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Engineering and Technology

COMPARISON OF THE CLASSIFICATION OF PHONOCARDIOGRAMS WITH BREATHING SOUND NOISE BY MACHINE LEARNING ALGORITHMS

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Abstract

This research aims to classify between normal heart sounds and abnormal heart sounds (heart murmurs and clicks) by machine learning techniques. This study made the assumption that the obtained heart sound may be interfered with by the breath sound noise. The test files were manipulated by overlaying the breathing sound noise on the phonocardiograms of heart sounds. The data of breathing sound noise and heart sound was obtained from Respiratory Auscultation (https://www.mediscuss.org/respiratory-auscultation/) and Heart Sound & Murmur Library, University of Michigan, respectively. Moreover, the files of heart sounds were processed by changing tempos to be faster from 0%, 10%, 20%, 30%, 40%, and 50%, which were done by Audacity software. The different tempos of each heart sound file represent the different heartbeat rates of the same person. In this work, five techniques of machine learning algorithm, which were Random Forest, Neural Network, Deep Learning, Support Vector Machine, Naïve Bayes, were applied for making the model of classification. The methods used for model validation were split validation and cross-validation. The data for classification were the images of the waveform of processed noisy heart sounds and spectrogram of the processed sound. Software used for the working of classification was RapidMiner studio. It was found that the Random Forest technique with cross-validation of a spectrogram of sound files provided the best performance, which had accuracy = 93.69%, precision = 97.41%, recall = 89.68%, and F1-score = 93.39%.

Keywords: Phonocardiogram Spectrogram Classification Spectrogram Machine Learning

Introduction

According to the World Health Organization, cardiovascular diseases (CVDs) are one of the main causes of death globally. An estimated 17.9 million people died from CVDs in 2019 representing 32% of all global deaths. Out of the 17 million premature deaths (under the age of 70) due to noncommunicable diseases in 2019, 38% were caused by CVDs. It is important to detect cardiovascular disease as early as possible so that management with counseling and medicines can begin (WHO, 2021). Auscultation by using a stethoscope for listening to the heart sound is a part of physical examination. The stethoscope is a basic medical device that doctors always use to listen to mechanical valvular activity. It is a valuable method for CVDs detection. These diseases could be identified easily with the variations in the sound produced due to heart activity. That is the most primary diagnosis method for the initial detection of heart valves which is also an economical and simple screening test.

Heart sounds are created by blood flow and vibrations of tissues during the cardiac cycle. Under normal conditions, blood flow is laminar and silent. With structural or hemodynamic changes turbulent flow results, which causes vibrational waves. These waves are transmitted through the chest wall that is translated into sounds known as heart sounds or Phonocardiogram "PCG". PCG signal analysis is a common method for evaluating the condition of the heart and detecting possible anomalies.

Artificial intelligence (AI) is a science that gathers knowledge in many disciplines. In particular, it is the combination of science and engineering to develop machines or computer systems to be intelligent, able to think, calculate, analyze, learn and make decisions as rational as the human brain, and be able to learn, develop and improve its work processes to increase the potential of artificial intelligence itself (Sittichanbuncha, 2021). AI has been developed since the 1950s to the present day and can be used in a variety of areas, including the medical fields and healthcare industry such as diagnosing diseases detecting lung cancer, classifying skin lesions in skin images assessing the risk of sudden cardiac death or other heart diseases based on electrocardiograms, cardiac MRI images, and including phonocardiogram (Schmitt, 2020). Currently, Artificial intelligence (AI) algorithms are widely used in the classification of heart sound abnormalities due to the analysis of heart sound signals playing an irreplaceable role in the early diagnosis of heart disease and containing a large amount of pathological information about each part of the human heart. Heart sounds can be detected and recorded by Phonocardiogram (PCG) (Yang et al., 2019). As a non-invasive method to detect and diagnose heart disease, PCG signals have been paid more and more attention by researchers.

Research Objectives

1. To classification normal heart sound and abnormal heart sound from obtained phonocardiogram with breathing sound noise fil es by machine learning algorithms.
2. To compare the performance of 5 machine learning algorithms in the classification.

Literature Review

Aktar, and Andrei (2020) proposed a heartbeat audio classifier software design that could differentiate normal heartbeats and heart murmurs by Convolutional Neural Network (CNN) algorithm. The software could also differentiate the types of heart sounds. The CNN achieved an accuracy of approximately 79% on unseen test data, with an AUROC score of 0.78.

