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A CONCEPTUAL STUDY ON INTERNET OF THINGS IMPLEMENTATION TO IMPROVE ACCURACY OF PRE-HOSPITAL CARE USING SMART STETHOSCOPES

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Abstract

Ever-evolving Pre-Hospital Care and Emergency Medical Services comes with great challenges. This paper provides a fundamental leap towards collaboration of Medicine and ICT, benefiting mankind. There were three major issues faced by pre-hospital care staff from the emergency department which are lack of sound interpretation accuracy due to the interference of noise during transfer, lack of acoustic performance accuracy during transfer and lack of resource and resource management. These issues lead to delay in patient transfer to the hospital or even delay in diagnosis as the sound is not accurately interpreted by the medical practitioners due to the interference of noise and unfavourable situations during transfer. This is also imposing on the overcrowding of emergency departments and increase of waiting time due to shortage of authorised medical personnel to be on the floor for clinical. Based on the literature, the use of hybrid neural networks with bio-inspired methods to improve the efficiency in detection and classification of sounds and enables searching of similar sounds to direct towards accurate diagnostic and management pathways. This solution might benefit largely in the improvement of clinical decision making and health care provided in terms of accuracy and limiting waiting time. Besides that, data collected will be able to serve as important evidence in court for medicolegal cases in enforcing jurisdiction and stature.

Keywords: Digital stethoscope, Internet of things (IoT) system, Pre-Hospital care.

1. Introduction

Once known as a slowly developing country, Malaysia has shown tremendous changes and evolvement in various fields and aspects. With the introduction of technology, the past decade has been marvellous for the emergency department not only in Malaysia but worldwide. Pre-Hospital care had a good kick start in Malaysia and currently has been one of the demands of the public for emergency medical services (EMS). Ever evolving EMS has now ventured into ambulance transfers and medical retrievals. As great as the service sounds, greater it is the challenges and limitations it comes with in order to excel. This demand has caused overcrowding in the emergency department with Pre-Hospital care that used to be nursing staff and non-medical ambulance driver territory, medical officers and medical assistants are slowly being cooperated into the EMS [1].

According to Shen and Lee [2], In addition to the surge of patients to the emergency department, elderly patients with an increasing severity level of disease progression, worsened with inadequate manpower and infrastructure makes efforts to overcome waiting time fairly difficult. When medical officers follow on ambulance calls and retrievals, the number of medical officers on floor in emergency department is cut short, thus making the wait times longer due to lack of manpower.

Digitalising the stethoscope as a diagnostic tool can provide a solution for this problem whereby medical officers can stay on floor in emergency department to provide treatments to patients, thus reducing the surge of patients and their wait time. Whereas the digital stethoscope acts as a diagnostic tool in clinical decisions making.

The increasing computational power as per Moore’s Law where the transistors are doubling devices are getting much smaller and smarter which enables the Internet of Things (IoT) to become a significant entity in every important technology in various industries which includes healthcare. There is an abundance of IoT based healthcare devices which are available in the market for end users but not for the healthcare workers. Introducing IoT into a device (stethoscope) which is used most frequently by all healthcare workers almost as important as their own hand helps the hospital operation become more effective especially in the emergency department.

1.1. Lung sound

Lungs are organs that expand to allow air via contraction of diaphragm. It contains a structure known as alveoli where gaseous exchange happens during inspiration and expiration. At a frequency range of 60-100 Hz to 2 kHz, lung sounds are produced [3]. Three categories of auscultatory findings of the lungs are breath sounds, vocal resonance, and adventitious sounds [4].

Respiratory sounds divided further into basic sounds which include normal lung sound and normal tracheal sound. Normal lung sound is a soft, non-rhythmic sound heard during inspiration and early expiration. It originates from the central part of airways during expiration and from the lobar to segmental part of the airway during inspiration with acoustics of low pass filtered noise ranging less than 100 Hz to more than 1000 Hz. Normal tracheal sound is hollow and non-musical sound which is often heard clearly during both inspiration and expiration as turbulent flow impinges on airway walls in pharynx, larynx, trachea, and large airways with acoustic of noise with resonances ranging from less than 100 Hz to more than 3000 Hz. Bronchial breathing is a soft, non-musical sound that mimics tracheal sound.

