LITERATURE REVIEW

TEAM - 18

AUSCULATION

SOUND CLASSIFICATION

TEAM MEMBERS

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Overview

04

Total Journals

01

Base Journal

01

Journal each Member

03

Supporting Journals

Journal Read

by

S Abhishek

(Base Paper)

Title

Respiratory sound classification for crackles, wheezes, and rhonchi in the clinical field using deep learning

URL : Open Access

Publsher : Scientific Reports - Open Access

Publication Year : August 2021

Relevancy of the Paper

- This paper presents a detailed overview of classification of normal respiratory sounds, crackles, wheezes, and rhonchi.
- This research also examines how accurately medical students, interns, residents, and fellows categorized breathing sounds to check the accuracy of auscultation classification in real clinical practice.

Motivation

This paper shows how deep learning-based classification model complements the inaccuracies of clinician's auscultation, and how the model aids in the rapid diagnosis and appropriate treatment of respiratory diseases.

Take Aways

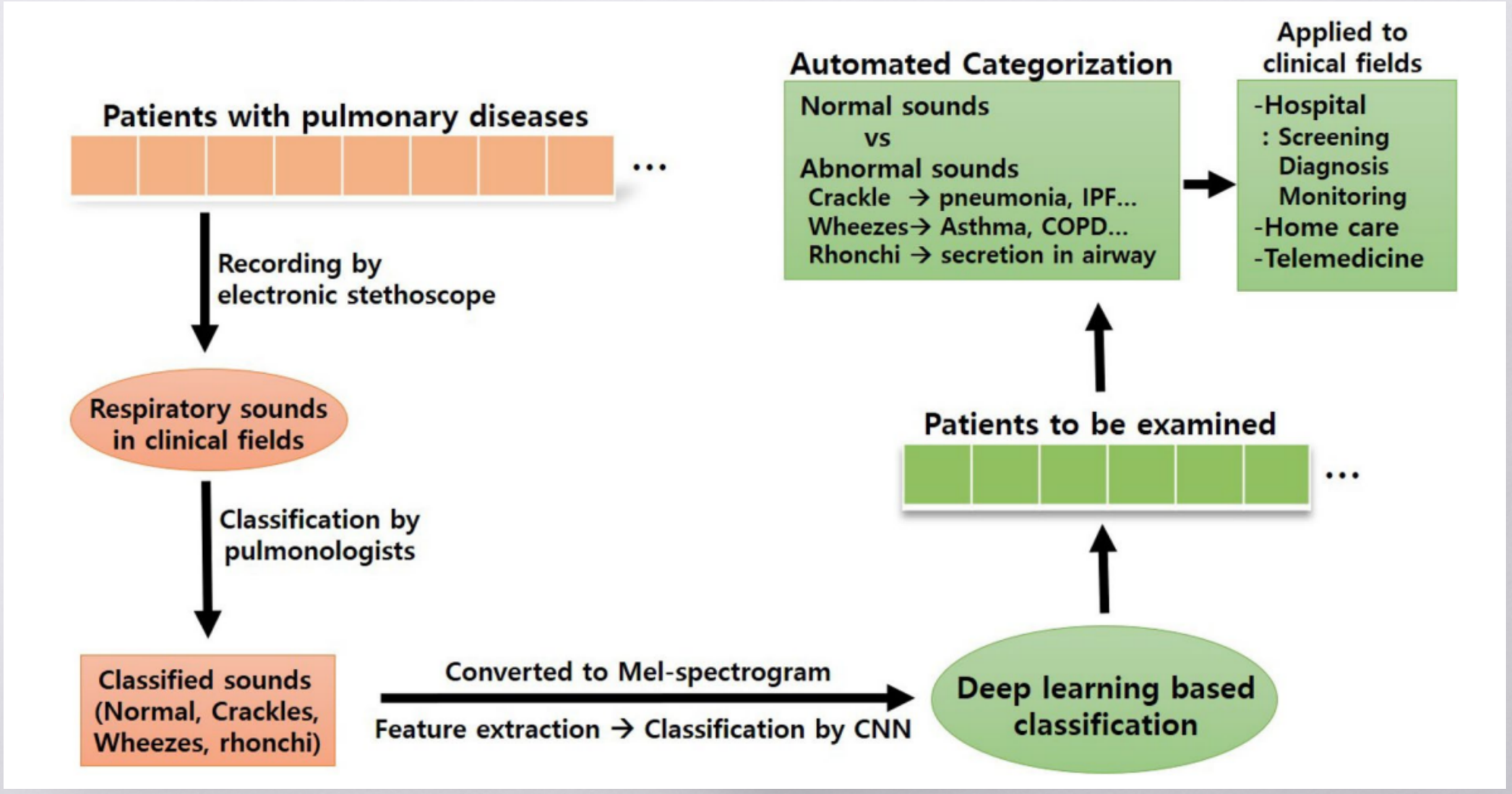
Usage of weights pre-trained on ImageNet by freezing all the five convolution blocks without fully-connected layer, and predicted the test sets with simple CNN with only one-layer.

Main Problem Addressed

This paper focuses on using transfer learning and convolutional neural network (CNN) to classify the normal respiratory sounds, crackles, wheezes, and rhonchi.

Methodology

- This research examined several lung sound classification models that applied machine learning or deep learning for lung sounds classification.
- This research used the modified deep learning algorithm of Bardou’s study which applied SVM46 and a pre-trained models VGG16 as feature extractors in transfer learning, which was built by Karen Simonyan.


Patients with pulmonary diseases
...
Recording by electronic stethoscope
Respiratory sounds in clinical fields
Classification by pulmonologists
Classified sounds (Normal, Crackles, Wheezes, rhonchi)
Converted to Mel-spectrogram
Feature extraction → Classification by CNN
Deep learning based classification
Patients to be examined
...
Automated Categorization
Normal sounds
vs
Abnormal sounds
Crackle → pneumonia, IPF...
Wheezes→ Asthma, COPD...
Rhonchi → secretion in airway
Applied to clinical fields
-Hospital
: Screening
Diagnosis
Monitoring
-Home care
-Telemedicine

