APPLICATION OF THE TWIN SUPPORT VECTOR MACHINE ALGORITHM TO HEART SOUND WITH BREATHING SOUND NOISE CLASSIFICATION

Warapron Srisup

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การประยุกต์ของขั้นตอนวิธีทวินซัพพอร์ตเวกเตอร์แมชชีน
เพื่อจำแนกเสียงหัวใจที่มีเสียงหายใจรบกวน

นางสาววราภรณ์ ศรีทรัพย์

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต

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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for a Master's Degree.

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ทวินซัพพอร์ตเวกเตอร์แมชชีน/เสียงหัวใจผิดปกติ/เสียงหายใจ/ข้อมูลไม่สมดุล

วิทยานิพนธ์นี้มีวัตถุประสงค์เพื่อการศึกษา และประยุกต์ใช้ขั้นตอนวิธีทวินซัพพอร์ตเวกเตอร์แมชชีน ในการจำแนกเสียงหัวใจปกติและเสียงหัวใจผิดปกติ จากข้อมูลเสียงหัวใจที่มีเสียงหายใจรบกวนความดังต่าง ๆ โดยใช้ข้อมูลเสียงหัวใจจาก Heart Sound & Murmur Library, University of Michigan ซึ่งประกอบด้วยเสียงหัวใจปกติ เสียงหัวใจผิดปกติแบบมีเสียงฟู่ของหัวใจ และแบบมีเสียงคลิก และเสียงหายใจจาก Respiratory Auscultation https://www.mediscuss.org/ การดำเนินการใช้โปรแกรมสำเร็จรูป Audacity ในการรวมเสียงของหัวใจและเสียงลมหายใจเข้าด้วยกัน จากนั้นพิจารณาฟีเจอร์ของข้อมูลเสียงที่ได้ ได้แก่ root-mean-square, the spectral centroid, a p'th-order spectral bandwidth, a spectral flatness, a roll-off frequency, coefficients of fitting an n^{th}-order polynomial to the columns of a spectrogram และ the zero-crossing rate of an audio time series และใช้วิธีการจัดการข้อมูลไม่สมดุลเพื่อใช้ในการปรับปรุงข้อมูลก่อนทำการสร้างตัวแบบ ในการสร้างตัวแบบได้ใช้เคอร์เนล Radial Basis Function ในการแปลงให้เป็นข้อมูลเชิงเส้น และใช้ขั้นตอนวิธีซัพพอร์ตเวกเตอร์แมชชีนและทวินซัพพอร์ตเวกเตอร์แมชชีนในการจำแนกเสียงหัวใจ โดยแบ่งข้อมูลเป็น 3 กลุ่ม ซึ่งแบ่งเป็นอัตราส่วนชุดฝึกและชุดทดสอบดังนี้ กลุ่มหนึ่ง ร้อยละ 70 ต่อ ร้อยละ 30 กลุ่มสอง ร้อยละ 75 ต่อ ร้อยละ 25 และ กลุ่มสาม ร้อยละ 80 ต่อ ร้อยละ 20 ทั้งนี้ได้พัฒนาโปรแกรมและใช้โปรแกรมสำเร็จบางส่วนของภาษาไพทอนในการดำเนินการสร้างตัวแบบ และวิเคราะห์ข้อมูล ผลการวิจัยพบว่าขั้นตอนวิธีซัพพอร์ตเวกเตอร์แมชชีนสามารถจำแนก เสียงหัวใจผิดปกติได้มีประสิทธิภาพสูงที่สุดในกรณีที่แบ่งอัตราส่วนชุดฝึกและชุดทดสอบ ตามกลุ่มสาม (ชุดฝึกร้อยละ 80 ชุดทดสอบร้อยละ 20) โดยความแม่นร้อยละ 94.12 มีความเที่ยงร้อยละ 89.19 และ ค่า

เรียกคืนร้อยละ 100 ส่วนขั้นตอนวิธีทวินซัพพอร์ตเวกเตอร์แมชชีน สามารถจำแนก เสียงหัวใจผิดปกติได้มีประสิทธิภาพสูงที่สุดในกรณีที่แบ่งอัตราส่วนชุดฝึกและชุดทดสอบ ตามกลุ่มหนึ่ง (ชุดฝึกร้อยละ 70 ชุดทดสอบร้อยละ 30) โดย ความแม่นร้อยละ 96.04 มีความเที่ยงร้อยละ 100 และ ค่าเรียกคืนร้อยละ 93.10 ซึ่งมีประสิทธิภาพในการจำแนกเสียงหัวใจที่ผิดปกติสูงกว่าขั้นตอนวิธีซัพพอร์ตเวกเตอร์แมชชีน

สาขาวิชาคณิตศาสตร์ ลายมือชื่อนักศึกษา ______________

ปีการศึกษา 2563 ลายมือชื่ออาจารย์ที่ปรึกษา Panu Yimmuang

ลายมือชื่ออาจารย์ที่ปรึกษาร่วม J. Tanthanuch

WARAPRON SRISUP : APPLICATION OF THE TWIN SUPPORT VECTOR MACHINE ALGORITHM TO HEART SOUND WITH BREATHING SOUND NOISE CLASSIFICATION. THESIS ADVISOR : ASST. PROF. PANU YIMMUANG , Ph.D. 49 PP.

TWIN SUPPORT VECTOR MACHINE/ABNORMAL HEART SOUND/ BREATH SOUND/IMBALANCE DATA

This thesis aims to study and apply the twin support vector machine for the heart sound classification (normal/abnormal) from the heart sound data overlaid with different-volume breath sound noise. The heart sound data was obtained from Heart Sound & Murmur Library, University of Michigan, which composed of normal heart sound, murmur abnormal heart sound and click abnormal heart sound. Whereas, the breathing sound was from Respiratory Auscultation https://www.mediscuss.org/. The heart sound data was manipulated with Audacity software to be overlaid with the breathing sound. Then the features of the files were extracted, which were root-mean-square, the spectral centroid, a p'th-order spectral bandwidth, a spectral flatness, a roll-off frequency, coefficients of fitting an n^{th}-order polynomial to the columns of a spectrogram, and the zero-crossing rate of an audio time series. Moreover, the imbalance data method was applied for the data improvement before the modelling. Here, the Radial Basis Function kernel was used to transform the data to be linear. After that, the support vector machine and the twin support vector machine methods were utilized to model. The classification were done of 3 groups of data according to the ratio of train set and test set, which were 1^{st} group 70%:30%, 2^{nd} group 75%:25% and the last group 80%:20%.The result showed that the support vector machine provided best performance with the ratio of train set and test set was 80%:20%, which had accuracy =

94.12%, precision = 89.19%, and recall = 100%. The twin support vector machine provided best performance with the ratio of train set and test set was 70%:30%, which had accuracy = 96.04%, precision = 100%, and recall = 93.10%. According to the results, the application of the twin support vector machine method to the heart sound classification could perform better accuracy and precision compared to the one of the support vector machine method.

School of Mathematics — Student's Signature ____________

Academic Year 2020 — Advisor's Signature ____________

Co-Advisor's Signature ____________

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Warapron Srisup

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CHAPTER I

INTRODUCTION

Cardiovascular diseases (CVDs) are a group of the heart and blood vessels disordering problem. They are classified into

- **coronary heart disease:** disease of the blood vessels become too narrow, which provides not enough blood supplying the heart muscle;
- **cerebrovascular disease:** disease of the blood vessels narrowing (stenosis), clot formation (thrombosis), blockage (embolism) or blood vessel rupture (hemorrhage), which restricts in blood flow to the brain;
- **peripheral arterial disease/peripheral artery disease:** disease of the common circulatory problem in which narrowed arteries reduce blood supplying to the limbs (arms/legs);
- **rheumatic heart disease:** condition of the heart muscle and heart valves damage from rheumatic fever, caused by streptococcal infection;
- **congenital heart disease:** disease of abnormal formations of the heart walls, valves, or blood vessels, which occur during embryonic development;
- **deep vein thrombosis and pulmonary embolism:** blood clots in the deep leg veins, which break off from vein walls and move to the heart and lungs.

CVDs were claimed to be the highest rank cause of death in worldwide (World Health Organization, 2017).

The diagnosis of CVDs can be done by stethoscope, chest X-ray, exercise test, echocardiogram (by the ultrasound), electrocardiogram (ECG or EKG), Cardiac Computed Tomography Imaging, mechanocardiography, polygraphic methods, and spirometry (Gillum, 1988). The cost of the diagnosis varies a lots according to the processes and the equipments. The most basic, simplest, widely used and high efficient method is the diagnosis by a stethoscope.