Baydoun, Safatly, Ghaziri, and El Hajj (2020) proposed an approach to combine multiple classification models of heart sounds to improve accuracy. The classification system by combining the LogitBoost model and the Bagging model provided the best score of 86.6% of accuracy, with a sensitivity and specificity of more than 90%, and 83% respectively.

Bourouhou, Jilbab, Nacir, and Hammouch (2020) proposed a classification algorithm based on the extraction of 20 features from segmented phonocardiogram (PCG) by applying four types of machine learning classifiers, which were k-nearest neighbor (KNN), support vector machines (SVM), Tree Classifier, and Naïve Bayes. The results showed that Naive Bayes had the best classification performance.

Zhang, Han, and Deng (2019) proposed the method for heart sound detection using the temporal quasi-periodic features of the heart sound signals. The analysis was done by AMDF of the heart sound spectrogram and the short-term and long-term dependency relation within the temporal quasi-periodic features extracted by long short-term memory (LSTM). This method could effectively detect abnormal heart sound.

Chowdhury, Khandakar, Alzoubi, Mansoor, Tahir, Reaz, and Al-Emadi (2019) proposed the prototype model of a smart digital-stethoscope system to monitor a patient's heart sounds. It helped in diagnosis any abnormality in a real-time manner. The model was designed by modifying an analog stethoscope. The stethoscope was added up by a miniaturized microcontroller with built-in Bluetooth low energy for digitization and transmission. The obtained data were classified by machine learning algorithms, which were Decision tree, discriminant analysis, support vector machines (SVM), k-nearest neighbor (KNN), and ensembles classifiers. The results showed that the Ensemble algorithm could outperform all the trained competition algorithms with an overall accuracy of 86.02%.

Yang, Li, Zhang, and Yang (2020) proposed the novel envelope extraction model which could use to estimate the cardiac cycle of each PCG signal. They combined the empirical mode decomposition (EMD) technique and the proposed envelope model to extract the time-domain features. The feature vectors were extracted from both the frequency-domain features and wavelet-domain features. By using the support vector machine (SVM) classifier to detect the normal and abnormal PCG signals, the model had an accuracy of more than 96%.

Methodology

1. The heart sound files

The PCG of heart sound files were obtained from Heart Sound & Murmur Library, University of Michigan. They were MP3-type with a 128kbps bit rate. There were 2 files of normal heart sounds and 21 files of abnormal heart sound including murmurs and clicks sounds.

2. Breathing sound noise preparation

The breathing sound noise was obtained from Respiratory Auscultation (https://www. mediscuss.org/respiratory-auscultation/). The file was also MP3 type with a 192kpbs bit rate. The sound was extended by repeating the sound to be longer closed to the time duration of heart sound by Audacity software.

3. Overlaying breathing sound noise over heart sound

In this step, we overlaid the extended breathing sound and heart sound files together by the Audacity software.

4. Changing tempo

We considered that the different activities of each person change the speed of breathing rate and heart rate. To simulate the situation, we made up the data by changing the tempos of the noisy heart sounds by Audacity software. The sound files were changed by setting the tempo to be faster from 0%, 10%, 20%, 30%, 40%, and 50%, and then exported to WAV files format. This technique still preserved the frequency of the wave.

5. Conversion to PNG spectrogram

Even the classification software, RapidMiner studio, had no audio library for classification, but it has many powerful functions for image processing. In this step, we wanted to make a comparison of using waveform files and spectrogram of sound as data sources for the machine learning part. Audacity software could display spectrogram in the Mel-frequency scale of each WAV file. The PNG files of the spectrogram were exported for classification.