Fundamentally, there are three types of adventitious sounds from lungs (wheeze, rhonchus, and crackle). Wheeze is a high-pitched musical sound produced from central to lower airways when the airway wall flutters or vortex shedding, with sinusoidal acoustics ranging approximately 100 to more than 1000 HZ with duration of typically more than 80 ms. Wheeze is a pathological lung sound that happens during airway obstruction causing flow limitations during inspiration and expiration. Rhonchus is also a musical sound but low-pitched that is similar to snoring, that arises from larger airways. Rhonchus is caused by rupture of fluid films in lungs and rapid series of airway wall vibrations showing dampened sinusoids typically less than 300 Hz at a duration more than 100 ms. Rhonchus usually signifies abnormal airway collapsibility that may be contributed to secretions. Crackle is a pathological sound found in central and lower airways due to airway wall stress-relaxation mechanisms due to airway closure or secretions. Crackle has an acoustics of rapidly dampened wave deflection with duration typically less than 20 ms. Crackles are differentiated into fine and coarse as both fine and coarse crackles are characterised as non-musical, short, explosive sound, there are some minute differences in between both the classification. Fine crackles are heard best during mid-to-late inspiration phase and occasionally during expiration. Coarse crackles are heard during early inspiration and throughout expiration. Fine crackles are not affected by cough, in which it differs from coarse crackles that are affected by cough mechanisms and transmitted to the mouth [5].

1.2. Heart sound

Heart sounds are closely related to its physiology of blood flow and valve. Heart sound signals range between 20-100 Hz. This frequency range overlaps with the abnormal lung sound frequency especially low frequency wheeze and rhonchi [3]. Heart sounds and murmurs are distinguished by four characteristics: 1. Their timing (i.e., systolic or diastolic), 2. Intensity (i.e., loud or soft), 3. Duration (i.e., long or short), and 4, Pitch (i.e., low or high frequency)[4].

The basics of the heart sounds are S1 and S2. S1 is apparent during isovolumetric contraction with closure of mitral and tricuspid valves while S2 occurs during isovolumetric relaxation associated with the remaining two valves namely aortic and pulmonic valves. During early ventricular filling, S3 is often heard if any as S3 is normal in children. In adults, S3 is associated with ventricular dilation (ventricular systolic failure). S4, during atrial contraction, happens in stiff, low compliant ventricles for example in ventricular hypertrophy or ischemic ventricle. Murmur happens due to diseased or abnormal heart valves may it be in terms of morphology or functional, or abnormal blood flow pathway within the heart or vessels. A faulty door either does not open properly or it does not close properly [6].

The frequencies of heart sounds and murmurs are 20-500 Hz, whereby low frequencies are of less than 100 Hz dominantly S3 and S4 and diastolic murmur of mitral stenosis. Aortic regurgitation contains the highest frequency of about 400 Hz. The principal frequencies of other sounds and murmur ranges between 100-400 Hz [4].

1.3. Abdomen sound

Bowel sounds are coming from the movements of the small intestine. It is due to normal peristalsis activity propelling its content. Bowel sound can be qualified as hyperactive, hypoactive, and absent. A loud, gurgling, and rushed sound is hyperactive whereas hypoactive is a soft sound that is low and widely separated sounds like one or two occurring in two minutes. Absent of bowel sound is no sound is heard during auscultation for at least three to five minutes.

2. Background Study

It has been years since public hospitals in the emergency department in Malaysia have been working with traditional stethoscopes. Stethoscope has been an essential asset in making clinical diagnosis and case-based judgement in treatment. In the setting of Pre-Hospital Care (PHC), there are limitations in the optimal usage of stethoscopes. The scope of PHC that we are looking into here involves ambulance calls and transfer and medical retrieval services (MEDEVAC) may it be via ambulance (road) or helicopter (air). In terms of road transfers, every time there is a need to get more precise reading, ambulances will have to stop by the roadside to obtain the sound auscultation with all the sirens off. This indirectly delays the delivery of patients to hospital. It is a totally different scenario in air transfer or retrieval were stopping the journey for the purpose of accuracy of sound perception is beyond discussion. There are few factors that affect the accuracy of sound perception such as surrounding sound or noise, bumpy roads and turbulence which affects the proper placement of the stethoscope on the go.

According to McGee [4], heart sounds and murmurs especially faint sounds are inaudible unless there is complete silence in the room. Clinicians will turn off all other sources of sound, even stop a conversation to auscultate and perceive the sound accurately. The interpretation of breath sounds through auscultation were significantly hindered by the situational and challenging conditions encountered in a moving ambulance [7]. Hunt et al. [8] concluded that even normal breath sounds auscultated via traditional or amplified stethoscope in a medically configured MBB BO-105 helicopter were not heard accurately and further suggested the need for improved or upgraded stethoscopes, new innovative techniques of listening, and efforts of discovery in reduction of aircraft noise will be beneficial as potential solutions as a breakthrough in breath sound assessment during air medical transport. Ambulance sounds, sirens, and noises produced by rotating helicopter blades and engines, during transfer interferes with the accuracy of the sound perceived in turn making clinical judgement and decisions difficult.