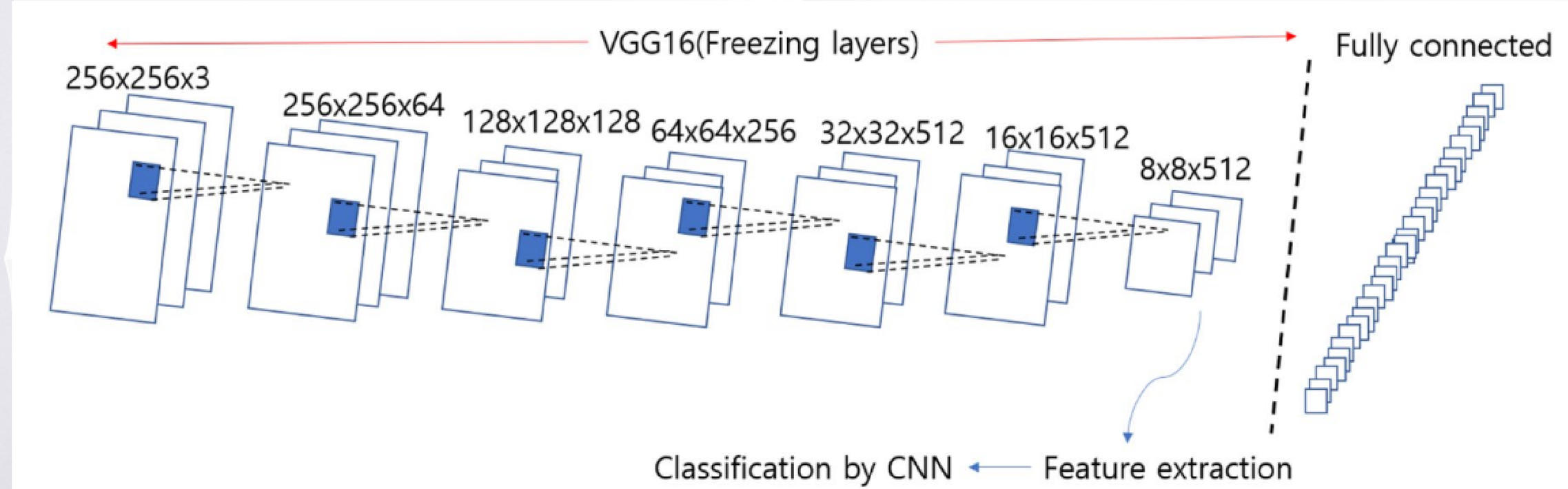
Contributing Results Achieved

- This research presents a deep learning-based classification which can detect abnormal lung sounds with an AUC of 0.93 and an accuracy of 86.5%.
- It has similar results in categorizing abnormal sounds into sub categorical sounds: crackles, wheezes, or rhonchi.

- The test results shows that the auscultation accuracy of interns and residents were less than 80% in all four kinds of sounds and rhonchi was the most difficult sound to discriminate.
- The result of the test is not conclusive since the number of participants is small, however, it looks obvious that there are marked differences in the ability of each clinician to classify breathing sounds.
- This suggests that AI-assisted classification standardize the identification and categorization of breath sounds and greatly aid the diagnosis of pulmonary diseases.

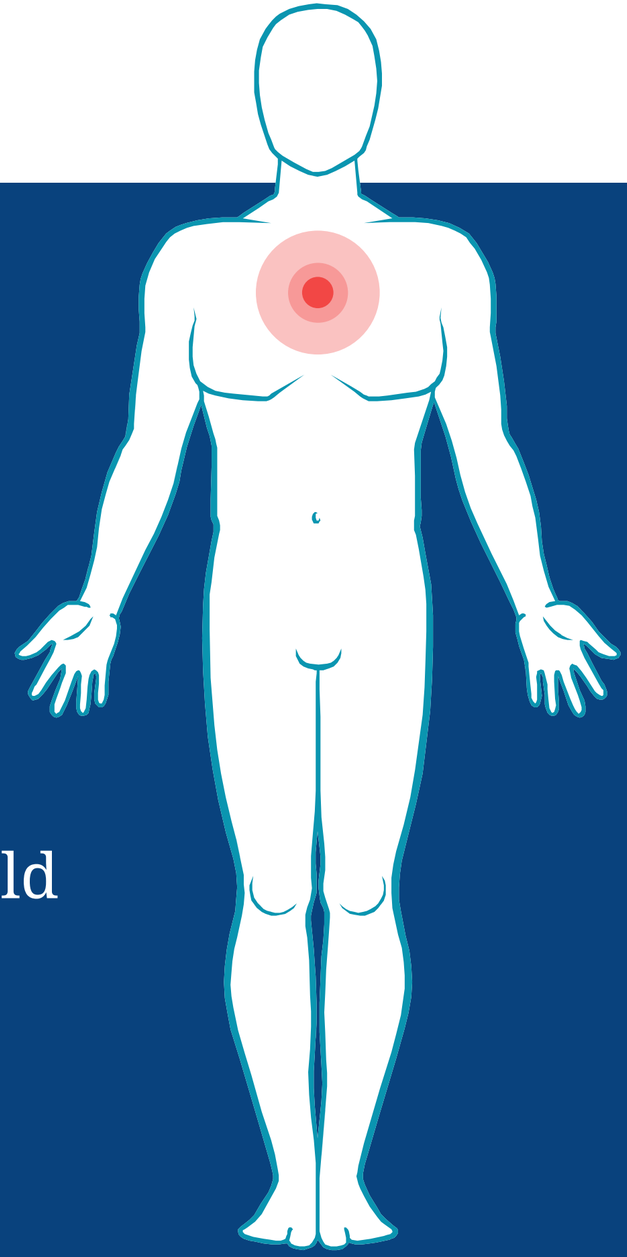
Advantages of the Solution Approach

- The proposed deep learning-based classification could classify the respiratory sounds accurately.
- Utilizing the transfer learning method, combining pre-trained image feature extraction from respiratory sound and CNN classification, worked well and was helpful for improving the classification accuracy.
- VGG16 is a model with 16 layers trained on fixed-size images and the input is processed through a set of convolution layers that use small-size kernels with a receptive field 3×3.


VGG16(Freezing layers)
Fully connected
256x256x3
256x256x64
128x128x128
64x64x256
32x32x512
16x16x512
8x8x512
Classification by CNN
Feature extraction

Limitations

Noises such as coughs, voices, heart sounds, and medical alarms are frequently recorded with breath sound, which reduces the accuracy of analysis, the technology for noise filtering is required to improve the sound quality which would help rationally classify a wider variety of automatically auscultated sounds.



Research Gap

- There are several respiratory sounds in which two or more abnormal breath sounds are mixed.
- This study classified mixed abnormal breathing sounds, so research about these sounds is necessary

Scope of Improvement

Respiratory sound analysis can improve more quickly with analytical algorithms and recording equipment and to develope a automated stethoscopes powered by deep learning.

Journal Read
by
M Mahima

Title

Extraction of low-dimensional features for single-channel common lung sound classifcation

URL : Springer

Publisher : International Federation for Medical and Biological Engineering 2022

Publication Year : April 2022

Relevancy of the Paper

- This paper divides respiratory sounds into three categories: Rhonchi, Fine crackle, and Coarse crackle.
- This paper, as the title suggests, is primarily concerned with feature extraction.