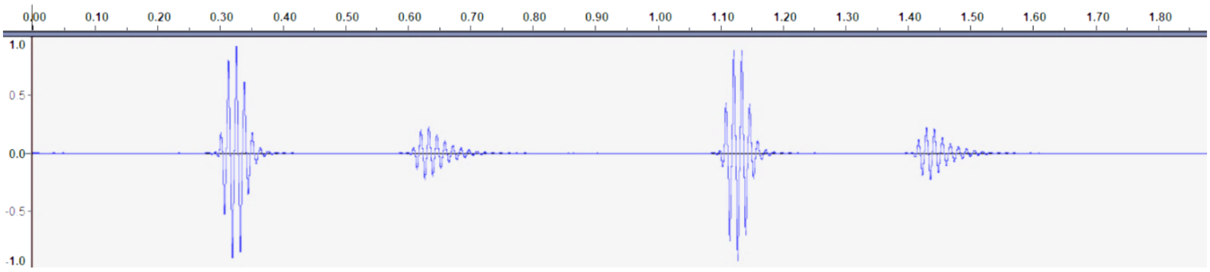
6. Setting the machine learning system for classification between normal heart sound and abnormal heart sound

In the last step, we set RapidMiner studio software to classify normal and abnormal heart sound. We used split validation and cross-validation for data manipulation. Here, 5 techniques of machine learning algorithm, which were Random Forest, Neural Net, Deep Learning, Support Vector Machine, Naïve Bayes, were applied for making the model of classification. The proposed 5 methods are very well-known machine learning techniques using in the classification. For the model obtained, we considered the confusion matrices and calculated accuracy, precision, recall, and F1-score.

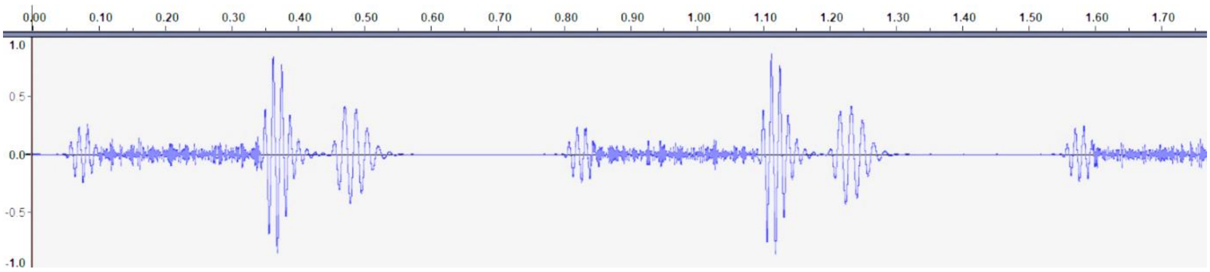
Results

1. The heart sound files

We provided examples of the time waveform of a PCG cardiac cycle in figure 1.



(a)

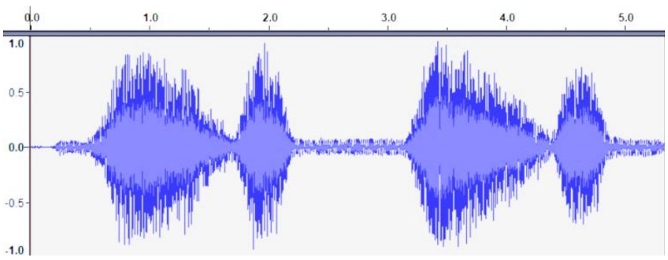


(b)

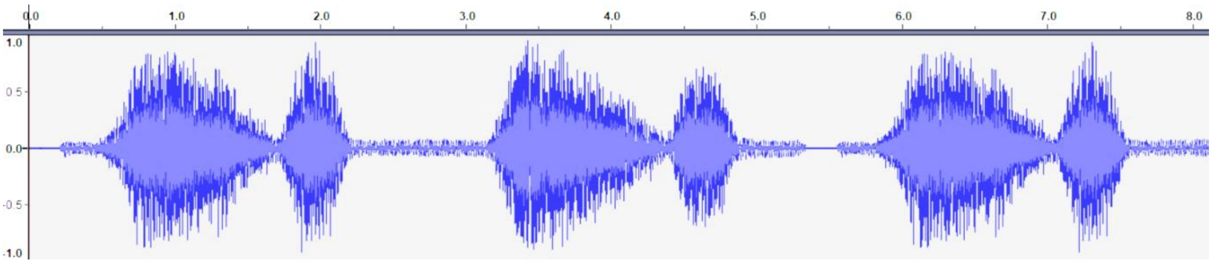
Figure 1: The time waveform of a PCG cardiac cycle in (a) normal and (b) abnormal

2. Breathing sound noise preparation

By the original breathing sound (figure 2 (a)), we extended the sound noise by repeating the sound (figure 2 (b)).