Acoustic performance greatly affects the performance of a stethoscope. It determines the quality of the sound that will be transmitted for the ears of the user to interpret. In reference to Kindig et al. [9] poor acoustic performance is mainly contributed by air leak resulting from poorly fitting earpieces. A diameter of 0.015 inch of air leak, as tiny as it seems, will reduce the transmission of sound by approximately 20 dB, especially for those sounds with a frequency less than 100 Hz [10]. In a moving ambulance and helicopter, the bumpers, speed breakers, bumpy roads, gravel platforms and turbulence can increase the air leak, thus causing decrease of acoustic performance, in turn affecting clinical precisions.

A comparison was done between analog stethoscope and electronic stethoscope by Silverman and Balk [11] in a clinical setting, whereby it was discovered that in

95% of examinations, the digital stethoscope was either equal to or superior to the acoustic device. Digital stethoscopes enable sounds to be transmitted electronically and further convert it into a digital signal which makes noise reduction feasible using an electronic stethoscope besides providing signal enhancement with both visual and audio output [11].

2.1. Sounds classification algorithms

Feature analysis of respiratory sounds has been a matter of interest that resulted in many discoveries by far. For example, Pesu et al. [12] used wavelet packet-based method to extract features of pathological lung sounds namely wheeze and crackles with perfect differentiation of fine and coarse crackle.

Basis search algorithm was used to select the most superior set of wavelet packet coefficients of abnormal respiratory sounds. On the other hand, Jin et al. [13] suggested a method which was based on instantaneous frequency that led towards construction of a temporal-spectral dominance spectrogram that enables classification of wheezes at high noise level. Power Spectral Density (PSD) was extracted on crackles and rhonchi using Welch method and feature classification was obtained using the ratio of max/min to be the feature classification [14].

Analysis of fine and coarse crackles was done by Hilbert-Huang spectrum which decomposes the sound into intrinsic mode function whereby the feature is obtained via the instantaneous frequency [15]. A comparison was done between features that was extracted from Fast Fourier transform, Linear Predictive Coding, MFCC and Wavelet transform, arrived at a conclusion that MFCC performed best in classifying normal sounds and wheezes [16].

Furthermore, k-Nearest Neighbour (k-NN) algorithms were used to arrive at respiratory disease diagnosis by Sankur et al. [17] in obtaining sounds from subjects of both healthy and diseased background using a microphone with preamplifier. Milicevic et al. [18] have introduced combinations of various machine learning methods like Support Vector Machine (SVM) , k- nearest neighbour algorithm (k-NN), Neural Network (NN), Random Forests (RF), Logistic Regression (LR), Naive Bayes (NB) and noted that SVM had an accuracy rate of 98.95% in comparison to other classification models studied. For both regression and classification tasks, SVM may be used, although it is commonly used for classification goals. In addition, SVM is to discover a hyperplane in an N-dimensional space (N-the number of characteristics) that separately classifies the data points.

Due to the profoundly ingrained mathematical ideas that it uses, KNN works. The first step is to transform data points into feature vectors, or their mathematical significance, when implementing KNN. By finding the gap between the mathematical values of these points, the algorithm comes alive. The Euclidean distance is the most common way of finding this distance, as shown in Eq. (1).

$$d(p,q) = d(q,p) = \sqrt{\sum_{i=1}^{n}(q^i - p^i)^2} \tag{1}$$

To compute the distance between each data point and the test data, KNN runs this formula. It then finds that these points are likely to be equivalent to the test data and classifies them based on which points share the highest probabilities.

Artificial Neural Network (ANN) model was applied into lung sounds signals by Sankur et al. [17] whereby the wavelet features were extracted and classified categorically into six domains namely normal, wheeze, crackle, squawk, stridor, and rhonchus. It showed that 19-40-6 was the optimal ANN architecture and the wavelet of order 8 provided the best efficiency in terms of classification. Similarly, feature extraction of 256-point Fourier Power Spectrum Density (PSD) was established using the Neural Network and Genetic Algorithm [19].