Motivation

This paper demonstrates the significance of using MFCC and LPC in feature extraction to improve accuracy and classify the sounds accordingly.

Take Aways

A more accurate model that accurately classifies sounds will be produced by using appropriate feature extraction and feature selection algorithms.

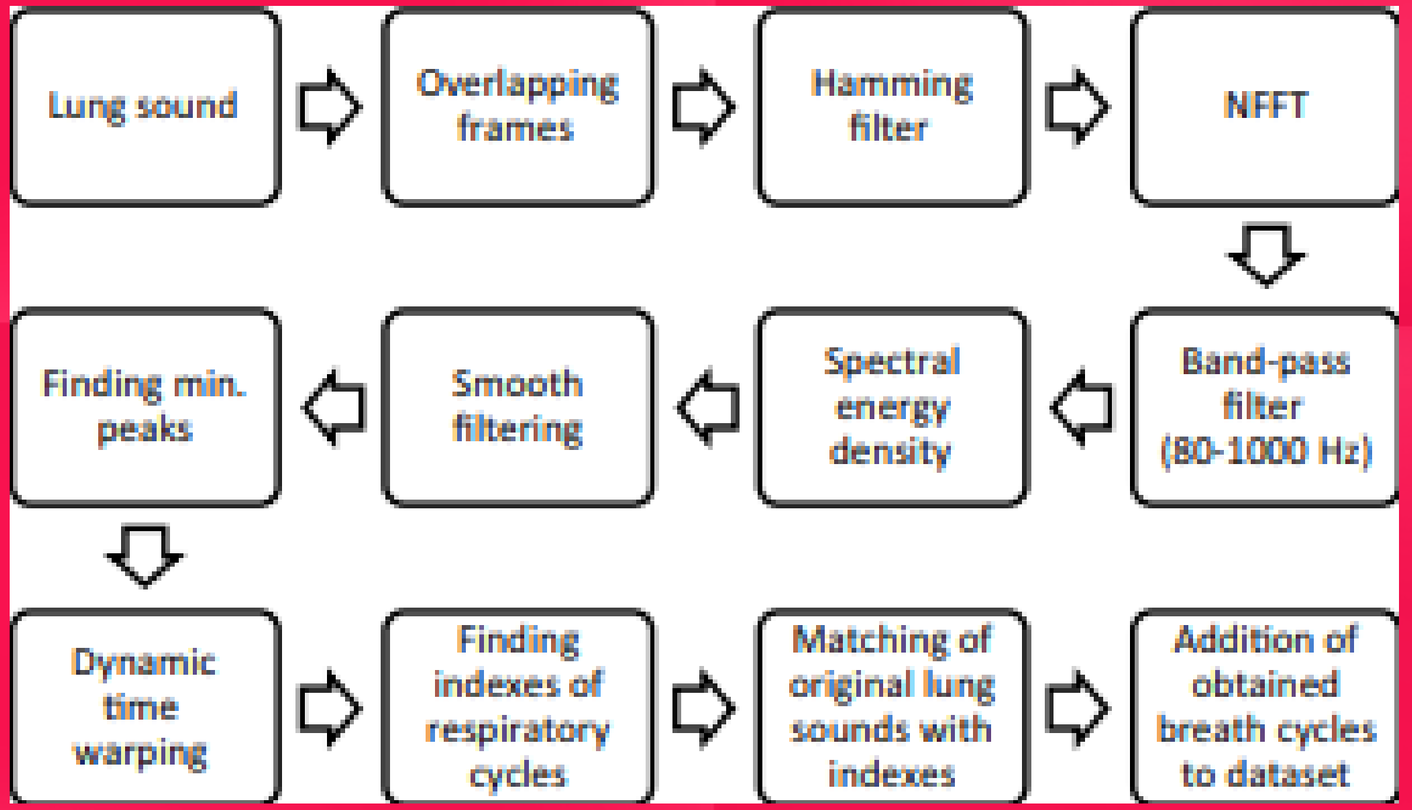
Main Problem Addressed

Majority of the papers focus on classifier algorithms. In contrast to them ,this paper discusses the significance of feature extraction and feature selection

Methodology

- The method employed consists primarily of three steps.
  - Recognition of respiratory cycles
  - Feature Extractions
  - Classification

Recognition of Respiratory Cycle



Feature Extraction

- MFCC,FDF,TDF,LPC,SFS methods are used for feature extraction.

Mel Frequency cepstrum Coefficients (MFCC)

- Steps involved in MFCC,
  - Overlapping Framing and windowing

- Power spectrum Computation using Fast Fourier Transform (FFT)
- Mel Scale triangular filter Banks(20)
- Logarithm - to reduce sensitivity of feature vectors
- Apply Doiscrete cosine tranformation

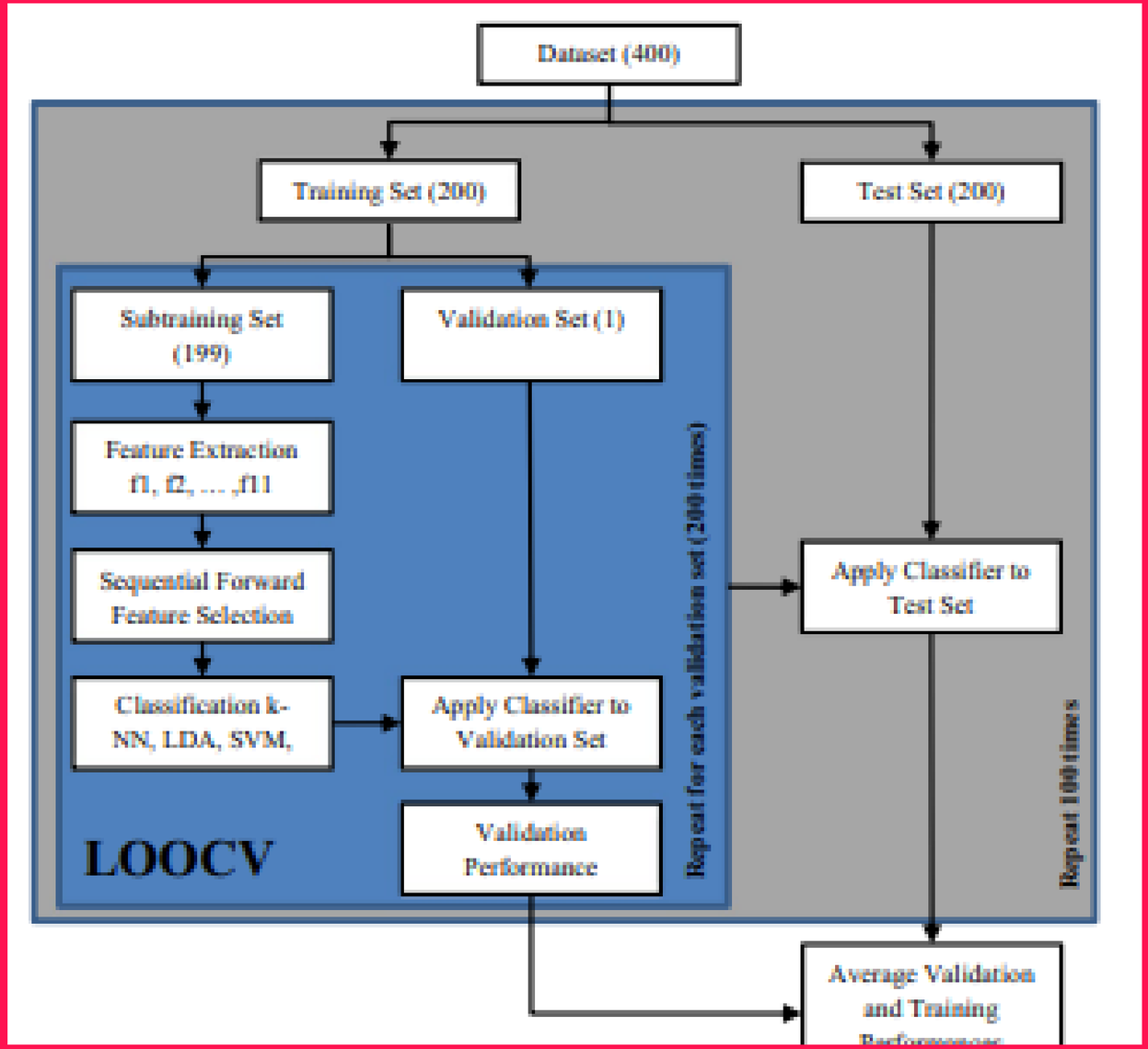
Frequency Domain Features(FDF)