The conventional stethoscope to hear cardiac auscultations is always used for the initial diagnosis. This technique may not be able to detect many types of CVDs precisely but it is noninvasive and less expense to patients. Some cardiac problems, e.g. heart valve disease, can be diagnosed from the abnormal sound (murmur, click, persistent, transient) when a doctor listens to the heart beating through a stethoscope. However during the listening the heart sound, there is always some interference by other noise, which are breathing sound or lung sound. This interruption may cause a misdiagnosis (Zipes et al., 2019).

Nowadays, there are a lots of wearable technology for health monitoring, e.g Motiv Ring, Smart glasses, Fibit, Garmin watch, Andriod smart watches, and Apple watch. They are able to detect movement behavior, heart rate, ECG, oxygen level, and etc. The techniques use artificial intelligence (AI) for helping in the monitoring and diagnosis. This research aims to applied mathematics and AI techniques to classify the abnormal heart sound with breathing sound/lung sound noise. Here, we focus on the application of modified support vector machine (SVM) techniques in the classification. SVM is a supervised learning AI algorithm for data classification. It is mostly establised in the applications of hand writing recognition, biometrics, bioinformatics, stock market forecasting and data mining (Campbell and Ying, 2011). There is an enhancement of support vector machine to be more generalized, twin support vector machince (TSVM).

TSVM was introduced by Khemchandani in 2017 by extending the concept of SVM to find two non-parallel hyperplanes that distinctly classify the data. In this research, we want to apply TSVM algorithm to classify heart sound (both normal and abnormal heart sound) with breathing sound noise.

1.1 Research Objectives

1. To classify abnormal heart sound with breathing sound noise by TSVM.

2. To evaluate performance of the model obtained.

1.2 Scope and Limitations

1. Heart sound wave files used in this research are from University of Michigan Heart Sound and Murmur Library, produced by The Learning Resource Center - Office of Medical Education ©copyright 2007.

2. Breathing sound wave file is downloaded from Respiratory Auscultation web page. https://www.mediscuss.org/respiratory-auscultation/

3. The abnormal heart sounds are scoped to murmur, click, persistent and transient sound only.

4. The study will consider the comparison of SVM and TSVM only.

1.3 Research Procedure

The research work proceeded as follows:

1. Study algorithm related with the classification of heart sound .

2. Study SVM and TSVM.

3. Analyze and construct the model from heart sound.
4. Analyze breath sound.
5. Classification heart sound with breath sound noise by proposed model.
6. Compare the performances between SVM and TSVM.

1.4 Expected Results

This thesis would be able to show that performance of classification of TSVM for heart sound signals.

CHAPTER II

LITERATURE REVIEW

This chapter talks about the knowledge of the heart sound, breathing sound, stethoscope, twin support vector machine, imbalance data techniques, radial basis function kernel, and related research work.

2.1 Heart anatomy

The human body has a vital organ. If missing it, then you can't be alive; this is called heart. The heart must pump deoxygenated blood to the lungs and pump oxygenated blood all over the body.

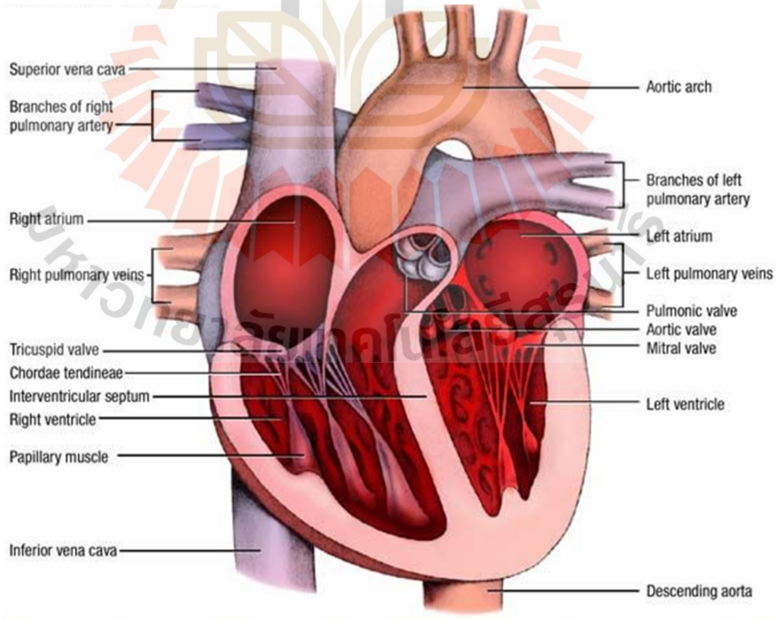

Figure 2.1 Heart structure.

credit: Auscultation Skills Breath Heart Sounds, 4th Edition by Lippincott.

The anatomy of the heart is separated into four chambers. The right-sided chambers are the right atrium and right ventricle, the left-sided chambers are the left atrium and left ventricle. The blood flows into each chambers control by cardiac valves to keep the blood flowing in one direction by the following:

1. Aortic valve is separate between the left ventricle and aorta.
2. Pulmonary valve is separate between the right ventricle and pulmonary artery.
3. Tricuspid valve is separate between the right atrium and the right ventricle.
4. Mitral valve is separate between the left atrium and the left ventricle.

The heart must create enough pressure to pump blood through the arterial circulation and have a cardiac cycle. The cardiac cycle is consists of systole that is rhythmically contracting and diastole that is relaxing.

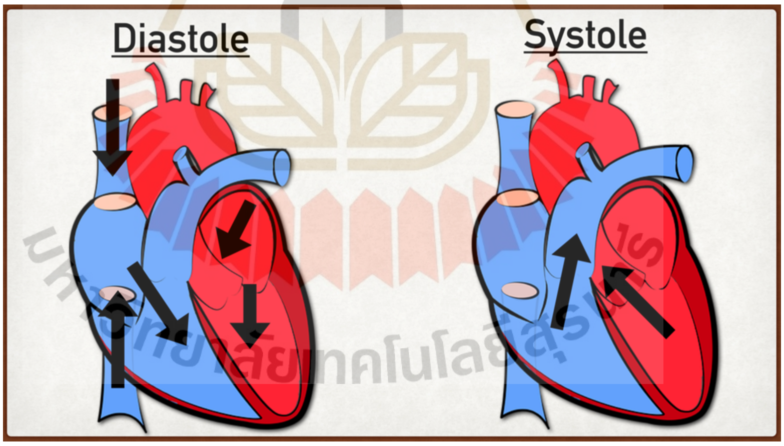

Figure 2.2 Cardiac cycle.

credit: https://www.ezmedlearning.com/blog/cardiac-cycle

2.2 Heart sound recognition

2.2.1 Normal heart sound

Heart sound is obtained by opening and closing of heart valves, contraction of heart, turbulent flow by the following:

1. The first heart sound (S1) is created by closing the tricuspid valve and mitral valve, obtain the Lub sound, and is heard at the beginning of the systole.
2. The second heart sound (S2) is created by closing the aortic valve and pulmonary valve, obtain the Dub sound, and is heard when the end of systole. S2 is louder than S1 and higher pitch than S1.
3. The third heart sound (S3) is heard at the diastole. This sound is considered in individuals younger than age 20 or people who get exercise otherwise heard this sound, then it may be some abnormal signs.
4. The fourth heart sound (S4) is created by atrial contraction. This sound is not considered ordinary. When heard this sound, will obtain some abnormal signs.

Therefore, in general, we can hear only S1 and S2.

2.2.2 Abnormal heart sound

This research considers murmur sounds and click sounds. The murmur sounds is created by the confusion of blood flow through the small hole, e.g., aortic valve stenosis, mitral insufficiency, ventricular septal defect.

The categories of murmur sound are following:

1. Systolic murmur is heard between S1 and S2 or at the ventricle contraction.

2. Diastolic murmur is heard between S2 and S1 or at the ventricle relaxing.

3. Continuous murmur is heard in systole and diastole.

The click sounds arise from The aortic valve or semilunar valves open noisily. The categories of click sound are following:

1. Ejection clicks occur in early systole and have a high pitch.

2. Non-ejection clicks occur in mid to late systole and have a high frequency.

3. Opening snaps occur in diastole and snappy character.

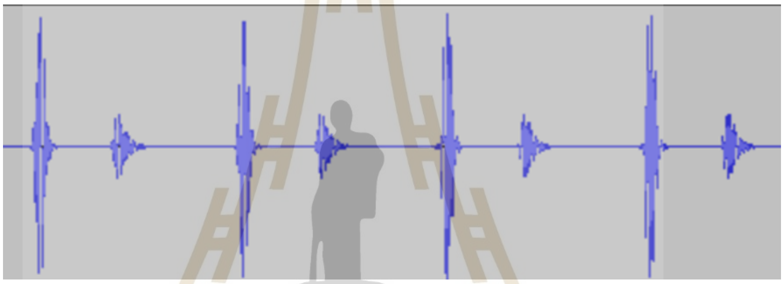

Figure 2.3 Normal heart sound signal.