(a)

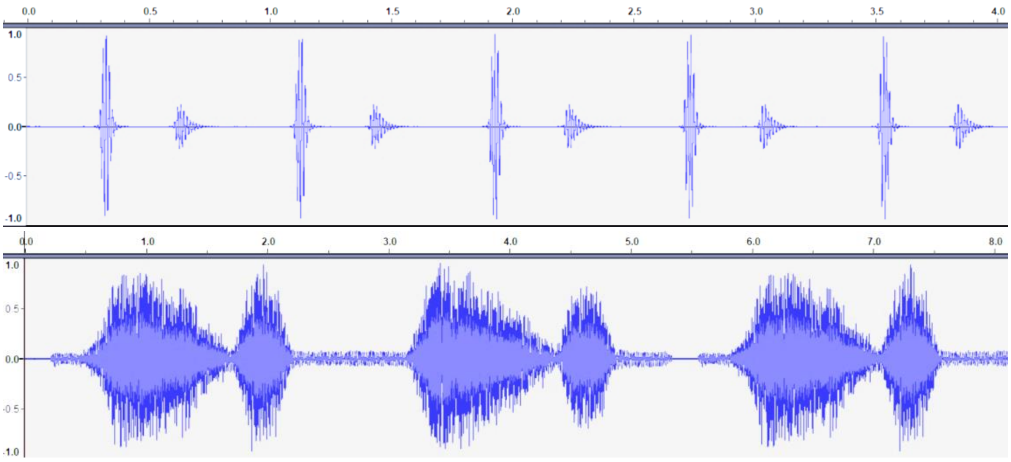


(b)

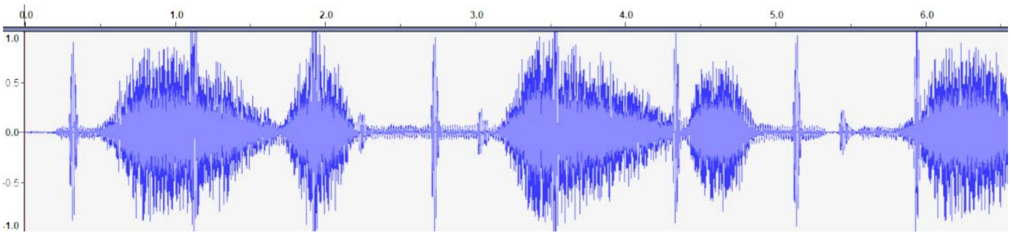
Figure 2: (a) Original breathing sound noise, and (b) extended sound noise

3. Overlaying breathing sound noise over heart sound

The PCG sound and extended breathing sound (figure 3 (a)) were combined by overlaying (figure 3 (b))



(a)

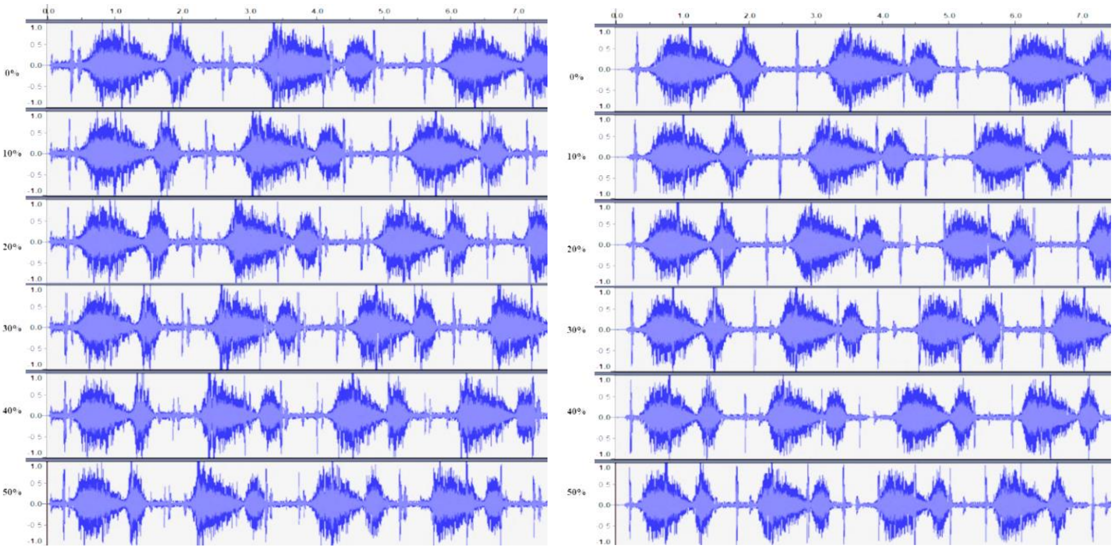


(b)

Figure 3: Combining PCG sound and extended breathing sound (a) and results (b)

4. Changing tempo

The results of changing tempos were presented in figure 4.

