FRAMEWORK FOR MACHINE LEARNING ARTEFACT REMOVAL AND EMPIRICAL MODE DECOMPOSITION FOR CAPNOGRAM-BASED ASTHMA DETECTION

ISMAIL MOHAMED IBRAHIM BAYOUMY ELBADAWY

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy

Faculty of Electrical Engineering
Universiti Teknologi Malaysia

JANUARY 2023

DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

ACKNOWLEDGEMENT

I am very grateful to **ALLAH** Subhanahu Wa Ta'ala who gave me an excellent family to live with and provided me the environment where I could finish my Ph.D. study and without whose will it would have been impossible to complete my degree.

Second only to **ALLAH**, thanks to my parents for what they have contributed towards my education. Their unconditional love, constant support, great advice and prayers over the years are something that I cannot thank them for enough.

Many special thanks go to my supervisor **Dr. Zaid Omar** for his active contribution to refining my research work and in filling the gaps. At times, when things looked difficult, he was the one who gave me hope. Whether it was studying existing research or writing articles, he was there to listen to my concerns, review the material, provide feedback and show direction.

I would like to express my heartily thanks to my colleagues. They always encouraged me in this challenge. This goes especially for **Mohamed Takey**, **Essam Abu-Bakr**, **Mohamed Gamal**, **Mohamed Atef** and **Om Prakash Singh** for their support and useful discussions. Also I would like to thank my sister **Nourhan El-Badawy** for providing the biological background necessary to complete this work.

I owe special thanks to my wife **Fatma Atef**, for her endless support and encouragement, for understanding and patiently enduring long hours of work I spent on this research.

ABSTRACT

Capnography has received considerable attention owing to its important applications in assessing asthma and other pulmonary diseases. Monitoring abnormal changes in the recorded carbon dioxide waveform (i.e., capnogram signal) allows for detecting respiratory malfunctioning and thereby averting potential asthma attacks. Detecting asthma based on the non-stationary capnogram signal remains an open research problem. In this thesis, an automatic computational framework is proposed to detect asthma. The presented framework includes two main stages. The first stage is responsible for discarding the distorted segments of the recorded capnogram signals. This task was performed in previous studies either manually by visual inspection, using threshold-based or template matching methods. In the current work, a machine learning-based approach is presented to automatically classify artefact-free and distorted capnogram segments. For this purpose, different time- and frequency-domain features are proposed. The time-domain features include energy, variance, skewness, kurtosis, Hjorth parameters and mean absolute deviation (MAD). The frequency-domain features include the area under the magnitude Fourier spectrum in addition to the number of relatively high spectral peaks for a particular frequency range. Different classifiers are trained and tested using the most relevant features: Hjorth activity and MAD. These classification models include Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT) and Naive Bayes (NB) classifiers. The results showed that the SVM classifier can provide classification accuracy, specificity, sensitivity and precision of 89%, 91%, 87% and 92.1%, respectively. In addition, a multiple classifiers voting approach is proposed for this classification task. Using this cooperative classification, the specificity is increased from 91% to 94%. The second stage accepts the clean capnogram segments from the first stage and carries out the classification of healthy and asthmatic capnograms. The proposed features are based on Empirical Mode Decomposition (EMD) which is suitable for analyzing the non-stationary capnogram signal in addition to the variance of the raw signal. Unlike the traditional features, the proposed features are extracted from the frequency-domain representation of the signal's first Intrinsic Mode Function (IMF). The results showed that the NB classifier can provide classification accuracy, specificity, sensitivity and precision of 96.5%, 97%, 96% and 97.18%, respectively.