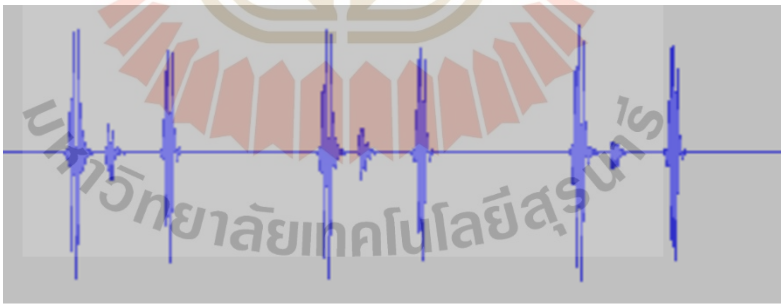

Figure 2.4 Abnormal heart sound signal.

2.2.3 Stethoscope

The stethoscope is an ordinary device to hear sounds inside the body, e.g., heart sound, heart vibrations, breathing sound. That is the primary diagnose. The stethoscope has two sides by the following:

1. Bell chest pieces look like a bowl or bell for hearing low pitch sound or low-frequency sound, e.g., S3, S4, diastolic rumbling murmur.

2. Diaphragm chest pieces look like a flat sheet for hearing high pitch sound or high-frequency sound, e.g., S2, systole ejection murmur, pulmonic stenosis.

Diagnose of murmur sound

Heart murmur sound classification is considered the feature by following:

1. Timing of murmur detects that systolic, diastolic, or continuous murmur.

2. Point of maximum intensity of the murmur

3. Pitch and quality of the murmur

4. Finer timing

2.2.4 Breathing sound

Breath sound is created by airflow in bronchia when inspiration and expiration. The stethoscope hears breath sounds through the chest wall. Thus the beath sound can disturb when listening to heart sound.

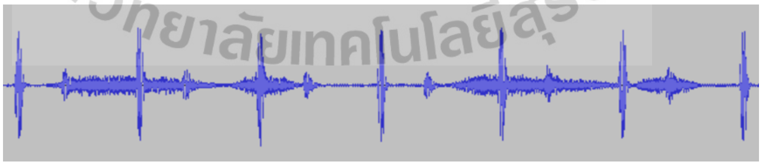

Figure 2.5 Heart sound signal with breath sound noise.

2.3 Methods of the classification

2.3.1 Support vector machine

SVM is an algorithm to solve classification problems and regression problems. This thesis is considering classification problems. The idea of SVM for classification problems find the hyperplane to separate the data. For example, we must find the line to separate the data in two dimensions space for binary classification by following the figure below.

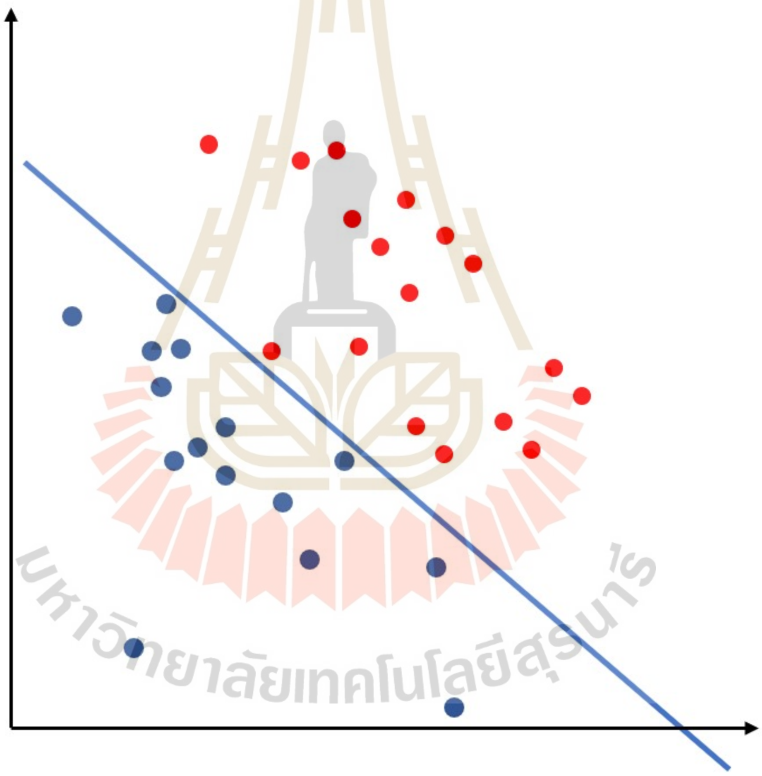

Figure 2.6 Primal idea of SVM.

From the figure above, we can find many lines to separate the data; therefore, the problem is to find the best line to classify the data, then the idea base on the optimization problem.

Let to know to formalize in mathematical as follows.

Classification problem:

Let a training set

$$T = (x_1, y_1), \cdots, (x_l, y_l), \tag{2.1}$$

where $x_i \in R^n, y_i \in Y = \{-1, 1\}, i = 1, \cdots, l$, find a real value function $g(x)$ in R^n, to obtain the value of y for any x by the decision function

$$f(x) = sqn(g(x)). \tag{2.2}$$

The distance between the hyperplane that separates the data and the data sample nearest to the hyperplane is called margin; the goal of SVM is to find the optimal hyperplane with the maximum margin.

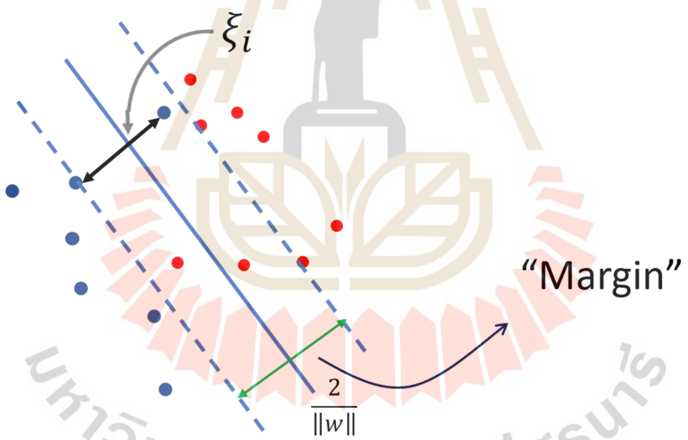

Figure 2.7 Support Vector Machine.

The primal SVM model is expressed in the form

$$\min_{w,b,\xi} \ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}\xi_i, \tag{2.3}$$

$$\text{subject to} \ \ y_i((w\cdot x_i) + b) \geq 1 - \xi_i, \tag{2.4}$$

$$\xi_i \geq 0, i = 1, 2, 3 \ldots, m, \tag{2.5}$$

where, $w \in \mathbb{R}^n$, $b \in \mathbb{R}$, C is the penalty parameter and ξ_i is slack variables. The decision function of the above formulation is $g(x) = (w \cdot x) + b$ where x is assigned to class 1 if the value is positive otherwise it is assigned to class -1.

2.3.2 Twin support vector machine

In 2007, Khemchandani et al. introduced a twin support vector machine (TSVM) . The goal of TSVM is to generate two non-parallel hyperplanes where each hyperplane is nearest one of two classes and as distant as possible from the other. Thus, TSVM solves a pair of quadratic programming problems, but SVM solves a quadratic programming problem. Furthermore, the TSVM pattern of one class gives the constraints of other quadratic programming problems, so this strategy makes TSVM work faster than SVM.

Consider two non-parallel hyperplanes in this function:

$$f_1(x) = w_1^T x + b_1 \quad \text{and} \quad f_2(x) = w_2^T x + b_2,$$

where, $w_1, w_2 \in \mathbb{R}^n$ and $b_1, b_2 \in \mathbb{R}$ are the weight vectors and biases of the hyperplane $f_1(x)$ and the hyperplane $f_2(x)$, respectively.