In the frequency domain, five feature matrices for each frame, i.e., spectral center, spectral spread, spectral entropy, spectral fux, and spectral roll-of are calculated.

Linear Predictive Coding(LPC)

Coefficients are calculated by applying autocorelation and LPC analysis

Classification



Contributing Results Achieved

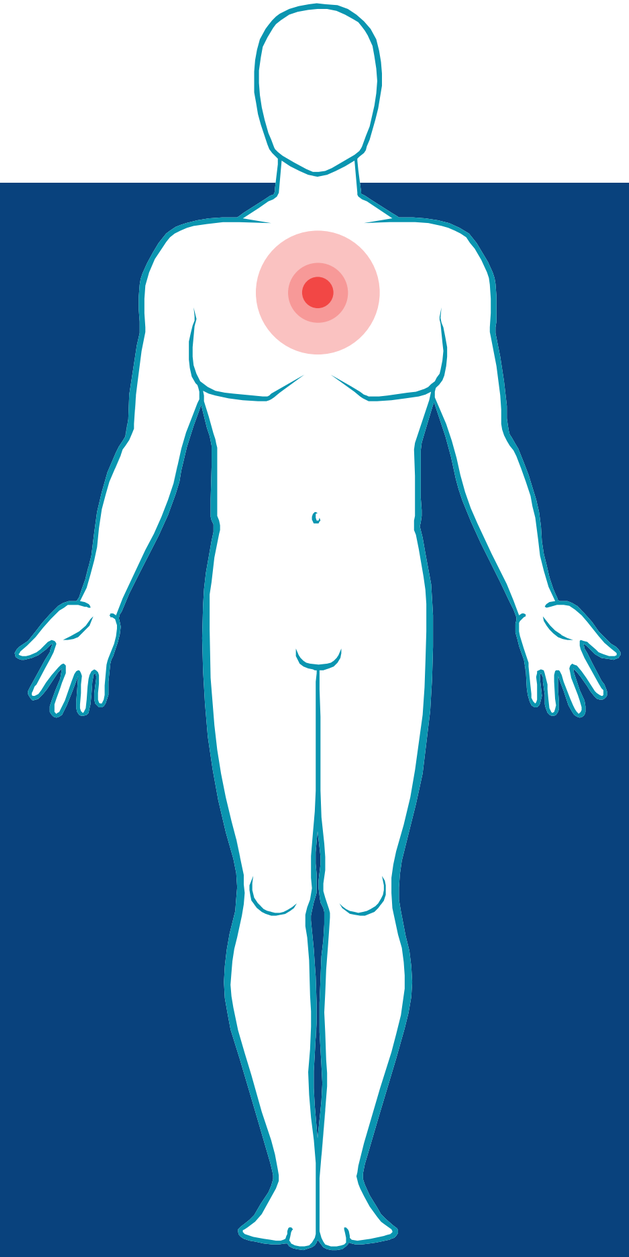
- SFS Method is used to see if it could improve classification accuracy by increasing the success rate.
- Success increased up to triple feature combinations, but because performance dropped in quadruple feature combinations, the calculations were stopped.

Advantages of the Solution Approach

As a result of the availability of sufficient training and test data in classification, the proposed method has high performance and balance in terms of accuracy and AUC values.

Limitations

- In the study, since lung sounds obtained with the single-channel recording method contain less information than multi-channel lung sounds.
- The only classifiers used are ML algorithms.



Research Gap

In this deep learning era, numerous deep learning techniques, such as CNN, RNN, and LSTM, can be used as feature extractors and classifiers simultaneously to improve the performance of the model.

Scope of Improvement

- To increase accuracy, classifiers can be created using CNN architectures.
- Multi-channels recording methods to be employed to obtain more detailed information.