ABSTRAK

Capnography telah mendapat perhatian besar kerana peranannya yang penting dalam menilai asma dan penyakit paru-paru yang lain. Di dalam thesis ini, rangka kerja pengiraan automatik dicadangkan bagi mengesan asma berdasarkan analisis isyarat capnogram. Rangka kerja yang dibentangkan merangkumi dua peringkat utama. Peringkat pertama berperanan menyingkirkan segmen terherot bagi isyarat capnogram yang dirakam. Langkah ini telah diamalkan dalam kajian terdahulu sama ada secara manual melalui pemeriksaan visual, menggunakan kaedah berasaskan ambang, atau pemadanan templat. Dalam kajian semasa, pendekatan berasaskan pembelajaran mesin dipamerkan bagi mengklasifikasikan secara automatik segmen bebas artifak dan capnogram terherot. Bagi tujuan ini, ciri domain masa dan domain frekuensi dicadangkan. Ciri domain masa termasuk tenaga, varians, kecondongan, kurtosis, parameter Hjorth dan sisihan mutlak min (MAD). Ciri domain frekuensi pula termasuk kawasan di bawah magnitud spektrum Fourier sebagai pelengkap kepada bilangan puncak spektrum yang tinggi untuk julat frekuensi tertentu. Pengelas yang berbeza termasuk Mesin Sokongan Vektor (SVM), Hutan Rawak (RF), Pohon Keputusan (DT) dan pengelas Naive Bayes (NB) dilatih dan diuji menggunakan ciri yang paling relevan. Keputusan menunjukkan bahawa pengelas SVM boleh memberikan ketepatan pengelasan, kekhususan, kepekaan dan ketepatan masing-masing sebanyak 89%, 91%, 87% dan 92.1%. Di samping itu, pendekatan berdasarkan pengundian berbilang pengelas dicadangkan untuk tugas pengelasan ini. Menggunakan klasifikasi yang digabungkan ini, kekhususan ditingkatkan daripada 91% kepada 94%. Peringkat kedua menerima segmen capnogram bersih dari peringkat pertama dan melaksanakan klasifikasi capnogram antara sihat dan asma. Ciri-ciri yang dicadangkan adalah berdasarkan Penguraian Mod Empirikal (EMD) di mana ianya sesuai untuk menganalisis isyarat capnogram yang tidak pegun. Berlainan dengan ciri tradisional yang diekstrak daripada perwakilan domain frekuensi bagi isyarat capnogram mentah, ciri yang dicadangkan diekstrak daripada perwakilan domain frekuensi bagi isyarat pertama Fungsi Mod Intrinsik (IMF). Keputusan menunjukkan bahawa pengelas NB mampu memberikan ketepatan pengelasan, kekhususan, kepekaan dan kejituan masing-masing sebanyak 96.5%, 97%, 96% dan 97.18%.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ABG	-	Arterial Blood Gas
ANN	-	Artificial Neural Network
AR	-	Auto Regressive
AUC	-	Area Under ROC Curve
BCI	-	Brain-Computer Interface
CHF	-	Congestive Heart Failure
CO_2	-	Carbon dioxide
COPD	-	Chronic Obstructive Pulmonary Disease
COVID	-	Coronavirus Diseases
CPR	-	Cardiopulmonary Resuscitation
CWD	-	Choi-William Distribution
DFT	-	Discrete Fourier Transform
DSP	-	Digital Signal Processing
DT	-	Decision Tree
EEG	-	Electroencephalogram
EMD	-	Empirical Mode Decomposition
EMG	-	Electromyography
ERD	-	Event-Related Desynchronization
$EtCO_2$	-	End-tidal Carbon dioxide
FAST	-	Feature Assessment by Sliding Thresholds
FEV_1	-	Forced Expiratory Volume in the first second
FEV_6	-	Forced Expiratory Volume in the first six seconds
FFT	-	Fast Fourier Transform
FIRS	-	Forum of International Respiratory Societies
FNR	-	False Negative Rate
FPR	-	False Positive Rate

FVC	-	Forced Vital Capacity
GMM	-	Gaussian Mixture Model
GINA	-	Global Initiative for Asthma
ICO_2	-	Inspired Carbon dioxide
IMF	-	Intrinsic Mode Function
IPCRG	-	International Primary Care Respiratory Group
IR	-	Infra Red
LLN	-	Lower Limits of Normal
LPC	-	Linear Predictive Coding
MAD	-	Mean Absolute Deviation
MBD	-	Modified-B Distribution
MFCCs	-	Mel Frequency Cepstral Coefficients
NAEPP	-	National Asthma Education and Prevention Program
NB	-	Naive Bayes
O_2	-	Oxygen
$PaCO_2$	-	Arterial Partial Pressure of Carbon Dioxide
PEFR	-	Peak Expiratory Flow Rate
PFT	-	Pulmonary Function Test
PSD	-	Power Spectral Density
QDA	-	Quadratic Discriminant Analysis
RBF	-	Radial Basis Function
RF	-	Random Forest
RIP	-	Respiratory Inductive Plethysmography
ROC	-	Receiver Operating Characteristics
RR	-	Respiratory Rate
SMI	-	Sustained Maximal Inspiration
SR	-	Slope Ratio
STFT	-	Short-time Fourier Transform
SVM	-	Support Vector Machine

TFD	-	Time-Frequency Distribution
TMR	-	Transparency Market Research
TNR	-	True Negative Rate
TPR	-	True Positive Rate
UTM	-	Universiti Teknologi Malaysia
VAE	-	Venous Air Embolism
WHO	-	World Health Organization
WVD	-	Wigner-Ville Distribution

