participants: 30; Recordings: 870; Source: Private	SVM	Accuracy: 94%; Precision: 95%; Sensitivity: 94%; Specificity: 94%
25	Chamberlain et al., 2016	Participants: 284; Recordings: 500; Source: Private	SVM	Wheeze AUC: 86%; Crackle AUC: 73%
26	Gronnesby et al., 2017	Recordings: 383	SVM	Precision: 86% Sensitivity: 84% F1: 84%
27	Jakovljevi´c & Lonˇcar-Turukalo, 2018	ICBHI dataset	HMM	Wheeze Sensitivity: 52%; Crackle Sensitivity: 56%; Normal Sensitivity: 52%
28	Chen et al., 2019b	50 lung recording	MFCC+SVM	BAC: 0.821 ±0.07 Sensitivity: 0.815 ±0.10 Specificity: 0.826 ±0.07
29	Bhowmik &Most, 2022	10,000 training files with coughs, 10,000 training files without coughs, 1000 testing files with coughs, and 1000 testing files without coughs.	Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Convolutional Recurrent Neural Network (CRNN), Spatio-Temporal AI Network (STAIN)	Accuracy: CNN: 92.7% RNN: 86.3% CRNN: 91.0% STAIN: 93.4%
30	Hassan et al., 2020	240 aucustic data	MFCC+LSTM+RNN	Accuracy: Cough Sound: 97% Breath Sound: 98.2% Voice: 84.4%
31	Laguarta et al.,2020	MIT open voice model (5,320 subjects have recorded a healthy COVID-19 cough dataset.)	MFCC, ResNet50 (CNN)	Accuracy: 98.5%

32	Paraschiv & Rotaru, 2020	ICBHI dataset	MFCC+CNN	Accuracy: 90.21%
33	Meng et al., 2020	705 respiratory sound signals (240 rales, 260 rhonchi, and 205 normal respiratory sounds) were obtained from 130 patients	ANN, SVM, KNN	ANN: %85,43 SVM: %69.50 KNN: %68.51
34	Güler et al., 2020	20 normal, 20 ral and 20 rhonchi voice data from 60 patients	k- Nearest Neighbor (kNN), Support Vector Machine (SVM), Naive Bayes, Decision Tree and Random Forest Classifier	Accuracy: Decision Tree: 0.98% KNN: 100% Naive Bayes: 0.98% Random Forest: 0.98%SVM: 100%

4. Conclusion and Discussion

This review of studies evaluating breath sounds using machine learning techniques provide an overview of current machine learning techniques for digitizing and analyzing breath sounds. For this purpose, the types and characteristics of respiratory sounds are mentioned. In addition, the accuracy rates and study results of the studies discussed and their suggestions for future studies were evaluated.

Many different models and datasets were used in the studies. In addition, it has been tried to increase the performance with feature extraction methods such as MFCC and OST. When the results are examined, it is observed that MFCC is used in feature extraction and CNN is used in model training. The largest dataset is the MIT dataset, which contains cough voice recordings from 5320 people. In addition, MFCC coefficients were used in the training of this dataset. The model trained with CNN achieved a very high accuracy rate of 98.5% (Laguarta et al., 2020). This performance and a large number of used datasets bring this work to the fore. In addition, 17930 lung data from 1630 people were used in another study with a high data number. In this study using CNN and SVM, 86% accuracy was achieved for both models. It has been seen that CNN algorithm works as well as SVM algorithms and machine learning algorithms that can classify respiratory sound (Aykanat et al., 2017). The most commonly used dataset in studies is the ICBHI dataset. In studies using this dataset, the highest peak results were obtained using optimized S-transform (OST) and deep residual networks (ResNets).

Convolutional networks are trainable, multi-stage architectures that can be applied to a wide range of perceptual tasks (LeCun et al., 2010). CNN was also highly preferred in the analysis of breath sounds. It is also frequently used in HMM and SVM. As a feature extraction method, MFCC was generally used and provided high accuracy.

This study has shown that AI-powered medical solutions can have a stimulating effect on healthcare. In addition, it supports the selection of a technologically innovative way of diagnosis and treatment monitoring processes. In this way, it is stated that technology has potential in the medical field and studies on this subject should be supported.

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