As a solution several algorithms can be used as a training feature to adjust the neuron weights and biases to decrease the ANN model's target functions. The goal function defines the error that is important to the success of the prediction. The mean square error (MSE) is obtained and used to verify the capacity of a given ANN architecture using Eq. (2) as the evaluation criterion.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(e_1 - c_i)^2 \quad (2)$$

Hidden Markov Models (HMM) for acoustic spectral features was used Matsunaga et al. [20] in classifying respiratory sounds and an accuracy of 84.2% prevailed amongst normal and abnormal respiratory sounds. The abnormal sounds mentioned were crackles, rhonchi, and wheezes.

3. Analysis

According to Gouda et al. [21], who have performed a study on classification techniques on diagnosing repository sounds have shown the sound accuracy using ANN is better compared to other methods. In [21], three different techniques namely Discrete Wavelet transform (DWT), Short Time Fourier Transform (STFT) and Mel-Frequency Cepstral Coefficients (MFCCs) were used in separate ways to compare its efficiency in sound feature extraction whereby extracted sounds were then categorised using classification techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbour (KNN) and Naïve Bayes (NB). Referring to Table 1, obtained from [21] the sound accuracy is almost perfect in normal situations and difference can only be seen in wheezing sounds. The sound accuracy is measured with 5 wavelet coefficients since the lung sounds do not have any useful frequency components below 50 Hz and above 4000 Hz. This is anticipated as the lung sound frequency spectrum ranges from 125 to 2000 Hz.

Table 1. Sound accuracy.

	ANN	**SVM**	**K-NN**
Normal	100%	100%	96.67%
Wheezing	100%	98.89%	90.00%

Besides that, Ma et al. [22], also proposed using a modified version of ANN which improves the accuracy of classification. Ma et al. [22] have proposed usage of bilinear bi-ResNet neural networks to clarify the respiratory sounds into classifications, which has the capability of both training and learning the critical features extracted via STFT and wavelet analysis.

In general, based on the latest studies, we would like to propose to the use artificial neural network will be the best for classification of sounds, but this can be further improved with the integration of bio-inspired algorithm such as Particle Swarm Optimization, Genetic Algorithm, Ant Colony Optimization, Artificial Bee Colony, Eagle Strategy Whale Optimization Algorithm and many more. Bio-inspired algorithms have been very efficient even working with large scale data, which not only to classify but also to make selection in future to show the prediction based on the sounds. According to Yang et al. [23], hybrid methodology will be able to improve performance in large scale data compared to a single methodology. As in overall we would like to propose a complete digital or smart stethoscope as presented in Fig. 1. The proposed architecture will be using hybrid neural networks to classify the sounds in the cloud environment and further use the Bio-inspired algorithm to select the similar sound to send the required action to be taken by the medical personnel. This proposal is formulated based on the cases which have been presented in the next section, which focuses on the retrieval process on land and air.

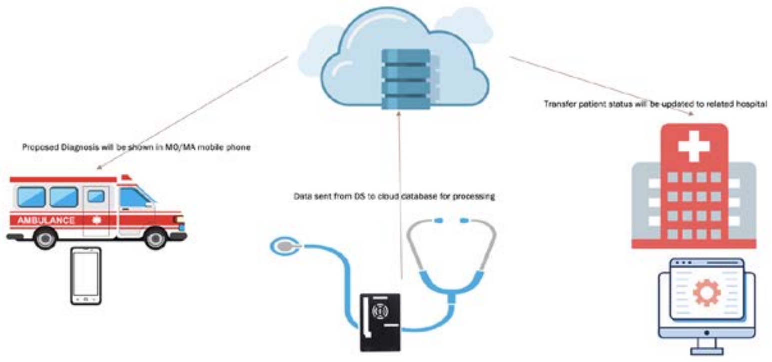

Fig. 1. Proposed overall architecture.

The flow of the proposed system is as shown in Fig. 2. The collected sound will be extracted based on its frequency. Those sound waves which does not come into the range will be removed and only will be focused on 50 Hz–4000 Hz only. Eagle strategy requires a smaller cluster loops to have a better performance in selecting the right sound.

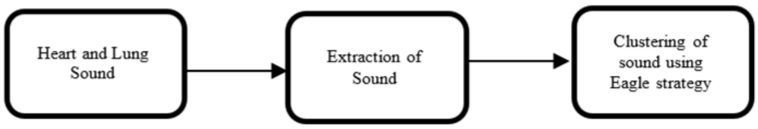

Fig. 2. Proposed sound extraction before storing into database.