LIST OF SYMBOLS

A_{f_o}	-	Area under magnitude spectrum for $0 < f \leq f_o$ Hz
$c(n)$	-	Normalized capnogram segment
$c'(n)$	-	First derivative of a capnogram segment
$c''(n)$	-	Second derivative of a capnogram segment
d	-	Binary classification decision from a single classifier
D_f	-	Final global decision from multiple classifiers
E_c	-	Energy of a capnogram segment
$e_l(n)$	-	Lower envelope
$e_u(n)$	-	Upper envelope
F	-	Feature vector
f_o	-	End frequency of a frequency range
f_s	-	Sampling frequency
IMF_i	-	i^{th} Intrinsic Mode Function
L	-	Target class labels vector
M	-	Length of class labels vector
N	-	Length of a capnogram segment
P	-	Number of high spectral peaks
$r(n)$	-	Residue signal
T_s	-	Sampling time interval
$x(n)$	-	Zero-mean capnogram segment
$X(k)$	-	Discrete Fourier transform of $x(n)$
$Y(k)$	-	Binary vector counting the number of high spectral peaks
ρ	-	Pearson's correlation coefficient
σ_c	-	Standard deviation of a capnogram segment
σ_c^2	-	Variance of a capnogram segment
μ_c	-	Mean value of a capnogram segment

CHAPTER 1

INTRODUCTION

1.1 Overview

Hundreds of millions of people worldwide suffer from chronic respiratory diseases, which are considered among the leading causes of morbidity and mortality [1, 2], especially with the broad spread of novel coronavirus disease (COVID) as healthy lungs are capable of fighting it better [3]. According to the statistical data reported by the world health organization (WHO) in 2019, respiratory illnesses represented 30% of the most prominent causes of death around the world [4]. Different environmental circumstances, such as dust, air pollution and tobacco smoke exposure, and other pathological and genetic risk factors are responsible for accelerating the prevalence of these ill-health conditions [5]. Consequently, the health and economic costs of these life-threatening respiratory conditions are dramatically high due to their pervasiveness and severity. The latest report released by the Forum of International Respiratory Societies (FIRS) identified asthma in addition to other four distress conditions: chronic obstructive pulmonary disease (COPD), acute lower respiratory tract infection, tuberculosis and lung cancer, as the most contributing to the global burden of pulmonary (respiratory) disorders [6].

Asthma is a remarkably common and serious obstructive respiratory disease that represents a global burden due to the alarming morbidity and mortality rates caused by this disease as reported by GINA [7]. The symptoms of this chronic disease, which affects millions of people around the world, include shortness of breath, wheeze, cough and chest tightness. The respiratory airways of an asthmatic patient are swollen and inflamed, as shown in Figure 1.1. During an asthma attack (also called an asthma exacerbation), the muscles around the airways contract causing the bronchial tubes to become even narrower. In addition, the narrowing of the airways is increased due to

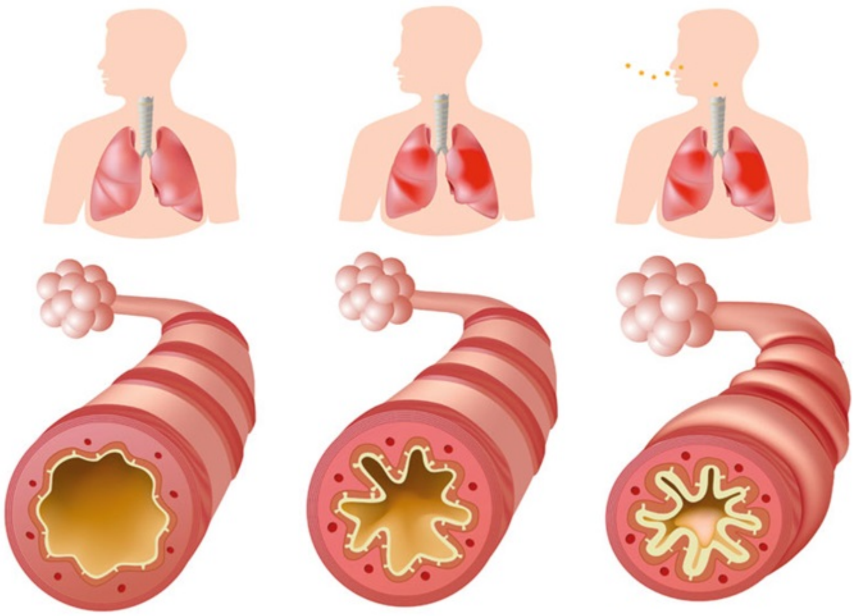

Figure 1.1 Respiratory airway shape in case of normal and asthmatic subjects.

the extra produced mucus and thereby the patient experiences tough trouble breathing and acute chest tightness.

With the recent spread of the COVID-19 pandemic, it is recommended for people with asthma to take the vaccination especially if they are not allergic to the vaccine ingredients [8]. However, regular assessment is still needed in order to manage asthma attacks and avoid their harmful consequences through determining the suitable dose of treatment. The diagnosis and assessment of asthma is performed by pulmonologists based on the history of the symptoms pattern besides the measures obtained from the PFTs [9]. Other traditional clinical examination methods, such as chest and tracheal auscultation, are also used to detect the presence of inspiratory and/or expiratory wheezing and other potential changes in lung sounds [10].