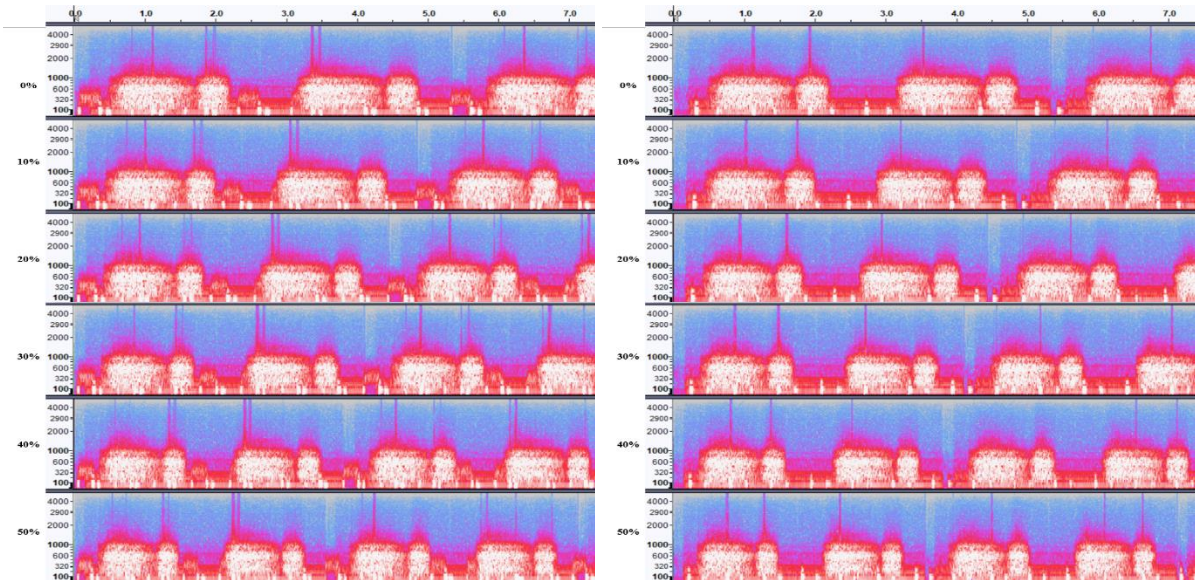


(a) (b)

Figure 4: Examples of PCG sound modified by changing tempos
(a) normal heart sound (b) abnormal heart sound

5. Conversion to PNG spectrogram (spectrogram in Mel-frequency scale)

By Audacity software, spectrogram in Mel-frequency scale of each WAV was created and exported as PNG files.



(a) (b)

Figure 5: Examples of a spectrogram of noisy PCG heart sound
(a) normal heart sound (b) abnormal heart sound

6. Setting the machine learning system for classification between normal heart sound and abnormal heart sound

RapidMiner Studio is a software that can do coding a program by block diagrams. For setting the machine learning system, we did programming as the following steps.

6.1 Prepare Datasets

The waveform and spectrogram images were separated into 2 groups, normal and abnormal. The data would be used for training and testing the models. The block diagram code and the setting were shown in figure 6. The data used as input data were waveform images and spectrogram images.

Figure 6: Block diagram for datasets preparation

6.2 SMOTE Up-sampling

Since the ratio of a number of normal heart sound data (12 files) and abnormal heart sound data (126 files) were quite different. For reducing the unbalance data problem, we applied Synthetic Minority Over-sampling Technique or SMOTE to up-sampling the number of normal heart sound data.