Journal Read

by

Ananthapadmanabhan

Title

Lung Sound Classification Using Co-tuning and Stochastic Normalization

URL : IEEE

Publisher : Open Access

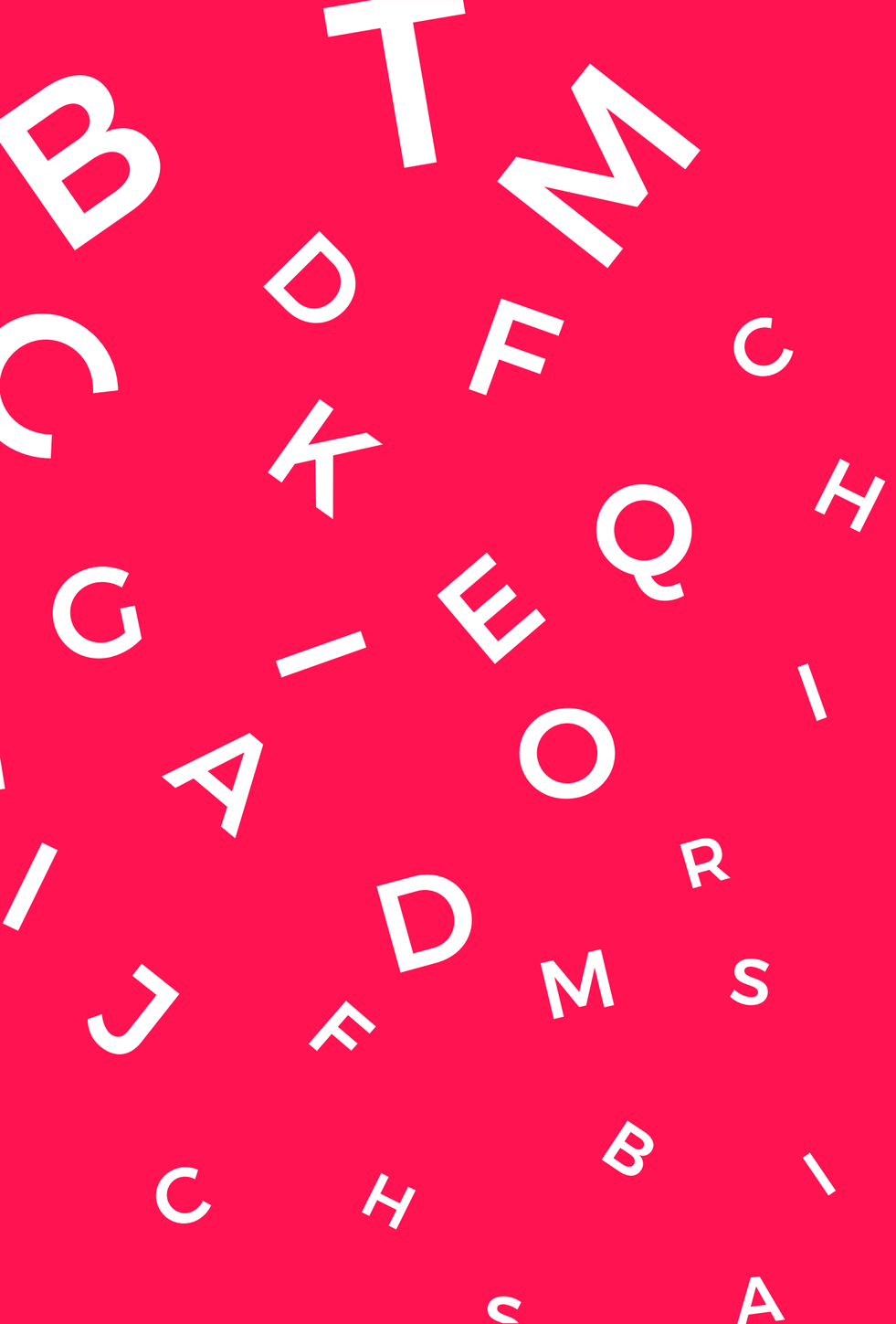
Year of Publication : March 2022

Relevancy of the Paper

- The main contribution of this paper is to exploit different transfer learning approaches, in which the pre-trained ResNet models of the ImageNet classification task are used as backbone architectures

Motivation

In this paper they used pre-trained ResNet models as backbone architectures for classification of adventitious lung sounds and respiratory diseases.



Take Aways

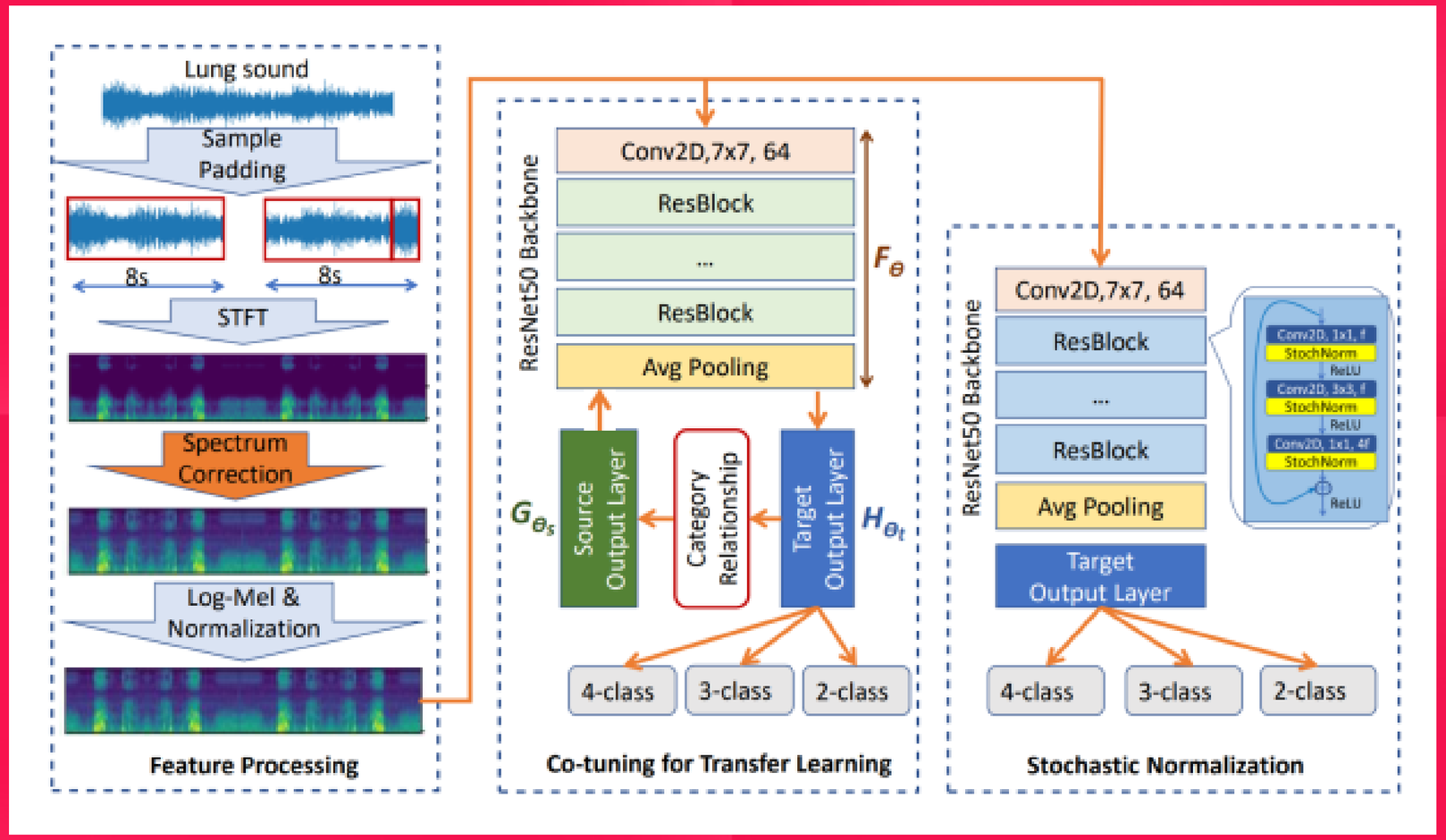
- Applied co-tuning to fully transfer the knowledge of the pre trained model.
- Also replaced batch normalization with stochastic normalization ,StochNorm is a parallel structure normalizing the activation of each channel by either mini-batch statistics or moving statistics to avoid influence of sample statistics during training.