1.1.1 Capnograph-based respiratory assessment

Capnograph is a medical device recommended by different healthcare societies for performing evaluations of respiratory conditions [11–13]. Being non-invasive and effort-independent, capnograph has the preference in medical diagnostics over traditional respiratory assessment methods described in the previous subsection. Capnograph also showed significance in other situations, besides the follow-up of patients with pulmonary diseases, where a patient's level of consciousness, ventilation, oxygenation or perfusion is deranged. For instance, using capnography in intensive care environments to monitor the respiratory status during sedation is needed to avoid sudden depression in the patient's ventilation [14]. Capnography is also used during neurosurgery to detect any abrupt decrease in the maximum exhaled CO_2 pressure which indicates the incidence of venous air embolism (VAE) [15]. Other clinical studies showed that capnography is helpful in cardiopulmonary resuscitation (CPR) during cardiac arrest [16]. In CPR, capnography is utilized in monitoring chest compressions and checking the accurate placement of the endotracheal tube in addition to observing the ventilation rate for the purpose of preventing inadvertent hyperventilation [17–19].

A capnography device measures the partial pressure of CO_2 gas in the real-time pulmonary airflow in human airways during inspiration and expiration and displays on its monitor a waveform, namely the capnogram signal [20, 21]. Typically, the CO_2 gas represents around 0.04% and 6% of the inhaled and exhaled air, respectively [22]. With reference to these standard levels, monitoring abnormal changes in the recorded capnographic wave (i.e., capnogram signal) allows for detecting respiratory malfunctioning and thereby averting potential harmful consequences. Other associated assessment parameters, including respiratory rate (RR), inspired CO_2 (ICO_2) and end-tidal CO_2 ($EtCO_2$), are also computed and displayed on the capnograph monitor. Capnography devices are either time-based, in which a capnogram waveform shows the respiratory CO_2 partial pressure variations in millimeters of mercury (mmHg) as a function of time, or volumetric, in which a capnogram signal is recorded and plotted versus expired volume [23–25]. The main idea of capnography technology is founded on the fact that infrared (IR) radiation of a specific wavelength is absorbed by CO_2 molecules. Hence, the calculation of the CO_2 concentration in the inspired and

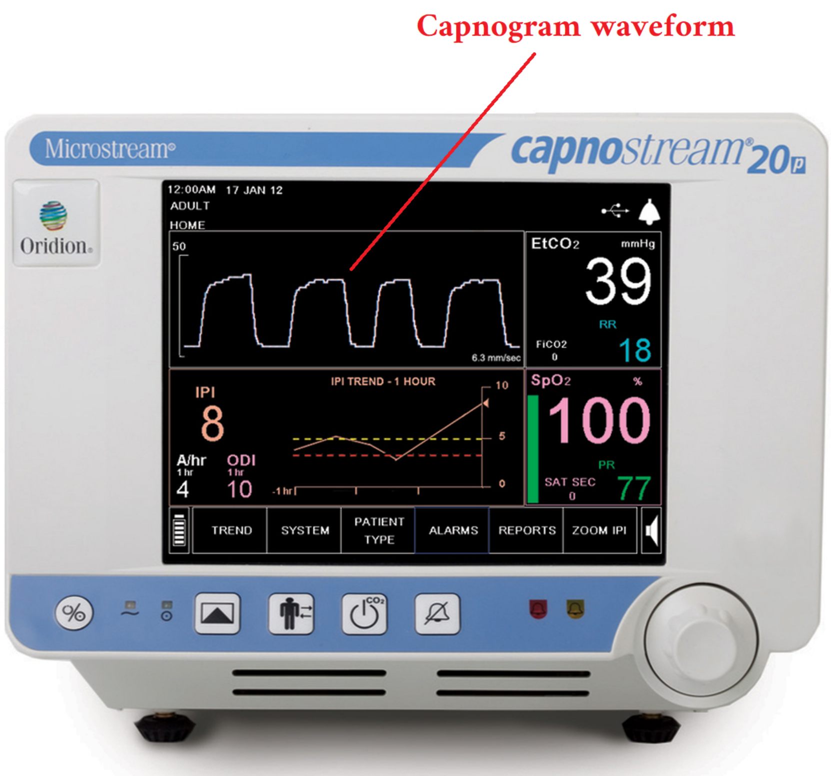

Figure 1.2 Capnostream^{TM} 20p capnography monitor.

expired gases is carried out via detecting the changes in IR radiation levels by means of sensitive photo-detectors [21, 26]. Accordingly, a CO_2 sensor is a principal component of a capnography system in addition to a gas sampling tube, through which the CO_2 signal is acquired from the subject, and a unit for signal acquisition and processing [21].