3.1. Case-based analysis

There are limitations and difficulties that lead towards clinical diagnostic judgement of a clinician in a limited setting particularly in pre-hospital care. During transfer of patients, regardless through land (ambulance) or air (helicopter), usage of stethoscope has shown reducing accuracy in sound interpretation by clinicians as limitations provided in the form of interfering noises.

3.1.1. Land (ambulance)

Case 1

A district referral from Tuaran Hospital, Sabah was received by PreHospital Care (PHC) for Obstetrics and Gynaecology Retrieval (O & G Retrieval) with an indication of maternal cardiac arrest. A 30 years old, female, in her second trimester of pregnancy, unsure of Antenatal Care booking and follow up, presented with respiratory distress to the district hospital. Initial lung auscultation findings were generalised rhonchi and crepitations, thus the case was managed as asthma with oxygenation and Beta agonist nebulization and intravenous steroid. Patient went into cardiac arrest, Cardiopulmonary Resuscitation (CPR) was initiated for two cycles, multiple intubations attempt due to difficult airway and finally the patient had ROSC and was put on inotropic support. An O&G Retrieval team was deployed to retrieve the patient to Sabah Woman and Children's Hospital Emergency Department.

Upon arrival at Tuaran Hospital, the patient was intubated and sedated with ventilatory support, and noted a lot of secretions from the ETT. Suctioning was done and once the patient was assessed, packaged, and transported into the ambulance. Upon transfer, we noted that the auscultation using a stethoscope was difficult. We were unable to appreciate the basal lung sounds and heart sounds.

The sound auscultated via stethoscope interfered with the ambulance siren sounds and noise. Thus, it was perceived as lungs auscultation was both sides equal air entry and heart auscultation was perceived as no abnormal heart sounds. Patient was safely transferred to ETD SWACH. In ETD SWACH, noted that the heart auscultation is actually diastolic murmur. Bedside ECHO was done which showed hockey stick appearance. This murmur correlated with the heart ECHO findings of mitral stenosis. The murmur was missed throughout usage of stethoscope in ambulances contributed by interference of noises.

Case 2

A distress call was received requesting for ambulance support for a case of Motor Vehicle Accident (MVA) Car versus Car. Emergency Medical Rescue Services (EMRS) Bomba Kota Kinabalu was at the scene with 4 victims per say. A team from ETD SWACH responded for the ambulance call. Upon arrival, scene size up and triage was done.

A patient aged approximately 40 years old with no underlying medical illness, was one of the victims. He was sitting as the front seat passenger upon impact. Incident happened as another car was taking a U-turn and hit the victim's car. Upon impact, the patient claims that he was wearing a seatbelt. Initial assessment of the patient showed clear airway, equal breathing with no circulatory compromise, chest spring and pelvic spring was negative.

Auscultation using a stethoscope showed equal air entry into lungs till basal and normal heart sounds. He sustained multiple laceration wounds and post-traumatic headache. We transported the patient by ambulance. During transfer, noted the patient had on and off chest discomfort when the ambulance was driving through the bumpers, thus the patient was assessed again in a moving ambulance where the auscultation was perceived as equal air entry which equal chest rise on inspection.

Upon arrival at the designated hospital, the patient was reassessed. Auscultation noted air entry was greatly reduced on the right side of the lungs. Patient developed spontaneous pneumothorax along the way.

3.1.2. Air (helicopter)

Case 1

A MEDEVAC was activated for a stepdown care. A 61-year-old female with underlying dyslipidemia, presented initially to Hospital Beaufort with one day history of shortness of breath, abnormal behaviour, and unresponsiveness. GCS upon arrival was E1V1M4, patient was transferred to Hospital Queen Elizabeth 1 (HQE1) and was admitted to ICU for Right Malignant MCA Infarct. In HQE1, the patient underwent right decompressive craniectomy and was intubated two days after post operation.

Subsequently, tracheostomy was done and DNR (Do Not Resuscitate) was issued. Two CT Brains were done throughout admission at HQE 1, first CT Brain on day one of admission showed acute right MCA territory infarction with subfalcine herniation and a leftward midline shift of 5mm. Repeated CT brain post right decompressive craniectomy showed findings of a postoperative case of right MCA territory infarction which currently showed worsening cerebral edema with postoperative changes.