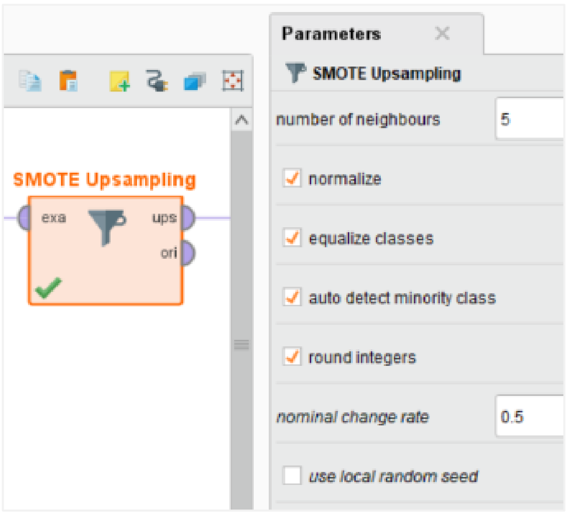


Figure 7: Block diagram for SMOTE up-sampling setting

6.3 Process

We used the “Multiply” operator for creating copies of our data. The Multiply operator helped us in making many machine learning techniques models according to our suggested algorithms parallelly. Here, the multiply” operator was connected to Random Forest, Neural Network (NN), Deep Learning, Support Vector Machine (SVM), Naïve Bayes block diagrams.

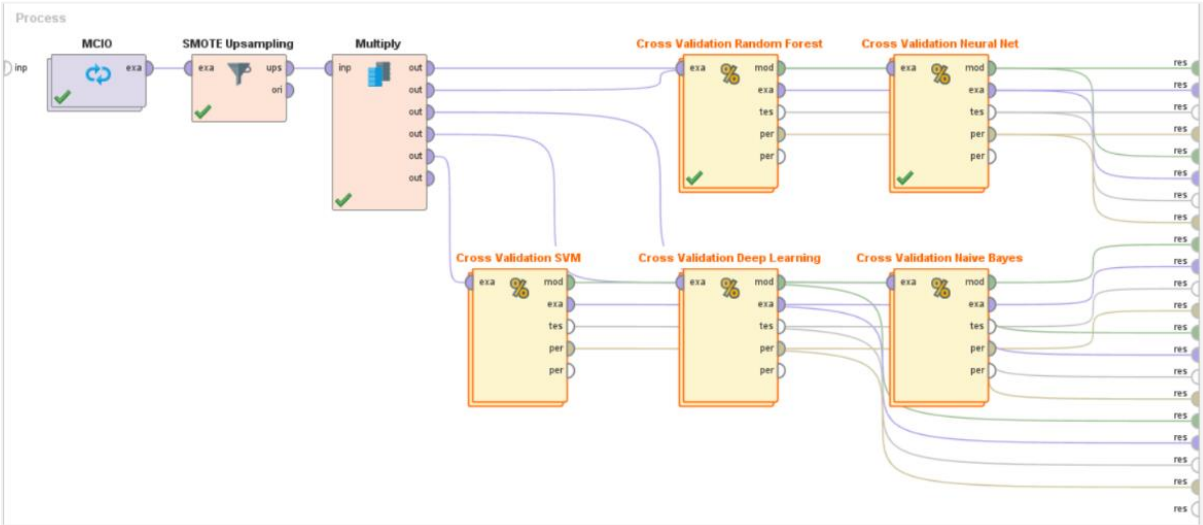
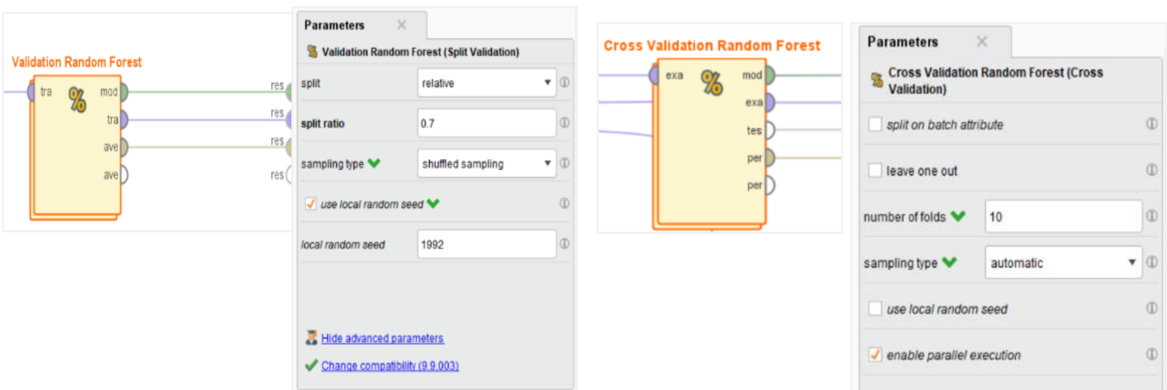


Figure 8: Block diagram for setting models parallelly by the Multiply operation

6.4 Validation setting

In this step, we used the data for making models and tested models obtained, called validation. The methods used for validation were split validation and cross-validation. For the split validation, 3 cases for ratios of training sets to testing sets were considered, 70%:30%, 75%:25%, and 80%:20%. All four methods were considered for performance evaluation.