Two main techniques are available for the CO_2 measurement in capnography devices: main- and side-stream techniques [27, 28]. In the main-stream technique, the CO_2 sensor is located close to the subject, particularly between the processing unit and the face mask that is used to attach the subject to the device. Thereby, neither a sampling tube nor a pump is needed in a main-stream capnography device. On the other hand, the CO_2 sensor in the side-stream technique is placed inside the main processing unit away from the subject who is attached to the device through a nasal cannula. During breathing, a mini pump aspirates the detected CO_2 samples from the sampling tube at a rate ranging from 50 to 200 millilitre per minute (ml/min). The main-stream capnograph has a simple mechanism and rapid signal acquisition, however the temperature of its CO_2 sensor increases above 40°C which may harm the subject's skin. The side-stream capnograph is easier to sterilize and can be used flexibly for both adults and children who are sometimes in unusual positions during measurement. In this thesis, the Capnostream^{TM} 20p capnographic monitoring device, shown in Figure 1.2, that is based on the side-stream technique is employed. This device records time-based capnogram waveforms and has the option of saving these CO_2 signals for further processing and analysis.

1.1.2 Capnogram signal analysis

In respiratory care, recognizing capnogram changes can provide better care for pulmonary patients by alerting the healthcare providers to critical situations where the airflow is restricted. Pulmonary physicians rely on their visual inspection of the recorded capnogram signal during a subjective clinical assessment of respiratory disorders, such as asthma and COPD [25, 29]. However, the automatic objective assessment and monitoring of such respiratory diseases are highly beneficial in clinical and home environments [20, 30, 31]. Hence, researchers have been incentivized to introduce different signal processing-based algorithms for capnogram signal analysis. The ultimate goal of these algorithms is airway management through the interpretation of capnogram features which reflect the functional performance of human respiratory system. For example, the authors in [32] performed a quantitative analysis of the capnogram signals acquired from patients suffering from COPD and congestive heart failure (CHF). In this study, different time-domain features extracted from the capnogram waveform morphology, such as the slope of the alveolar plateau phase, were employed together with quadratic discriminant analysis (QDA) to distinguish between normal subjects and patients with COPD or CHF.

Other studies [33, 34] investigated the significance of time-domain and statistical features of capnogram signals in detecting asthmatic conditions. The suggested features in these studies included signal shape descriptive indices, such as the gradients of different capnogram phases and the angles between these phases, in addition to the Hjorth parameters [35]. Besides, different frequency-domain features of capnograms were also proposed in [36] to differentiate normal pulmonary function from asthma. The fast Fourier transform (FFT) and autoregressive (AR) modelling were utilized to compute the power spectral density (PSD) of a CO_2 signal. Subsequently, the magnitudes and positions of the spectral peaks were employed as discriminating features between normal and asthmatic capnograms, and the artificial neural network (ANN) was used to carry out the classification task. A broad overview of capnogram signal analysis and feature extraction methods can be found in [37].

Although capnogram signal analysis showed significance in detecting different respiratory distress conditions, our focus in this thesis is mainly on asthma disease due to its rising prevalence in Malaysia and other Asia-Pacific countries. Being a tropical country, Malaysia's environmental risk factors such as high humidity, mould and dampness contribute to the wide spread of asthma [38–40]. Furthermore, CO_2 emissions from the burning of fossil fuels in Malaysia reached 262.2 million tons in 2020 [41] and so this growing level of air pollution increases the susceptibility to asthma infection. According to the global initiative for asthma (GINA) guidelines, asthmatic patients are divided into three categories based on the level of control of symptoms: well-controlled, partly-controlled and uncontrolled [42]. In Malaysia, only 6% of patients suffering from asthma are well-controlled, while more than 90% are partly- and uncontrolled, which reflects the alarming burden imposed by this chronic non-communicable disease [43].

1.2 Problem statement

Asthma is considered one of the top causes of death worldwide and thereby detecting this serious disease through the analysis of capnogram signal is an issue of great significance in medical technology. Hence, researchers proposed a number of methods to analyze the CO_2 waveform using digital signal processing (DSP) techniques. However, accurate and automatic detection of asthma using a computerized program remains an open research problem, especially for long-term monitoring with the aim of an early detection of an asthma attack. This is also encouraged by the ongoing research on developing portable capnography devices for home monitoring purpose.