Main Problem Addressed

- ALSC: Adventitious lung sound classification (ALSC) is separated into two sub-tasks for respiratory cycles.
  - The first one is a 4-class task classifying respiratory cycles into four classes (Normal, Crackles, Wheezes and both Crackles and Wheezes).
  - The second sub-tasks is a 2- class task of normal and abnormal lung sounds including Crackles, Wheezes and both Crackles and Wheezes.

Methodology

- The proposed systems include two key stages i.e. feature processing and classification
- The respiratory cycles recordings are pre-processed in time domain and transformed into log-mel spectrograms of fixed size.
- The features are fed to the CNN model where co-tuning or stochastic normalization are explored for the different classification tasks


Lung sound
Sample Padding
8s
8s
STFT
Spectrum Correction
Log-Mel & Normalization
Feature Processing
ResNet50 Backbone
Conv2D,7x7, 64
ResBlock
...
ResBlock
Avg Pooling
F_θ
G_{θ_s}
Source Output Layer
Category Relationship
Target Output Layer
H_{θ_t}
4-class
3-class
2-class
Co-tuning for Transfer Learning
ResNet50 Backbone
Conv2D,7x7, 64
ResBlock
...
ResBlock
Avg Pooling
Target Output Layer
Conv2D, 1x1, f
StochNorm
ReLU
Conv2D, 3x3, f
StochNorm
ReLU
Conv2D, 1x1, 4f
StochNorm
ReLU
4-class
3-class
2-class
Stochastic Normalization

Contributing Results Achieved

- Spectrum correction is useful to improve the performance of ALSC and RDC system on the ICBHI dataset.
- The ALSC system using the flipping data augmentation enhances performance on both ICBHI andour multi-channel lung sound dataset.

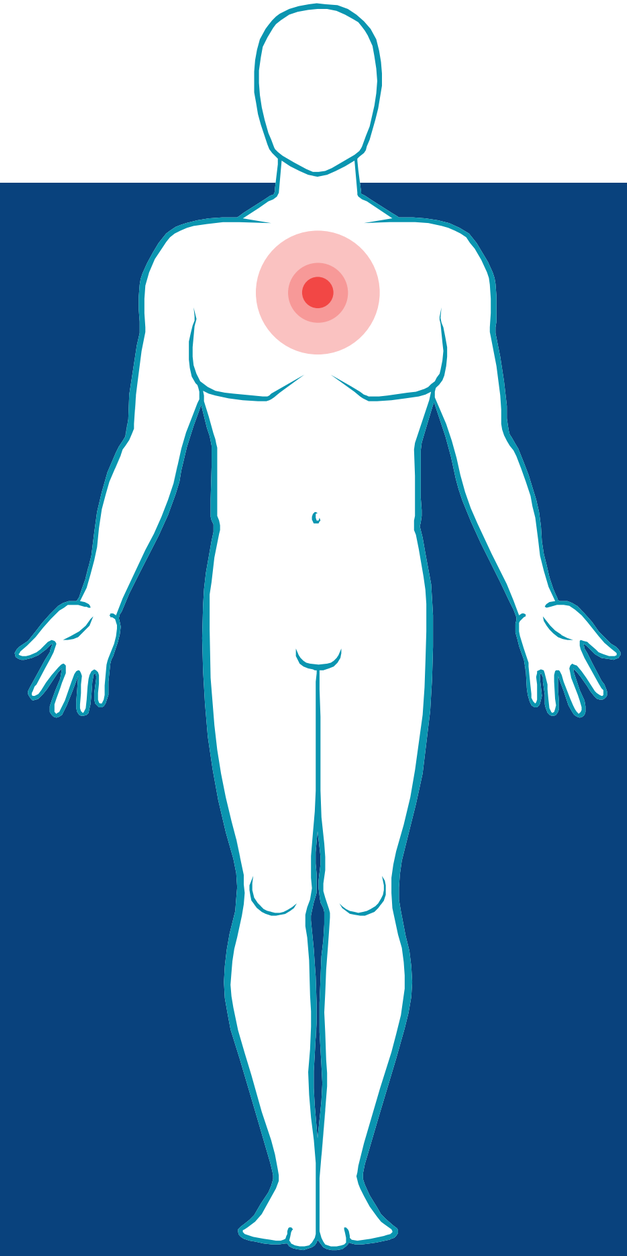
- Co-tuning works better for the ALSC task while StochNorm and its combination with co-tuning achieve higher performance for the RDC task.
- ResNet34 and ResNet50 are more suitable for the ALSC tasks, while a large ResNet101 model tends to be more robust for the RDC task in most transfer learning settings.

Advantages of the Solution Approach

- Co-tuning works better for the ALSC task while StochNorm and its combination with co-tuning achieve higher performance for the RDC task.
- Co-tuning system for 2-class lung sound classification achieves a better F-score (2.82%) compared to the previous work using a multi-input convolutional neural network.
- This model obtained 58.29±0.24% and 64.74±0.05% average score for the 4- and 2-class adventitious lung sound task and for the 3- and 2-class respiratory disease classification task, obtained 92.72±1.30% and 93.77±1.41% average score.

Limitations

Although CoTuning and StochNorm improve significantly the performance of VanillaFineTuning, the combination of cotuning and StochNorm is not able to outperform the respective techniques for this task.



Research Gap

The combination of cotuning and StochNorm is not able to outperform the respective techniques for this task and thus need to be improved.

Scope of Improvement

Despite the fact that CoTuning and StochNorm considerably boost VanillaFineTuning's performance, they are unable to exceed the individual strategies for this work.

Journal Read

by all

3 Members

Title

Accurate respiratory sound classification model based on piccolo pattern

URL : Elsevier

Publisher : Science Direct - Elsevier

Year of Publication : January 2022

Relevancy of the Paper

Variable models and methods have been introduced to in this paper to develope a high accurate sound classification model using a nonlinear histogram-based generator.