The purpose of the transfer was to step down care from HQE 1 to Hospital Duchess of Kent, Sandakan (HDOK). A team was deployed from SWACH for the MEDEVAC. Case passover was done at Layang-layang Aerospace Sabah. On assessment prior to transfer showed a GCS of E 3VtM3, pupils 3mm/3mm reactive, patient on trachymask 24% (4L), good pulse volume, CRT less than two seconds, lungs auscultation showed transmitted sounds, cardiac auscultation showed no murmur with S1S2 detection, per abdomen showed soft, not distended with bowel sounds . Initial vital sounds were stable for transfer.

Once the patient was packaged, she was transported into a Bell 206 Helicopter and strapped. Along the transfer to Sandakan, regular suctioning was done to ensure no secretion was blocking her tracymask and the oxygen saturation was maintained more than 95%. Auscultation using stethoscope was done prior and post suction to ensure good and equal air entry. It was difficult to ensure proper interpretation of the sounds perceived as the sound of a rotating helicopter blade was clouding the process of clinical decision due to its masking effect of the actual lung sounds.

Case 2

A Medical Retrieval (MEDEVAC) was activated for a paediatric case as air retrieval from Hospital Lahad Datu to SWACH. A retrieval team was deployed from SWACH to retrieve a patient with penetrating head injury with intracranial foreign body and intracranial bleeding from Hospital Lahad Datu. She is a six-year-old that visited the emergency department of Hospital Lahad Datu with a complaint of an alleged shot with a slingshot (marble) by her older brother while playing, over the forehead.

She displayed signs and symptoms of increased intracranial pressure and fluctuating GCS, further which CT Brain was noted to have foreign body at the frontal region, skull fracture and intracranial bleeding. She was intubated for airway protection and was referred to the Neurosurgery team from SWACH for further management. Case passover was done in hospital Lahad Datu Intensive Care Unit.

Upon assessment prior to transfer, the child was intubated, ventilated with a low ventilator setting, sedated with Midazolam and Morphine, kept nil by mouth with two-third maintenance intravenous fluid regime with stable initial vital signs.

Patient was packaged, secured, and transferred into a GAF Nomad Helicopter. Throughout the transfer patient was monitored to ensure oxygen saturation of more than 95%. Auscultation was very difficult due to the interference of noise from rotating helicopter blades, motor turbine noise and was worsened with the combined sound of rain and instability caused by helicopter stability.

4. Conclusion

The specific goal of this research is digitalization of stethoscopes that will propel clinical decisions more precise in unfavourable conditions and situations. We have proposed to develop a cloud-based Digital stethoscope which not only captures the sound but the AI which works together with neural networks which hybrid together with bio inspired methods to classify the sound, selecting the similar sound from a large-scale database which advances into creation of diagnostic pathways that facilitate into fool-proof step-by step clinical interventions. As the data collected is well saved with preservation of privacy according to Confidentiality Guidelines MMC 2011, the data can be used as legalised evidence in cases of medicolegal.

Nomenclatures

c_i	Predicted value
$d()$	Distance between two points
e_1	Observed value
n	Number of data points
p	Point 1
q	Point 2

Abbreviation

AI	Artificial Intelligence
ANN	Artificial Neural Network
CT	Computerized Tomography
CPR	Cardiopulmonary Resuscitation
DNR	Do Not Resuscitate
ED	Emergency Department
ECHO	Echocardiogram
EMS	Emergency Medical Services
EMRS	Emergency Medical Rescue Services
ETT	Endotracheal Tube
ETD SWACH	Emergency and Trauma Department, Sabah Women and Children Hospital
GCS	Glascow Coma Scale
HMM	Hidden Markov Models
HDOK	Hospital Duchess of Kent
HQE1	Hospital Queen Elizabeth 1
ICT	Information and Communications Technology
ICU	Intensive Care Unit
IoT	Internet of Things
k-NN	k-Nearest Neighbour
LR	Logistic Regression
MA	Medical Assistant

MO	Medical Officers
MCA	Middle Cerebral Artery
MMC	Malaysian Medical Council
MSE	Mean Square Error
MVA	Motor Vehicle Accidents
MFCC	Mel-frequency cepstral coefficients
MEDEVAC	Medical Evacuation
NB	Naive Bayes
NN	Neural Network
O&G Retrieval	Obstetrics and Gynaecology Retrieval
PHC	Pre-Hospital Care
PSD	Power Spectral Density
PSD	Fourier Power Spectrum Density
RF	Random Forests
SVM	Support Vector Machine
STFT	Short Time Fourier Transform
SWACH	Sabah Women and Children’s Hospital
S1	First Heart Sound
S2	Second Heart Sound
S3	Third Heart Sound
S4	Fourth Heart Sound

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