Let us consider a training set

$$T = \{(x_i, y_i) \in \mathbb{R}^n \times \{1, -1\} : i = 1, 2, \ldots, m\}, \tag{2.6}$$

Let m_1 patterns in class +1 and m_1 patterns in class +1 and m_2 patterns in class -1, where $m_1 + m_2 = m$. Let matrix A and matrix B be $(m_1 \times n)$ for which $y_i = +1$ and $(m_2 \times n)$ for which $y_i = -1$, respectively. The optimization problems of TSVM with constraints are written as

$$\min_{w_1,b_1,\xi_2} \frac{1}{2}\left\|Aw_1 + e_1b_1\right\|_2 + c_1e_2^T\xi_2, \tag{2.7}$$

$$\text{subject to} - (Bw_1 + e_2b_1) + \xi_2 \geq e_2,$$

$$\xi_2 \geq 0,$$

and

$$\min_{w_2,b_2,\xi_1} \frac{1}{2}\left\|Bw_2 + e_2b_2\right\|_2 + c_2e_1^T\xi_1, \tag{2.8}$$

$$\text{subject to } (Aw_2 + e_1b_2) + \xi_1 \geq e_1,$$

$$\xi_1 \geq 0,$$

where $c_1, c_2 > 0$ are the penalty parameters, $\xi_1 \in \mathbb{R}^{m_1},\ \xi_2 \in \mathbb{R}^{m_2}$ are slack vectors, $b_1, b_2 \in \mathbb{R}$and $e_1 \in \mathbb{R}^{m_1}, e_2 \in \mathbb{R}^{m_2}$ are vectors each component is 'one'.

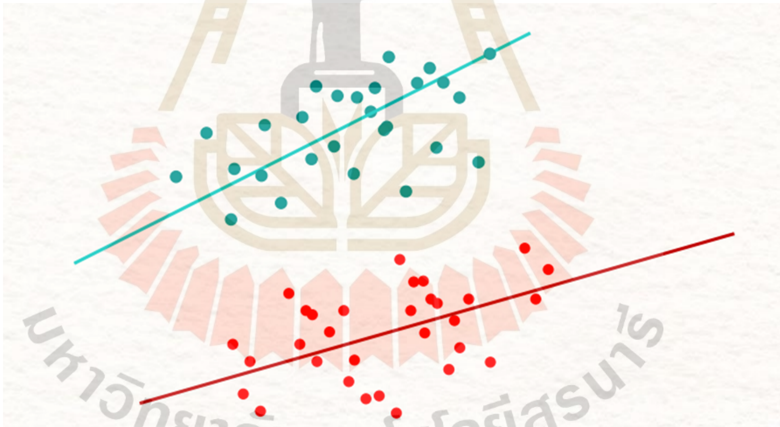

Figure 2.8 Twin Support Vector Machine.

2.4 Kernel

Consider non-linear classification problem is a problem that can not find the hyperplane to solve. Then there is the function to convert the data set to the data that extend dimension, makes non-linear classification become linear classification problem.

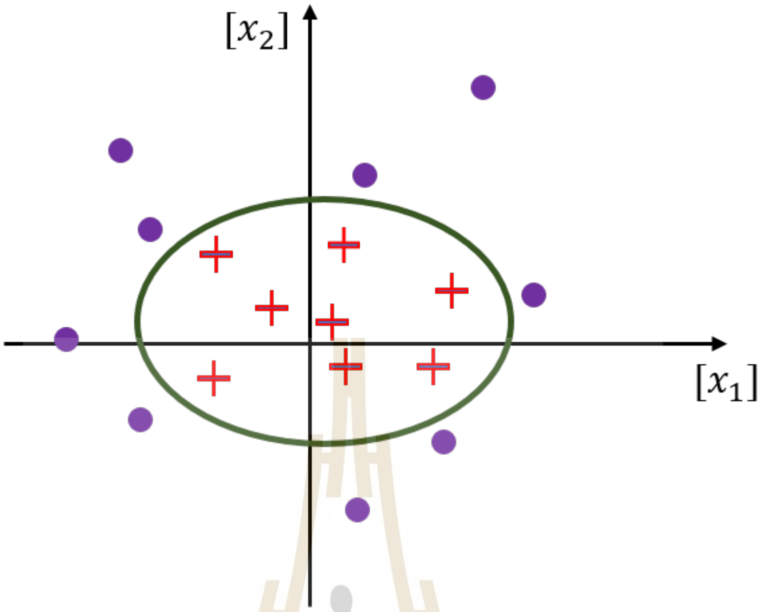

Figure 2.9 Non linear classification problem.

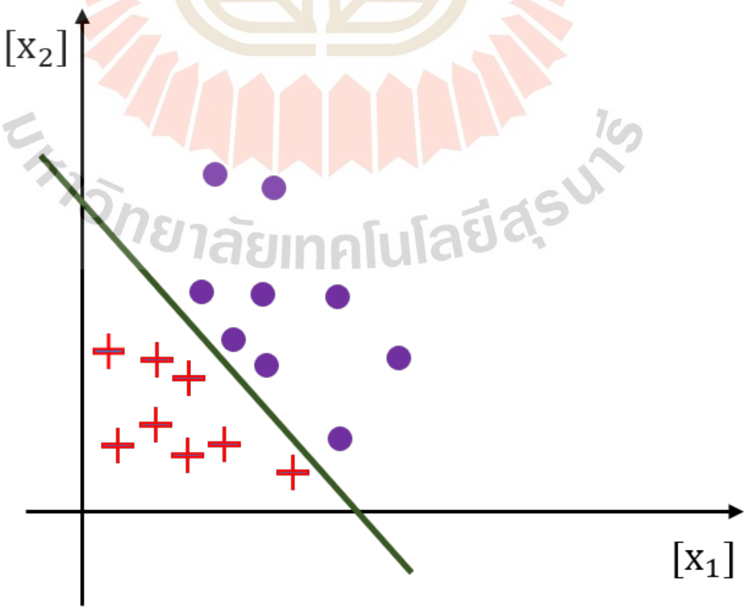

Figure 2.10 Linear classification problem.

Definition 1. (Kernel) A function $K(x, x')$ defined on $\mathbb{R}^n \times \mathbb{R}^n$ is called a kernel on $\mathbb{R}^n \times \mathbb{R}^n$ if there exists a map Φ from the space $\mathbb{R}$ to the Hilbert space

$$\Phi : x \longmapsto \Phi(x), \tag{2.9}$$

such that

$$K(x, x') = (\Phi(x) \cdot \Phi(x')), \tag{2.10}$$

where $(\cdot)$ denotes the inner product of space $\mathcal{H}$

This research examines the radial basis function kernel.

Theorem 1. Radial basis function with a parameter σ.

$$K(x, x') = exp(\frac{-\|x - x'\|^2}{\sigma^2}) \tag{2.11}$$

is a kernel.

2.5 Imbalance data technique

Imbalance data is the number of data in class, is more than other classes. The class with more data than others is called the majority class; otherwise, it is called the minority class. Imbalance data affect classification performance because the result must classify into the majority class. So we must find the technique to solve this problem.

1. Over sampling is the technique that adds the data to the minority class approximate to the majority class. **SMOTE** technique generates data from generating the neighborhood of example data in the minority class.

2. Under sampling is the technique that removes the data from the majority class approximate to the minority class.

2.6 Performance Evaluation

2.6.1 Confusion Matrix

The confusion matrix evaluates the performance of the classification model in machine learning, evaluate by predicted values and actual values.

Table 2.1 Confusion matrix.

		Actual value	
		True	False
Predicted value	True	TP	FP
	Flase	FN	TN

Where;

True Positive(TP) is when the predicted value is yes, and the actual output is yes.

True Negative(TN) is when the predicted value is no, and the actual output is no.

False-Positive(FP) is when the predicted value is yes, and the actual output is no.

False-Negative(FN) is when the predicted value is no, and the actual output is yes.

Accuracy, Classification precision, and Recall rate for the matrix can be calculated as

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2.12}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2.13}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2.14}$$

2.7 Related Researches

Ilias et al. (2009) propose an automated diagnosis system for the identification of heart valve diseases based on the SVM classification of heart sounds. This system was applied in a dataset of 198 heart sound signals from both healthy cases and abnormal cases. First, the heart sounds were classified using the SVM classifier as normal or abnormal, and then abnormal cases were classified in more detail.