(a) (b)

Figure 9: Block diagram for setting parameters for validation
(a) split validation (b) cross-validation

6.5 Making models

In this part, all models of 5 algorithms with 4 methods of validation were created and evaluated the performance.

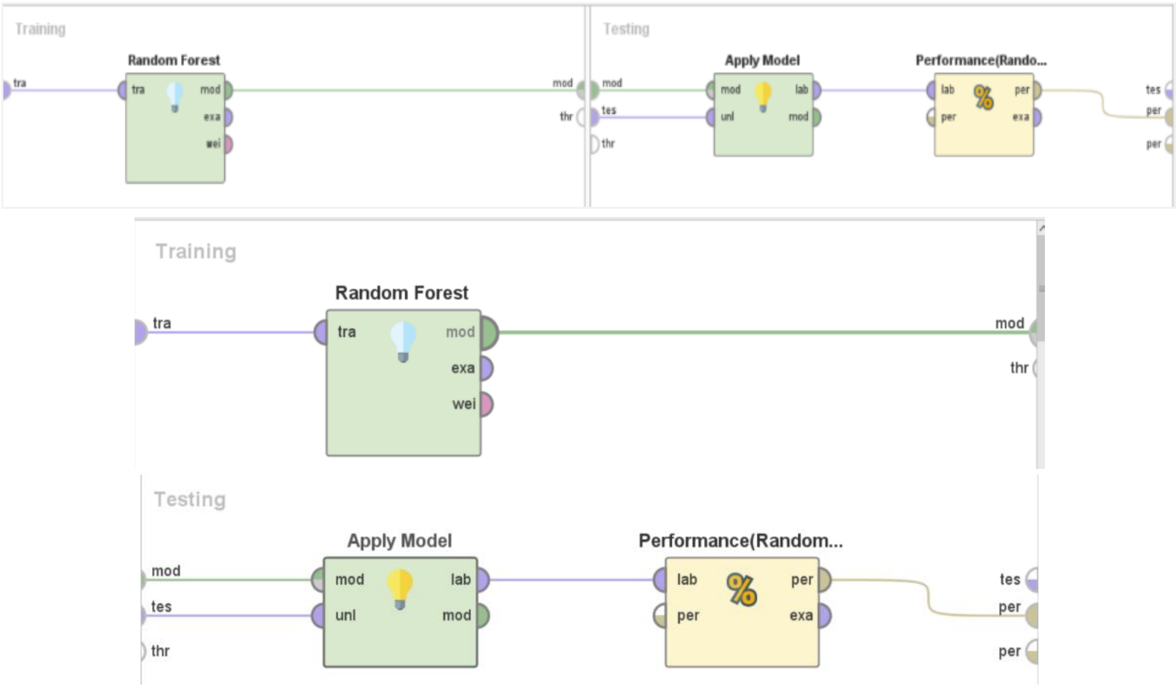


Figure 10: Example of a Block Diagram for Model Creating and Model Evaluation

7. Performance Evaluation

7.1 Results by using waveform files

Table 1: 70% Training and 30% Testing Split Validation

Method	Accuracy	Recall	Precision	F1-score
Random Forest	82.89%	77.50%	88.57%	82.67%
Neural Net	80.26%	62.50%	100.00%	76.92%
Deep Learning	82.89%	80.00%	86.49%	83.12%
Support Vector Machine	76.32%	65.00%	86.67%	74.29%
Naïve Bayes	78.00%	56.00%	100.00%	71.79%