Previous studies on capnogram signal analysis have employed different features extracted from time- and frequency-domain for automatic asthma detection. However, the non-stationary nature of capnogram signals implies that their statistical characteristics and frequency contents are time-varying. Thus, traditional time-domain and frequency-domain methods are not reliable analysis tools to detect asthmatic conditions for their limited accuracy. In addition, the quantitative features of a capnogram signal should be quantified from selected clean (i.e., artefact-free) segments of the capnogram waveform. However, the automatization of this selection step using machine learning techniques has not yet received the attention it deserves in the literature. In previous work, selection of clean capnogram segments were performed manually by visual inspection, by template matching or using threshold-based methods. That being the case, this thesis is concerned with conducting research on these issues.

1.3 Research aim

The main aim of the current research is to introduce a fully automated computerized framework for automatic capnogram-based asthma detection. This framework is intended to process the input capnogram signal, which may include deformed parts, and give a final classification decision regarding the pulmonary status of the subject. This framework can be integrated with capnography devices for monitoring purposes to automatically give an alarm before an expected asthma attack.

1.4 Research Objectives

Limitations of previous work motivated the current study to achieve the research aim through setting the following objectives:

1. To propose a Machine Learning algorithm for classifying clean and deformed capnogram segments, with Hjorth activity and mean absolute deviation features.
2. To propose an Empirical Mode Decomposition based algorithm for classifying control and asthmatic capnogram segments.

3. To evaluate the classification performance of the above research objectives in terms of accuracy, specificity, sensitivity and precision, on real capnogram segments.

1.5 Scope of research

The scope of research of this thesis includes the following:

- Real capnogram signals are recorded from adult healthy subjects and asthmatic patients admitted to Universiti Teknologi Malaysisa (UTM) healthcare center after getting the ethical approval.
- Two capnogram datasets are prepared: the first one includes 100 artefact-free (regular) and 100 distorted (irregular) capnogram segments, while the second one includes 200 regular capnogram segments (100 healthy and 100 asthmatic).
- MATLAB is used for simulation purpose to process and analyze the capnogram datasets using empirical mode decomposition and machine learning algorithms with the aim of achieving the research objectives. The MATLAB version is (R2015a) run on a computer with Intel®Core™ i7 processor, 2.5 GHz speed and 16 GB RAM.
- The classification performance is evaluated in terms of accuracy, specificity, sensitivity and precision.

1.6 Thesis outline

Chapter 1 provides an overview of the thesis in addition to traditional and recent respiratory assessment methods. In this chapter, the problem statement along with the research objectives and scope are presented.

Chapter 2 gives the biological background needed to present the existing capnogram-based asthma detection methods in the literature. Asthma detection using other physiological signals, rather than capnogram, is also presented.

Chapter 3 details out the currently proposed method for capnogram-based asthma detection using empirical mode decomposition (EMD), in addition to the proposed machine learning approach for classifying clean and deformed capnogram segments.

Chapter 4 presents the results of the proposed methods accompanied by a comparison with the lately proposed methods using the available capnogram dataset.

Finally, Chapter 5 concludes the thesis and suggests future research directions.

REFERENCES

1. Ferkol, T. and Schraufnagel, D. The global burden of respiratory disease. *Annals of the American Thoracic Society*, 2014. 11(3): 404–406.

2. Marciniuk, D. D. and Schraufnagel, D. E. *The global impact of respiratory disease*. European Respiratory Society. 2017.

3. Khan, S., Siddique, R., Ali, A., Bai, Q., Li, Z., Li, H., Shereen, M. A., Xue, M. and Nabi, G. The spread of novel coronavirus has created an alarming situation worldwide. *Journal of infection and public health*, 2020. 13(4): 469.

4. Organization, W. H. *et al. World health statistics 2019: monitoring health for the SDGs, sustainable development goals*. World Health Organization. 2019.

5. Shaheen, S. The beginnings of chronic airflow obstruction. *British medical bulletin*, 1997. 53(1): 58–70.

6. *Forum of International Respiratory Societies (FIRS) - Third Edition*. European Respiratory Society, 2021. [Accessed 22 Sep 2021]. Available from: https://firsnet.org/images/publications/FIRS_Master_09202021.pdf.

7. Bousquet, J., Clark, T., Hurd, S., Khaltaev, N., Lenfant, C., O'byrne, P. and Sheffer, A. GINA guidelines on asthma and beyond. *Allergy*, 2007. 62(2): 102–112.

8. Novembre, E., Giovannini, M., Barni, S. and Mori, F. From the Global Initiative for Asthma report and asthma guidelines to real-life asthma control: is there room for improvement? *Italian Journal of Pediatrics*, 2022. 48(1): 1–3.

9. Reddel, H. K., Bacharier, L. B., Bateman, E. D., Brightling, C. E., Brusselle, G. G., Buhl, R., Cruz, A. A., Duijts, L., Drazen, J. M., FitzGerald, J. M. *et al.* Global Initiative for Asthma (GINA) Strategy 2021–Executive summary and rationale for key changes. *The Journal of Allergy and Clinical Immunology: In Practice*, 2021.