Güraksin and Uğuz (2010) using artificial intelligence method in the diagnosis of heart sound signals in 120 heart sounds. First, the data set was separated into sub-bands by using discrete wavelet transform. Next, they calculate the entropy of each sub-band by using the Shannon entropy algorithm to reduce the dimensionality of the feature vectors with the discrete wavelet transform. And then, heart sound signals were classified by least-square SVM and compared with the classification performance of previous studies.

Abbasi (2013) proposes feature extraction of lung sounds by using wavelet coefficients, then categorization by neural network and SVM. Firstly, the wavelet coefficients were calculated. The comparison of performance between the neural network and SVM for classification show that the SVM has a better performance.

Bouril et al. (2016) create and train a SVM for categorizing signals as normal or abnormal was generated in Matlab. Seventy-four features were chosen by both time and frequency domains. The SVM using a Gaussian kernel.

Monika et al. (2017) using computer aided diagnosis(CAD) to detect cardiac disorders by heart sound, that is provided by acoustic stethoscope. This equipment be able to diagnose heart beat in real-time , and then convert analog acoustic signals into digital signal, and this paper propose to make available audio as well as image signal to medical for detect heart sound.

Muhammad et al. (2019) proposes a prototype model of a smart digital-stethoscope system to monitor patient's heart sounds and diagnose any abnormality in a real-time manner. This system consists of two subsystems that communicate wirelessly using Bluetooth low energy technology.

Li et al. (2019) propose a new method of feature extraction and classification of heart sound signal by a combination of wavelet scattering and TSVM. The wavelet scattering method creates the training set and the testing set from the heart sound signals, which is called the scattering feature matrix of the heart sound signal. This research reduces the dimension by using multidimensional scaling (MDS) method. And then, the dimensionality-reduced feature matrix is input into the TSVM for classification.

CHAPTER III

RESEARCH METHODOLOGY

This chapter presents the method applied in this research. The method consists of 5 parts by the following:

1. Data collection

2. Data preparation

3. Feature extraction

4. Imbalance data management

5. Model creation and evaluation

3.1 Data Collection

There are 23 files of the heart sound. The file type is MP3. The bit rate is 128Kpbs. There are normal heart sounds, and abnormal heart sounds with the murmur and clicks from **Heart Sound & Murmur Library, University of Michigan** https://open.umich.edu/find/open-educational-resources/medical/heart-sound-murmur-library. Therefore, there are 2 files of the normal heart sound and 21 files of the abnormal heart sound.

There is a vesicular breath sound such that the file type is MP3 and the bit rate is 192Kpbs from https://www.mediscuss.org/respiratory-auscultation.

3.2 Data Preparation

This process managed the sound files in order to be used in the machine learning process.

1. Since the heart sound and the vesicular breath sound have different length, then the vesicular breath sound was extended for the simplicity. In this part, Audacity version 2.4.2 software was the main software using the sound file manipulation. Audacity is free software for sound management, for example, recording, editing, analysis.

2. After that use Audacity to combine heart sounds and a breath sound to make heart sound with breath sound noise. This research adjusts the volume of breath sound as follows: 0.0dB(default), -5.0dB, -10.0dB, -15.0dB, -20.0dB, -25.0dB , -30.0dB and -35.0 dB.

The detail of both processes is shown in Appendix A. By the results, there are 16 files of the normal heart sound, 168 files of the abnormal heart sound.

3.3 Feature Extraction

Here, the features of sound data considering in this thesis are presented in table 3.1.

In this part, the process was done by the Python code with **librosa** package. The detail this process is also shown in Appendix B. The results after the feature extraction were exported into CSV files.

Table 3.1 Features of sound data using in this thesis.

feature	description
rms	a root-mean-square (RMS) value for each frame
spectral_centroid	the spectral centroid
spectral_bandwidth	a p'th-order spectral bandwidth
spectral_flatness	a spectral flatness
spectral_rolloff	a roll-off frequency
poly_features	coefficients of fitting an n^{th}-order polynomial to the columns of a spectrogram
zero_crossing_rate	the zero-crossing rate of an audio time series

3.4 Imbalance data management

Since the amount of data for each class are much different then it effects to the accuracy of the machine learning part. Here, there was 16 normal heart sound data, where the 168 abnormal heart sound data was used to compare. Therefore this research use the SMOTE technique to manage the imbalance problem. In this part, the process was done by the Python code with **imblearn** package. The detail this process is shown in Appendix B.

3.5 Model creation and evaluation

This research considered SVM and TSVM to classify the heart sound data into two classes: normal and abnormal. By using radial basis function kernel to transform non-linear classification problem to linear classification problem. The models were done by considering 3 groups of different ratio of training data and testing data, which are 70%:30%, 75%:25% and 80%:20%.

In this research we applied the confusion matrix for classification problems of the 6 obtained models to calculate the performance (accuracy, precision, and recall).

CHAPTER IV

RESULTS AND DISCUSSION

This chapter presents the results of the research.

4.1 Data Collection

The sound data can be represented in the image types as the following.

- **Normal heart sound**

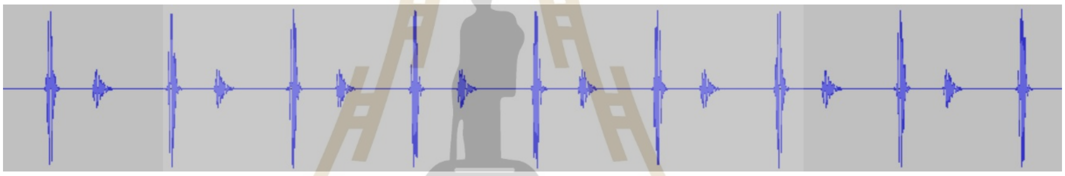

Figure 4.1 Normal heart sound.

Figure 4.1 shows that normal heart sound waves was created by Audacity.

- **Abnormal heart sound**

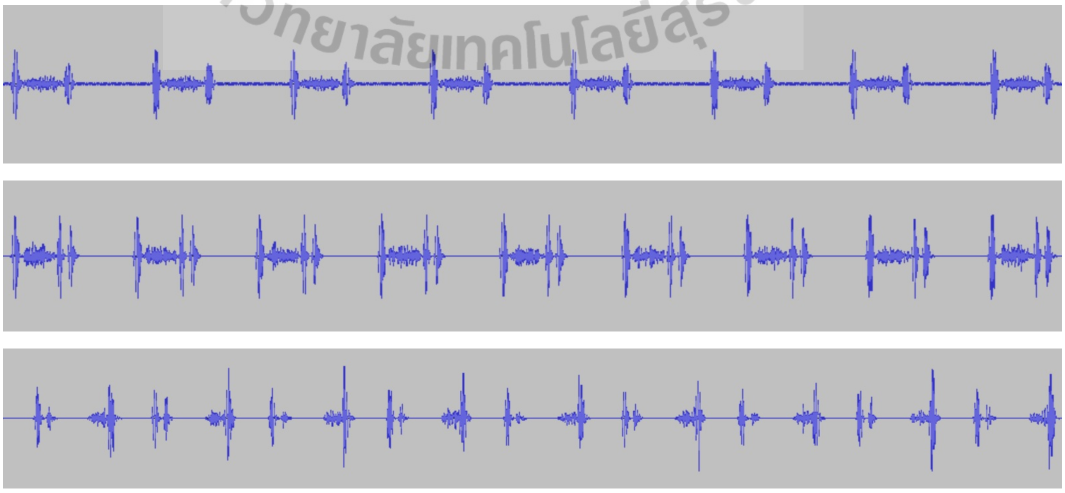

Figure 4.2 Abnormal heart sound.

Figure 4.2 shows that abnormal heart sound waves was created by Audacity.

- **Breath sound**

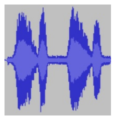

Figure 4.3 Breath sound.

Figure 4.3 shows that breath sound waves was created by Audacity.

4.2 Data Preparation

4.2.1 Breath sound extension

The breath sound was extended the length as the follow.

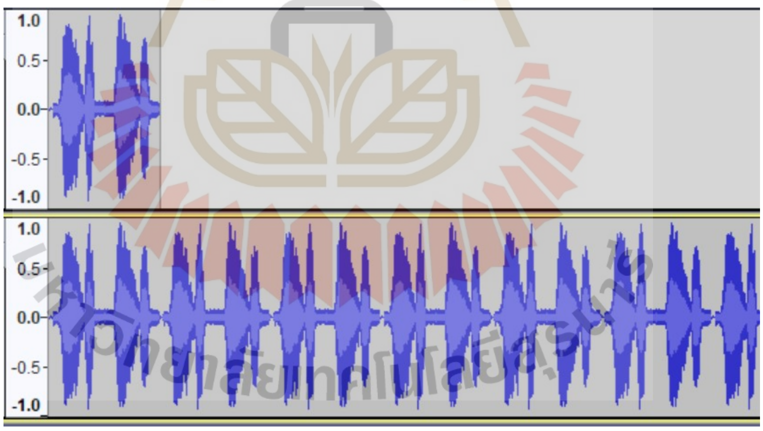

Figure 4.4 Breath sound with the extension length.