Table 2: 75% Training and 25% Testing Split Validation

Method	Accuracy	Recall	Precision	F1-score
Random Forest	82.54%	78.79%	86.67%	82.54%
Neural Net	87.30%	78.79%	96.30%	86.67%
Deep Learning	80.95%	63.64%	100.00%	77.79%
Support Vector Machine	79.37%	69.70%	88.46%	77.97%
Naïve Bayes	78.00%	56.00%	100.00%	71.79%

Table 3: 80% Training and 20% Testing Split Validation

Method	Accuracy	Recall	Precision	F1-score
Random Forest	80.00%	84.00%	77.78%	80.77%
Neural Net	86.00%	72.00%	100.00%	83.72%
Deep Learning	88.00%	80.00%	95.24%	86.96%
Support Vector Machine	76.00%	72.00%	78.26%	75.00%
Naïve Bayes	78.00%	56.00%	100.00%	71.79%

Table 4: Cross-Validation

Method	Accuracy	Recall	Precision	F1-score
Random Forest*	86.20%	82.54%	88.89%	85.60%
Neural Net	83.74%	75.40%	90.48%	82.25%
Deep Learning	83.37%	76.98%	88.18%	82.20%
Support Vector Machine	77.37%	70.63%	81.65%	75.74%
Naïve Bayes	71.78%	46.03%	95.08%	62.03%

7.2 Results by using spectrogram of sound files

Table 5: 70% Training and 30% Testing Split Validation

Method	Accuracy	Recall	Precision	F1-score
Random Forest	92.11%	90.00%	91.74%	90.86%
Neural Net	81.58%	85.00%	80.95%	82.93%
Deep Learning	80.26%	75.00%	85.71%	80.00%
Support Vector Machine	75.00%	52.50%	100.00%	68.85%
Naïve Bayes	70.00%	44.00%	91.67%	59.46%

Table 6: 75% Training and 25% Testing Split Validation

Method	Accuracy	Recall	Precision	F1-score
Random Forest	92.06%	90.91%	93.75%	92.31%
Neural Net	74.60%	66.67%	81.48%	73.33%
Deep Learning	80.95%	48.48%	80.00%	60.37%
Support Vector Machine	73.02%	44.00%	100.00%	61.11%
Naïve Bayes	70.00%	44.00%	91.67%	59.46%

Table 7: 80% Training and 20% Testing Split Validation

Method	Accuracy	Recall	Precision	F1-score
Random Forest	92.00%	88.00%	95.65%	91.67%
Neural Net	88.00%	80.00%	95.24%	86.96%
Deep Learning	82.00%	84.00%	80.77%	82.35%
Support Vector Machine	74.00%	48.00%	100.00%	64.86%
Naïve Bayes	70.00%	44.00%	91.67%	59.46%

Table 8: Cross Validation

Method	Accuracy	Recall	Precision	F1-score
Random Forest*	93.69%*	89.68%*	97.41%*	93.39%*
Neural Net	86.89%	76.98%	96.04%	85.46%
Deep Learning	87.31%	83.33%	90.52%	86.78%
Support Vector Machine	75.78%	51.59%	100.00%	68.07%
Naïve Bayes	69.46%	48.41%	83.56%	61.30%

Remark *The model which had the highest performance.

Discussion

By the results proposed, we found that the Random Forest algorithm was the best one for sound classification. It provided the highest accuracy in almost all validations. For the validation of the model, the cross-validation technique always performed better than split validation. Random Forest algorithm also worked better in the classification of spectrogram compared to the classification of spectrogram waveform directly, which had accuracy, precision, and F1-score more than 90%.

Conclusion

It was found that the Random Forest technique with cross-validation of a spectrogram of sound files provided the best performance, which had accuracy = 93.69%, precision = 97.41%, recall = 89.68%, and F1-score = 93.39%.

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This work was supported by Suranaree University of Technology One Research One Graduate scholarship (SUT OROG scholarship). We also want to express our sincere gratitude to the center of excellence in biomechanics medicine, school of biomedical innovation engineering, school of electric engineer, and school of mathematics, Suranaree University of Technology, Thailand.

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NEUNGREUTAI PRASERT, THANASET THOSDEEKORAPHAT, AND JESSADA TANTHANUCH

Have presented an article titled:

COMPARISON OF THE CLASSIFICATION OF PHONOCARDIOGRAMS WITH BREATHING SOUND NOISE BY MACHINE LEARNING ALGORITHMS

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(Associate Professor Dr. Sompop Manarungsan)

President of Panyapiwat Institute of Management