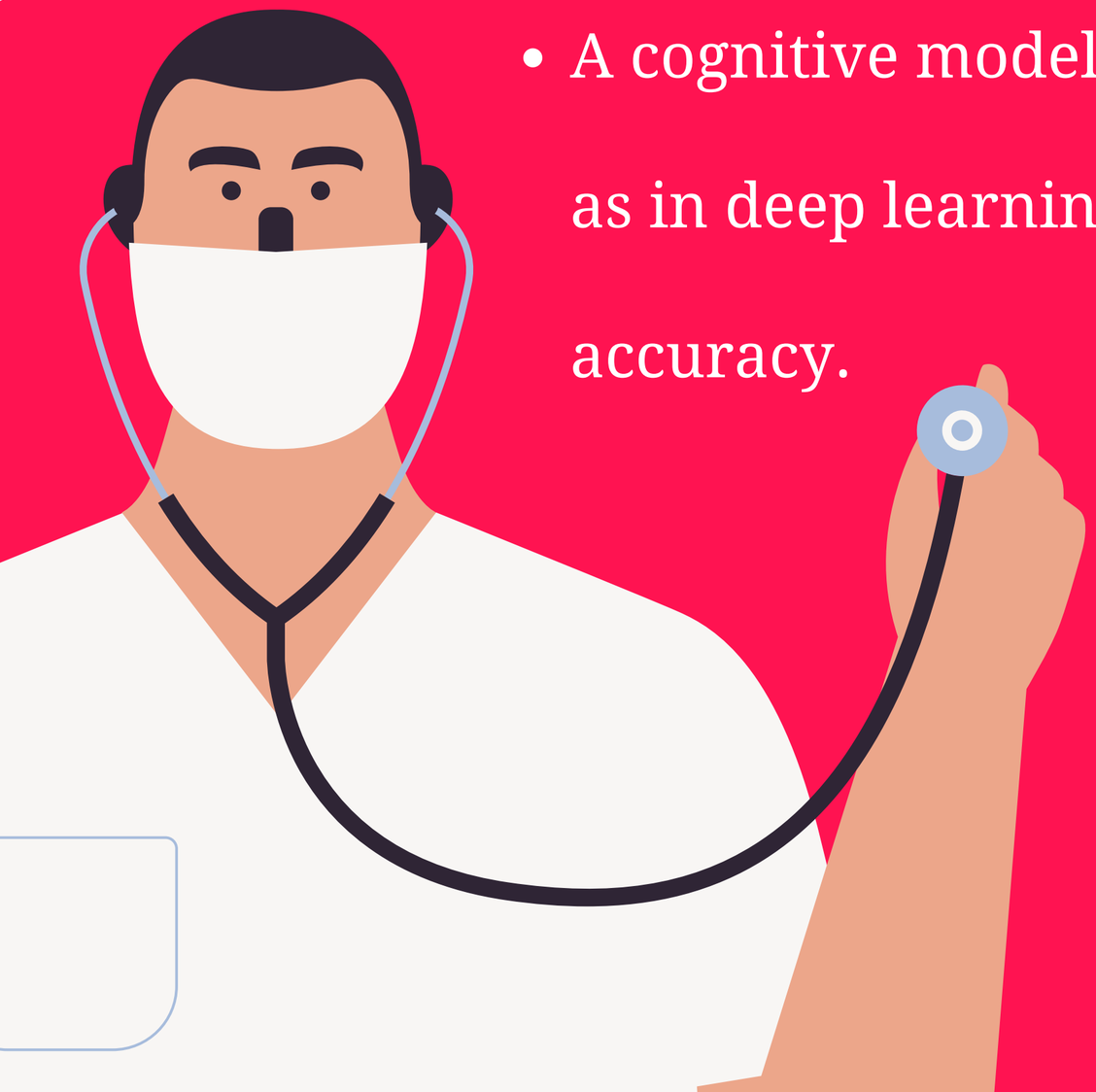
Motivation

- Auscultation, or listening to body sounds with a stethoscope, is the most basic and instructive part of the physical examination.
- Although it is a quick and effective way of diagnosing respiratory tract disorders, the precision of the diagnosis demands a considerable deal of clinical knowledge.

Take Aways

- Piccolo pattern (it uses S-box of the piccolo cipher as a pattern), statistical moments, tunable q-factor wavelet transform (TQWT), iterative neighborhood component analysis (INCA), and conventional classifiers are used together.
- This model uses TQWT to create levels.