Figure 4.4 shows the extension length of the breath sound since the heart and breath sounds are different.

4.2.2 Sound overlaying

The heart sound was overlaid by the breath sound of difference volume 0.0dB(default), -5.0dB, -10.0dB, -15.0dB, -20.0dB, -25.0dB, -30.0dB and -35.0 dB. The following gives examples of the results.

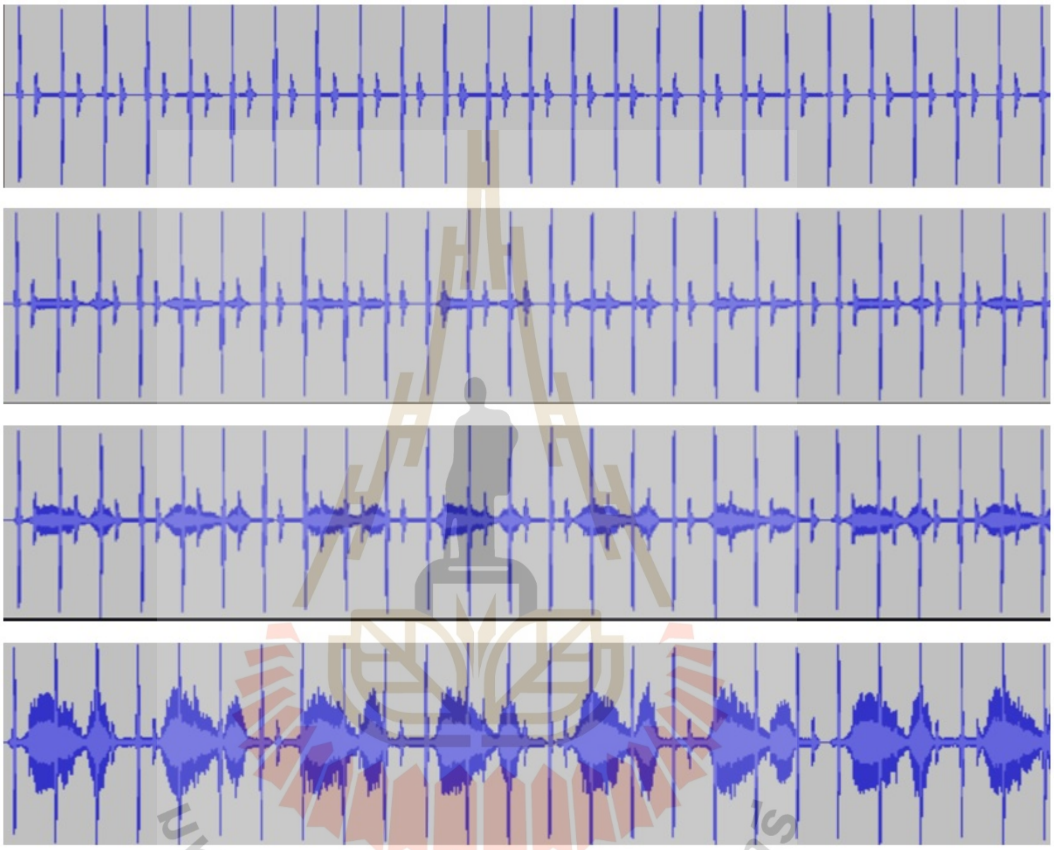

Figure 4.5 Heart sound with overlaid breath sound.

When the heart sound length and the breath sound length are approximate, overlaid heart sound with breath sound is shown in figure 4.5.

Here, we extended from the 23 types of heart sound to be 184 heart sound with overlaid breath sound files.

4.3 Feature extraction

By the Python code and **librosa** package, the mp3 heart sound files were converged to CSV type. The obtained files were multi column type with detail shown in table 4.1

Table 4.1 Detail of CSV files.

columns	description
1-235	spectral centroid
236-470	rms
471-705	spec bw
706-940	flatness
941-1175	spectral rolloff
1176-1410	polynomial
1411-121410	zero crossing
121411	label

4.4 Imbalance data management

The Python code using **imblearn** package provided more files. In this research, we applied SMOTE technique to generate more files from minority group to be the same number of files from majority group. In this process, we got the same number of files, which were 168 CSV files of normal and of abnormal heart sound data.

4.5 Model creation and evaluation

This section shows that the results of the classification of heart sound with breath sound noise by TSVM and SVM. The result presents in the confusion matrix.

4.5.1 Support vector machine

This part shows that the confusion matrix of SVM and performance of classification by SVM.

Ratio of training sets 70% vs testing set 30%

Table 4.2 The confusion matrix of SVM (70%:30%).

		Actual values	
		Abnormal	Normal
Predicted Values	Abnormal	48	6
	Normal	0	47

Accuracy = 0.9406

Precision = 0.8889

Recall = 1.0000

Ratio of training sets 75% vs testing set 25%

Table 4.3 The confusion matrix of SVM (75%:25%).

		Actual values	
		Abnormal	Normal
Predicted Values	Abnormal	42	5
	Normal	0	37

$$\text{Accuracy} = 0.9405$$

$$\text{Precision} = 0.8936$$

$$\text{Recall} = 1.0000$$

Ratio of training sets 80% vs testing set 20%

Table 4.4 The confusion matrix of SVM (80%:20%).

		Actual values	
		Abnormal	Normal
Predicted Values	Abnormal	33	4
	Normal	0	31

$$\text{Accuracy} = 0.9412$$

$$\text{Precision} = 0.8919$$

$$\text{Recall} = 1.0000$$

4.5.2 Twin Support vector machine

This part shows that the confusion matrix of TSVM and performance of classification by TSVM.

Ratio of training sets 70% vs testing set 30%

Table 4.5 The confusion matrix of TSVM (70%:30%).

		Actual values	
		Abnormal	Normal
Predicted Values	Abnormal	54	0
	Normal	4	43

$$\text{Accuracy} = 0.9604$$

$$\text{Precision} = 1.0000$$

$$\text{Recall} = 0.9310$$

Ratio of training sets 75% vs testing set 25%

Table 4.6 The confusion matrix of TSVM (75%:25%).

		Actual values	
		Abnormal	Normal
Predicted Values	Abnormal	47	0
	Normal	4	33

$$\text{Accuracy} = 0.9524$$

$$\text{Precision} = 1.0000$$

$$\text{Recall} = 0.9216$$

Ratio of training sets 80% vs testing set 20%

Table 4.7 The confusion matrix of TSVM (80%:20%).

		Actual values	
		Abnormal	Normal
Predicted Values	Abnormal	37	0
	Normal	3	28

$$\text{Accuracy} = 0.9559$$

$$\text{Precision} = 1.0000$$

$$\text{Recall} = 0.9250$$

4.5.3 Model comparison

This part explains that the comparison between TSVM and SVM performance of classification.

Table 4.8 Perfromance comparison between SVM and TSVM.

Train : Test	70:30		75:25		80:20	
Model	SVM	TSVM	SVM	TSVM	SVM	TSVM
Accuracy	0.9406	0.9604	0.9405	0.9524	0.9412	0.9559
Precision	0.8889	1	0.8936	1	0.8919	1
Recall	1	0.9310	1	0.9216	1	0.9250

The table 4.8 confirms that the support vector machine provided best performance with the ratio of train set and test set was 80%:20%, which had accuracy = 94.12%, precision = 89.19%, and recall = 100%. The twin support vector machine provided best performance with the ratio of train set and test set was 70%:

30%, which had accuracy = 96.04%, precision = 100%, and recall = 93.10%. According to the results, the application of the twin support vector machine method to the heart sound classification could perform better accuracy and precision compared to the one of the support vector machine method.

CHAPTER V

CONCLUSION AND RECOMMENDATION

This research presents heart sound with breath sound classification by Twin Support Vector Machine with radial basis function kernel. The data set was obtained from Heart Sound & Murmur Library, University of Michigan, and www.mediscuss.org/respiratory-auscultation. The software uses in this research is Audacity 2.4.2. The SMOTE technique was used for the imbalanced data set. The process is calculated in Python 3. The approximate process in this research is to combine the heart sound and the breath sound, following use imbalance data technique to solve the imbalance problem. The classification were done of 3 groups of data according to the ratio of train set and test set, which were 1st group 70%: 30%, 2nd group 75%:25% and the last group 80%:20% and then we use the support vector machine and the twin support vector machine to solve the classification problem. Finally, we analyze and compare the model's performance.