10. Sprikkelman, A., Schouten, J., Lourens, M., Heymans, H. and Van Aalderen, W. Agreement between spirometry and tracheal auscultation in assessing

bronchial responsiveness in asthmatic children. *Respiratory medicine*, 1999. 93(2): 102–107.

11. Manara, A., D'hoore, W. and Thys, F. Capnography as a diagnostic tool for pulmonary embolism: a meta-analysis. *Annals of emergency medicine*, 2013. 62(6): 584–591.

12. Nassar, B. S. and Schmidt, G. A. Capnography during critical illness. *Chest*, 2016. 149(2): 576–85.

13. Kerslake, I. and Kelly, F. Uses of capnography in the critical care unit. *Bja Education*, 2017. 17(5): 178–183.

14. Conway, A., Douglas, C. and Sutherland, J. A systematic review of capnography for sedation. *Anaesthesia*, 2016. 71(4): 450–454.

15. Vinay, B., Sriganesh, K. and Gopala Krishna, K. N. An abrupt reduction in end-tidal carbon-dioxide during neurosurgery is not always due to venous air embolism: a capnograph artefact. *Journal of clinical monitoring and computing*, 2014. 28(2): 217–219.

16. Sandroni, C., De Santis, P. and D'Arrigo, S. Capnography during cardiac arrest. *Resuscitation*, 2018. 132: 73–77.

17. Repetto, J. E., Donohue, P.-C., Pamela, K., Baker, S. F., Kelly, L. and Nogee, L. M. Use of capnography in the delivery room for assessment of endotracheal tube placement. *Journal of Perinatology*, 2001. 21(5): 284–287.

18. Meaney, P. A., Bobrow, B. J., Mancini, M. E., Christenson, J., De Caen, A. R., Bhanji, F., Abella, B. S., Kleinman, M. E., Edelson, D. P., Berg, R. A. *et al.* Cardiopulmonary resuscitation quality: improving cardiac resuscitation outcomes both inside and outside the hospital: a consensus statement from the American Heart Association. *Circulation*, 2013. 128(4): 417–435.

19. Qvigstad, E., Kramer-Johansen, J., Tømte, Ø., Skålhegg, T., Sørensen, Ø., Sunde, K. and Olasveengen, T. M. Clinical pilot study of different hand positions during manual chest compressions monitored with capnography. *Resuscitation*, 2013. 84(9): 1203–1207.

20. Goepp, J. G. Effort-Independent, Portable, User-Operated Capnograph Devices And Related Methods, 2009.

21. Gravenstein, J. S., Jaffe, M. B., Gravenstein, N. and Paulus, D. A. *Capnography*. Cambridge University Press. 2011.

22. Berntson, G. G., Cacioppo, J. T. and Quigley, K. S. Respiratory sinus arrhythmia: autonomic origins, physiological mechanisms, and psychophysiological implications. *Psychophysiology*, 1993. 30(2): 183–196.

23. Thompson, J. E. and Jaffe, M. B. Capnographic waveforms in the mechanically ventilated patient. *Respiratory care*, 2005. 50(1): 100–109.

24. Veronez, L., Pereira, M. C., da Silva, S. M. D., Barcaui, L. A., De Capitani, E. M., Moreira, M. M. and Paschoal, I. A. Volumetric capnography for the evaluation of chronic airways diseases. *International journal of chronic obstructive pulmonary disease*, 2014. 9: 983.

25. Long, B., Koyfman, A. and Vivirito, M. A. Capnography in the emergency department: a review of uses, waveforms, and limitations. *The Journal of Emergency Medicine*, 2017. 53(6): 829–42.

26. AL-Khalidi, F. Q., Saatchi, R., Burke, D., Elphick, H. and Tan, S. Respiration rate monitoring methods: A review. *Pediatric pulmonology*, 2011. 46(6): 523–529.

27. Santoso, D. and Setiaji, F. D. Design and implementation of capnograph for laparoscopic surgery. *International Journal of Information and Electronics Engineering*, 2013. 3(5): 523.

28. Singh, O. P., Howe, T. A. and Malarvili, M. Real-time human respiration carbon dioxide measurement device for cardiorespiratory assessment. *Journal of breath research*, 2018. 12(2): 026003.

29. Hisamuddin, N. N., Rashidi, A., Chew, K. S., Kamaruddin, J., Idzwan, Z. and Teo, A. H. Correlations between capnographic waveforms and peak flow meter measurement in emergency department management of asthma. *International journal of emergency medicine*, 2009. 2(2): 83–9.

30. Howe, T. A., Jaalam, K., Ahmad, R., Sheng, C. K. and Ab Rahman, N. H. N. The use of end-tidal capnography to monitor non-intubated patients presenting with acute exacerbation of asthma in the emergency department. *The Journal of emergency medicine*, 2011. 41(6): 581–589.