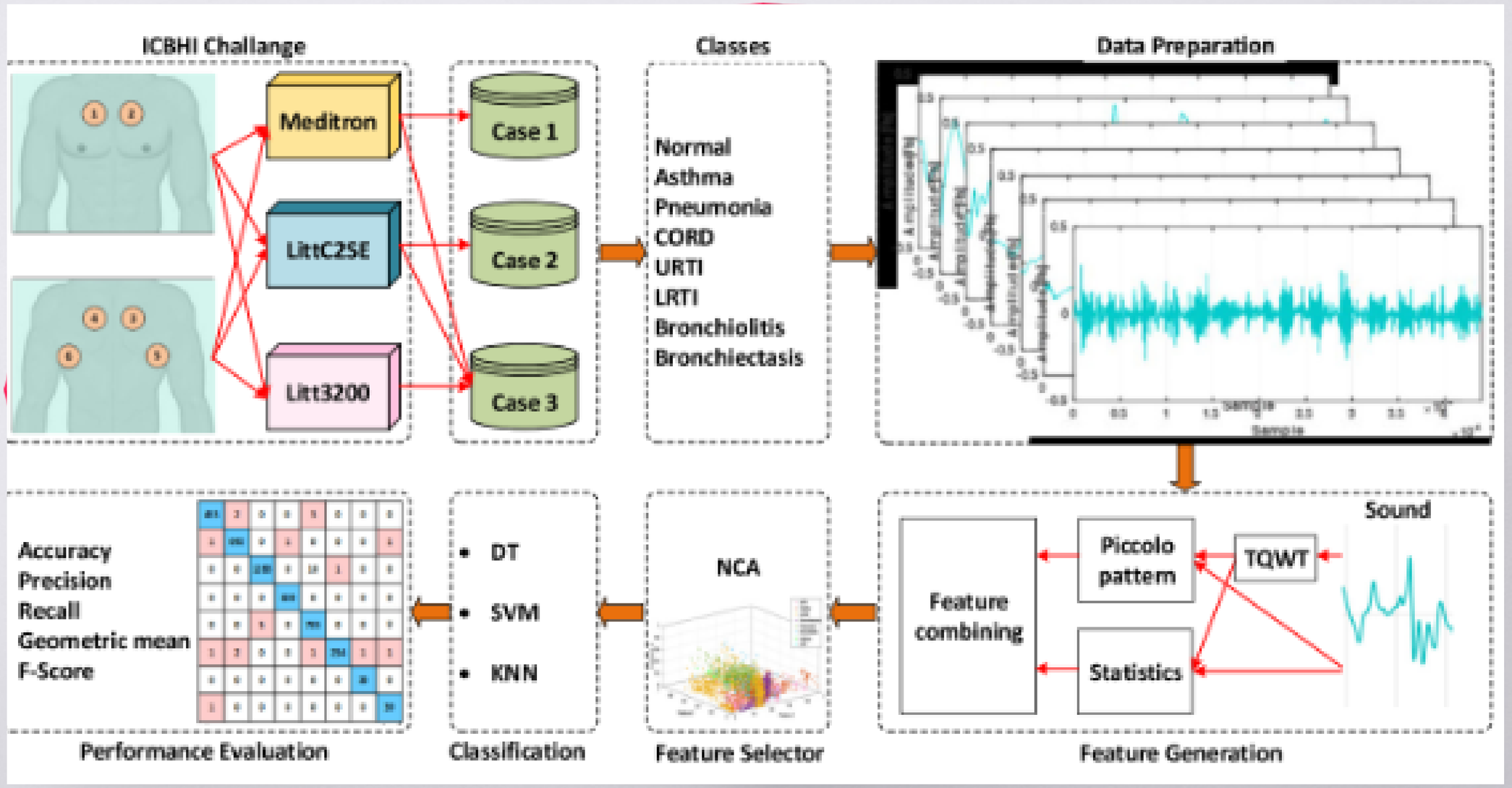
Main Problem Addressed



- A cognitive model has been developed in the proposed method as in deep learning networks to achieve high classification accuracy.
- In the study the most reliable and most accessible data type ICHBI17 lung respiratory sound dataset has been used.

Methodology

- The iterative neighborhood component analysis (INCA) method has been used to select the NCA algorithm’s optimum features.
- DT, SVM, and KNN algorithms have been used for the classification of the optimum features selected.
- This study presents a naïve and basic acoustical sound classification method to detect the type of lung disease.


ICBHI Challange
Meditron
LittC2SE
Litt3200
Case 1
Case 2
Case 3
Classes
Normal
Asthma
Pneumonia
CORD
URTI
LRTI
Bronchiolitis
Bronchiectasis
Data Preparation
Sound
TQWT
Piccolo pattern
Statistics
Feature combining
Feature Generation
NCA
Feature Selector
DT
SVM
KNN
Classification
Accuracy
Precision
Recall
Geometric mean
F-Score
Performance Evaluation

Contributing Results Achieved

In the proposed method, Accuracy, Precision, Recall, Geometric mean, and F Score values have been calculated by running 1000 iterations of Case 1, Case 2, and Case 3 datasets with three classification algorithms.

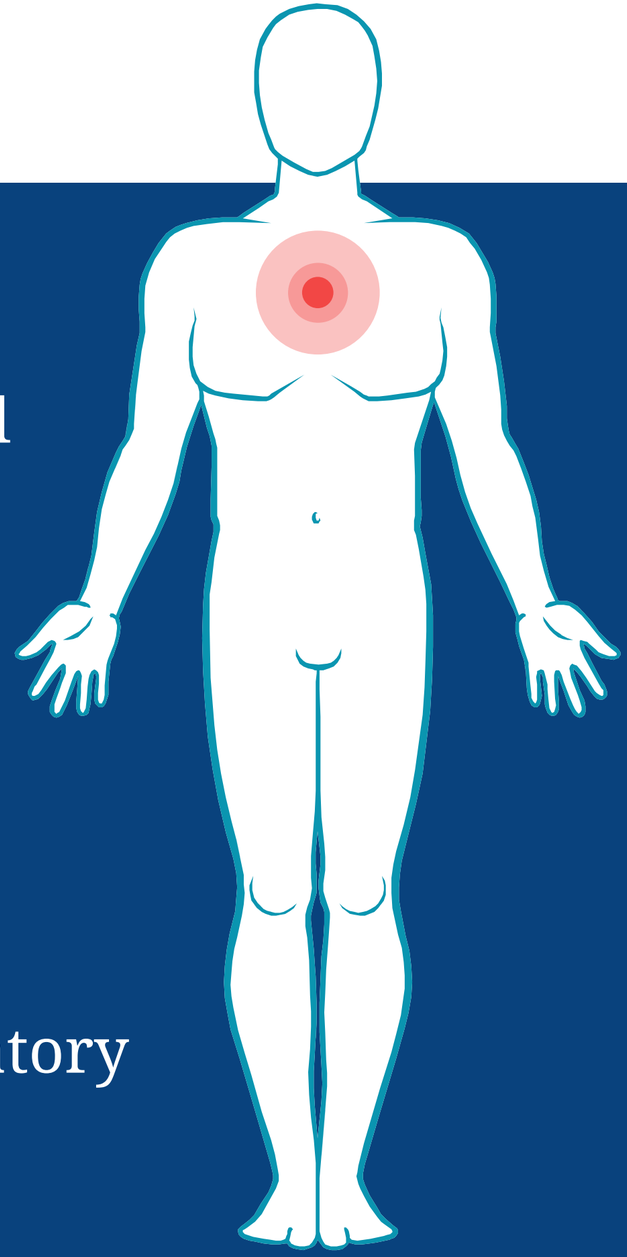
- In the KNN algorithm, the best result has been computed for the COPD, Bronchiectasis, Pneumonia, and LRTI classes.
- The best result for Case 1 has been calculated with the KNN algorithm. While calculating 83.7% with the DT algorithm and 98.41% with SVM, an accuracy of 99.45% has been calculated with KNN.
- For Case 2, an accuracy of 96.66%, 97.87%, and 99.31% has been computed using DT, SVM, and KNN algorithms, respectively and 86.41%, 97.8%, and 99.19% has been calculated for Case 3, respectively.

Advantages of the Solution Approach

- The iterative neighborhood component analysis (INCA) method has been used to select the NCA algorithm’s optimum features.
- DT, SVM, and KNN algorithms have been used for the classification of the optimum features selected.
- To detect the type of lung disease, a new and naïve method has been presented: Piccolo and INCA-based lung pathology identification method.

Limitations

- As compared to multi-channel lung sounds, single-channel lung sounds acquired for the study include less information.
- With the use of recording tools, analytical algorithms, and automatic stethoscopes powered by deep learning, respiratory sound analysis can advance more swiftly.



Research Gap

These days, a variety of deep learning approaches, including CNN, RNN, and LSTM, may be utilized concurrently as feature extractors and classifiers to enhance the performance of the model.

Scope of Improvement

- Classifiers may be developed using CNN architectures to improve accuracy.
- The use of multi-channel recording techniques will be used to get more precise data.

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