The twin support vector machine provided best performance with the ratio of train set and test set was 70%:30%, which had accuracy = 96.04%, precision = 100%, and recall = 93.10%. According to the results, the application of the twin support vector machine method to the heart sound classification could perform better accuracy and precision compared to the one of the support vector machine method. This show that the twin support vector machine effective classify the heart sound although it has the breath sound noise.

We have obviously seen that the number of data is too scanty, so it should have more data for training and testing for a more effective model.

In the future, we have to study more algorithms to find the appropriate algorithm for heart sound classification and some medical problems, and we may change parameter or choose orther kernels that make more accurate results.

REFERENCES

REFERENCES

Anthony, B., Darya, A., Maria, S. G., and Grace, M. M. (2016). Automated Classification of Normal and Abnormal Heart Sounds using Support Vector Machines. **Computing in Cardiology**. 43: 549-525.

Campbell, C., and Ying, Y. (2011). **Learning with Support Vector Machine**. Morgan & Claypool.

Gillum, R. F. (1988). Diagnostic technology in cardiovascular disease: review of noninvasive methods for population studies. **Bulktin of the World Health Organizion**. 66(2): 249-258.

Gür, E. G., and Harun, U. (2011). CLASSIFICATION OF HEART SOUNDS BASED ON THE LEAST SQUARES SUPPORT VECTOR MACHINE. **International Journal of Innovative Computing, Information and Control**. 7(12): 7131-7144.

Hanif, A., and Azhar, N. (2017). Resolving class imbalance and feature selection in customer churn dataset. In: **the 2017 International Conference on Frontiers of Information Technology (FIT)**. pp. 82-86.

He, H., and Ma, Y. (2013). **IMBALANCED LEARNING : Foundations, Algorithms, and Applications**. John Wiley & Sons.

Ilias, M., Euripidis, L., Elias, Z., and Antonis, S. (2009). Support Vectors Machine-based identification of heart valve diseases using heart sounds. **computer methods and programs in biomedicine**. 95: 47-61.

Jayadeva, Reshma, K., and Suresh, C. (2017). **Twin Support Vector Machines Models, Extensions and Applications**, Springer.

Jinghui, L., Qiang, D., Xiaodi, D., Xiangmin, C., and Danni, W. (2019). Heart Sound Signal Classification Algorithm: A Combination of Wavelet Scattering Transform and Twin Support Vector Machine. **IEEE Access**, 7, 179339-179348. doi:0.1109/ACCESS.2019.2959081

Judith, A. S. (2010). **Auscultation Skills Breath Heart Sounds**, Lippincott Williams & Wilkins .

Michael, A. G., Gary, D. W., and Piers, E. F. D. (2011). **Diagnosis and Management of Adult Congenital Heart Disease**, ELSEVIER.

Michael, E. M. (2008). **Pediatric Heart Sounds**, Springer.

Monika, V., Bommi, R. M., Harish, P. L., Murali, M., and Nirmala, S. (2017). Embedded Stethoscope for Real Time Diagnosis of Cardiovascular Diseases. **IEEE International Conference on Computational Intelligence and Computing Research**.

Muhammad, E. H. C., Amith, K., Khawla, A., Samar, M., Anas, M. T., Mamun, B. I. R., and Nasser, A. (2019). Real-Time Smart-Digital Stethoscope System for Heart Diseases Monitoring. **Multidisciplinary Digital Publishing Institute**. 19: 1-22. doi:10.3390/s19122781.

Samira, A., Roya, D., Ataollah, A., and Yashar, S. (2013). **Classification Of Normal and Abnormal Lung Sounds Using Neural Network and Support Vector Machines**, n. p.

Umakanth, S. (2018). Respiratory Auscultation. Retrieved from https://www.mediscuss.org/respiratory-auscultation/.

World Health Organization. (2017). **Cardiovascular diseases (CVDs)**, https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds).

Zipes, D. P., Libby, P., Bonow, R. O., Mann, D. L., Tomaselli, G. F., and Braunwald, E. (2019). **Braunwald's heart disease: A textbook of cardiovascular medicine.** Philadelphia, PA : Elsevier/Saunders

APPENDICES

APPENDIX A

DATA PREPARATION

A.1 Data normalization with Audacity

In this chapter, we show data preparation in the Audacity program.

1. Extend the period of breath sound approximate to heart sound.

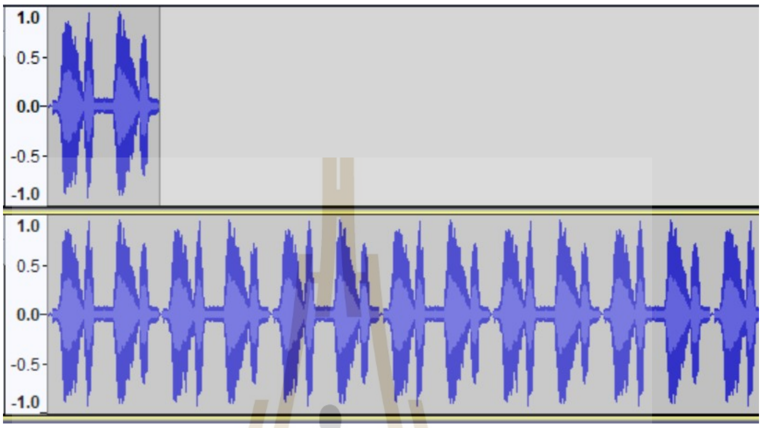

Figure A.1 Extended the breath sound.

2. Combine the heart sound with breath sound.

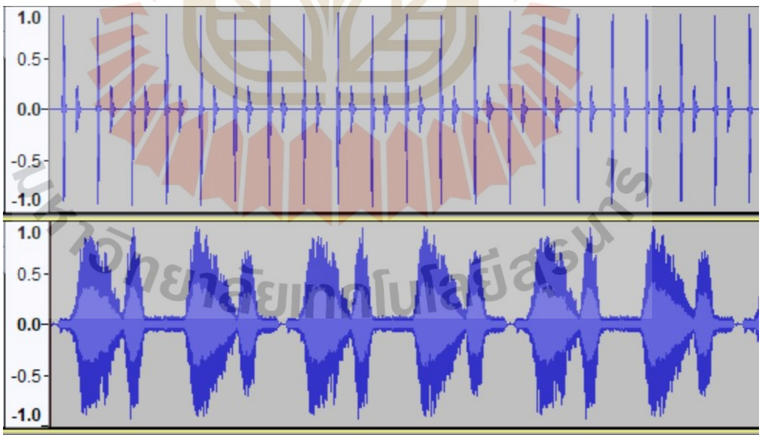

Figure A.2 Combine the heart sound with breath sound

3. Adjust the volume of breath sound as follow: 0.0dB (default), -5.0dB, -10.0dB, -15.0dB, -20.0dB, -25.0dB , -30.0dB and -35.0dB.

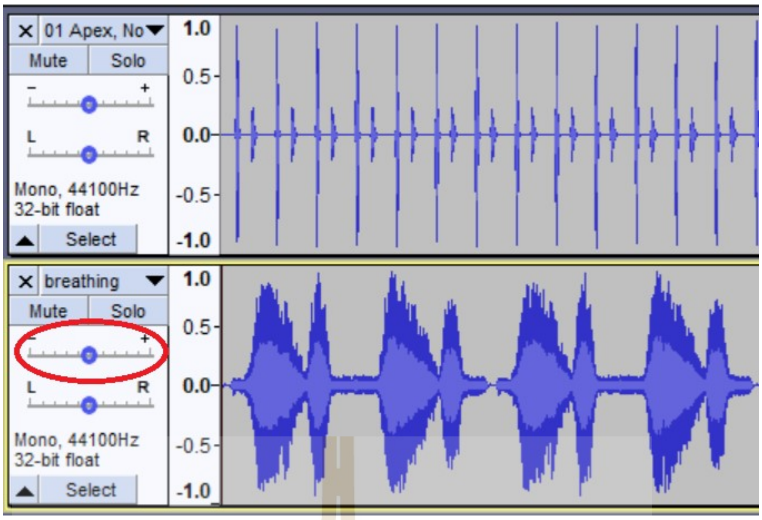

Figure A.3 Adjust the volume of breath sound.

4. Export heart sound with breath sound noise to the data set.

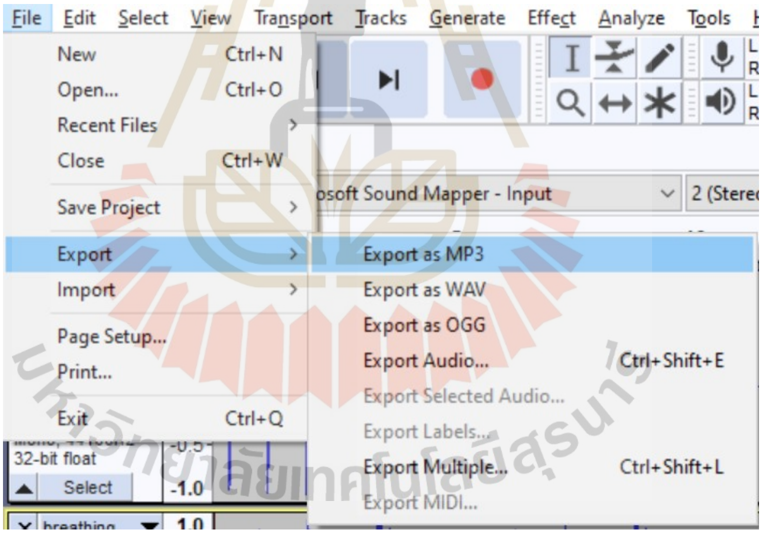

Figure A.4 Export heart sound with breath sound noise.

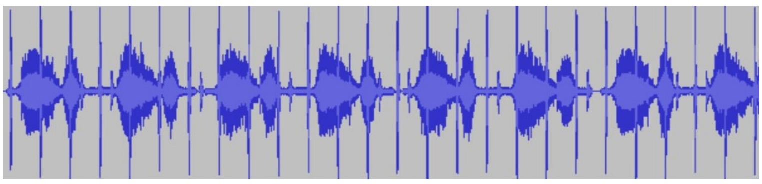

Figure A.5 Heart sound with breath sound noise.

APPENDIX B

EXAMPLE OF PYTHON CODE USING IN THE THESIS

This chapter presents the Python code using in this research.

B.1 Feature Extraction

```
import librosa
import numpy as np
import pandas as pd
from google.colab import files
audio_path = '/content/drive/MyDrive/new/22-15.mp3'
x , sr = librosa.load(audio_path)
librosa.load(audio_path)
n0 = 0
n1 = 120000
y=x[n0:n1]
zero_crossings = librosa.zero_crossings(y, pad=False)
zero_crossings_df=pd.DataFrame(zero_crossings)
t_zero_crossings_df=zero_crossings_df.T
t_zero_crossings_df.replace({False: 0, True: 1}, inplace=True)
cent = librosa.feature.spectral_centroid(y, sr=sr)
cent_df=pd.DataFrame(cent)
rms=librosa.feature.rms(y=y)
rms_df=pd.DataFrame(rms)
spec_bw = librosa.feature.spectral_bandwidth(y=y, sr=sr)
spec_bw_df=pd.DataFrame(spec_bw)
flatness = librosa.feature.spectral_flatness(y=y)
flatness_df=pd.DataFrame(flatness)
spectral_rolloff=librosa.feature.spectral_rolloff(y=y, sr=sr)
spectral_rolloff_df=pd.DataFrame(spectral_rolloff)
S = np.abs(librosa.stft(y))
p0 = librosa.feature.poly_features(S=S, order=0)
p0_df=pd.DataFrame(p0)
df=pd.concat([cent_df,rms_df,spec_bw_df,flatness_df,spectral_rolloff_df,p0
_df, t_zero_crossings_df], axis=1,ignore_index=True)
df['121410']=1
df.to_csv('/content/drive/MyDrive/new/file/abnormal22_15.csv')
```

Figure B.1 Feature Extraction.

B.2 Creating Dataframe

```
import os
import glob
import pandas as pd
os.chdir("/content/drive/MyDrive/new/file")
extension = 'csv'
all_filenames = [i for i in glob.glob('*.{}'.format(extension))]
combined_csv = pd.concat([pd.read_csv(f) for f in all_filenames ])
combined_csv.to_csv( "/content/drive/MyDrive/new/combined/combined_csv.csv
", index=False, encoding='utf-8-sig')
```

Figure B.2 Creating Dataframe.

B.3 Handing Imbalanced Data

```
import pandas as pd
df = pd.read_csv('/content/drive/MyDrive/new/combined/full_data.csv')
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=42)
X_res, y_res = sm.fit_resample(X, y)
```

Figure B.3 Handing Imbalanced Data.

B.4 Classification with SVM (train 70% test 30%)

```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import confusion_matrix
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_siz
e=0.3, random_state=42)
clf = SVC(kernel='rbf')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy",metrics.accuracy_score(y_test,y_pred))
print("Confusion Matrix", confusion_matrix(y_test,y_pred))
```

Figure B.4 Classification with SVM (train 70% test 30%).

B.5 Classification with SVM (train 75% test 25%)

```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import confusion_matrix
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_siz
e=0.25, random_state=42)
clf = SVC(kernel='rbf')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy",metrics.accuracy_score(y_test,y_pred))
print("Confusion Matrix", confusion_matrix(y_test,y_pred))
```

Figure B.5 Classification with SVM (train 75% test 25%).

B.6 Classification with SVM (train 80% test 20%)

```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import confusion_matrix
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_siz
e=0.2, random_state=42)
clf = SVC(kernel='rbf')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy",metrics.accuracy_score(y_test,y_pred))
print("Confusion Matrix", confusion_matrix(y_test,y_pred))
```

Figure B.6 Classification with SVM (train 80% test 20%).

B.7 Classification with TSVM (train 70% test 30%)

```
from TVSVM import TwinSVMClassifier

from sklearn.model_selection import train_test_split

from sklearn.metrics import confusion_matrix

params2 = {'Epsilon1': 0.1, 'Epsilon2': 0.1, 'C1': 1, 'C2':
1,'kernel_type':3,'kernel_param': 2,'fuzzy':0}

clf = TwinSVMClassifier(**params2)

X_train, X_test, y_train, y_test = train_test_split(x, t, test_size=0.30,
random_state=42)

# Train the classifier

clf = clf.fit(X_train, y_train)

# Output prediction

y_predicted = clf.predict(X_test)

# Test classifier prediction

score = clf.score(y_test, y_predicted)

cnf_matrix = confusion_matrix(y_test, y_predicted)

print('Accuracy', score)

print(' confusion_matrix', cnf_matrix)
```

Figure B.7 Classification with TSVM (train 70% test 30%).

B.8 Classification with TSVM (train 75% test 25%)

```
from TVSVM import TwinSVMClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
params2 = {'Epsilon1': 0.1, 'Epsilon2': 0.1, 'C1': 1, 'C2':
1,'kernel_type':3,'kernel_param': 2,'fuzzy':0}
clf = TwinSVMClassifier(**params2)
X_train, X_test, y_train, y_test = train_test_split(x, t, test_size=0.25,
random_state=42)
# Train the classifier
clf = clf.fit(X_train, y_train)
# Output prediction
y_predicted = clf.predict(X_test)
# Test classifier prediction
score = clf.score(y_test, y_predicted)
cnf_matrix = confusion_matrix(y_test, y_predicted)
print('Accuracy', score)
print(' confusion_matrix', cnf_matrix)
```

Figure B.8 Classification with TSVM (train 75% test 25%).

B.9 Classification with TSVM (train 80% test 20%)

```
from TVSVM import TwinSVMClassifier

from sklearn.model_selection import train_test_split

from sklearn.metrics import confusion_matrix

params2 = {'Epsilon1': 0.1, 'Epsilon2': 0.1, 'C1': 1, 'C2':
1,'kernel_type':3,'kernel_param': 2,'fuzzy':0}

clf = TwinSVMClassifier(**params2)

X_train, X_test, y_train, y_test = train_test_split(x, t, test_size=0.20,
random_state=42)

# Train the classifier

clf = clf.fit(X_train, y_train)

# Output prediction

y_predicted = clf.predict(X_test)

# Test classifier prediction

score = clf.score(y_test, y_predicted)

cnf_matrix = confusion_matrix(y_test, y_predicted)

print('Accuracy', score)

print(' confusion_matrix', cnf_matrix)
```

Figure B.9 Classification with TSVM (train 80% test 20%).

CURRICULUM VITAE

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