31. Singh, O. P., Ahmed, I. B. and Malarvili, M. B. Assessment of newly developed real-time human respiration carbon dioxide measurement device for management of asthma outside of hospital. *Technology and Health Care*, 2018. 26(5): 785–94.

32. Mieloszyk, R. J., Verghese, G. C., Deitch, K., Cooney, B., Khalid, A., Mirre-González, M. A., Heldt, T. and Krauss, B. S. Automated quantitative analysis of capnogram shape for COPD–normal and COPD–CHF classification. *IEEE Transactions on Biomedical Engineering*, 2014. 61(12): 2882–90.

33. Kean, T. T. and Malarvili, M. B. Analysis of capnography for asthmatic patient. *Proceedings of the 2009 IEEE International Conference on Signal and Image Processing Applications*. IEEE. 2009. 464–7.

34. Kean, T. T., Teo, A. H. and Malarvili, M. B. Feature extraction of capnogram for asthmatic patient. *Proceedings of the 2010 Second International Conference on Computer Engineering and Applications*. IEEE. 2010. 251–5.

35. Hjorth, B. EEG analysis based on time domain properties. *Electroencephalography and clinical neurophysiology*, 1970. 29(3): 306–310.

36. Kazemi, M. and Malarvili, M. B. Investigating Frequency Contents of Capnogram using Fast Fourier Transform (FFT) and Autoregressive Modeling (AR). *Life Science Journal*, 2017. 14(10): 71–8.

37. Jaffe, M. B. Using the features of the time and volumetric capnogram for classification and prediction. *Journal of clinical monitoring and computing*, 2017. 31(1): 19–41.

38. Karvala, K., Toskala, E., Luukkonen, R., Uitti, J., Lappalainen, S. and Nordman, H. Prolonged exposure to damp and moldy workplaces and new-onset asthma. *International archives of occupational and environmental health*, 2011. 84(7): 713–721.

39. Lim, F. L., Hashim, Z., Than, L. T. L., Md Said, S., Hisham Hashim, J. and Norbäck, D. Asthma, airway symptoms and rhinitis in office workers in Malaysia: associations with house dust mite (HDM) allergy, cat allergy

and levels of house dust mite allergens in office dust. *PloS one*, 2015. 10(4): e0124905.

40. Norbäck, D., Hashim, J. H., Hashim, Z., Cai, G.-H., Sooria, V., Ismail, S. A. and Wieslander, G. Respiratory symptoms and fractional exhaled nitric oxide (FeNO) among students in Penang, Malaysia in relation to signs of dampness at school and fungal DNA in school dust. *Science of The Total Environment*, 2017. 577: 148–154.

41. `https://knoema.com/atlas/Malaysia/CO2-emissions`, 2020. [Online; accessed 04-June-2022].

42. Bateman, E. D., Hurd, S. S., Barnes, P. J., Bousquet, J., Drazen, J. M., FitzGerald, M., Gibson, P., Ohta, K., O'Byrne, P., Pedersen, S. E. *et al.* Global strategy for asthma management and prevention: GINA executive summary. *European Respiratory Journal*, 2008. 31(1): 143–178.

43. Gold, L. S., Thompson, P., Salvi, S., Faruqi, R. A. and Sullivan, S. D. Level of asthma control and health care utilization in Asia-Pacific countries. *Respiratory medicine*, 2014. 108(2): 271–277.

44. Robinson, N. E. and Furlow, P. W. Anatomy of the respiratory system. *Equine respiratory medicine and surgery*, 2007: 3–17.

45. Ionescu, C. M. *The human respiratory system: an analysis of the interplay between anatomy, structure, breathing and fractal dynamics*. Springer Science & Business Media. 2013.

46. Stocks, J. and Hislop, A. A. *Structure and function of the respiratory system*. Marcel Dekker, NY, USA. 2002.

47. Terpenning, M. S. The relationship between infections and chronic respiratory diseases: an overview. *Annals of periodontology*, 2001. 6(1): 66–70.

48. Weinberger, S. E., Cockrill, B. A. and Mandel, J. *Principles of Pulmonary Medicine E-Book*. Elsevier Health Sciences. 2017.

49. Stieb, D. M., Szyszkowicz, M., Rowe, B. H. and Leech, J. A. Air pollution and emergency department visits for cardiac and respiratory conditions: a multi-city time-series analysis. *Environmental Health*, 2009. 8(1): 1–13.

50. Miller, M. R., Crapo, R., Hankinson, J., Brusasco, V., Burgos, F., Casaburi, R., Coates, A., Enright, P., van der Grinten, C. M., Gustafsson, P. *et al.* General considerations for lung function testing. *European Respiratory Journal*, 2005. 26(1): 153–161.

51. Bailey, W. C., Ferguson, G. T., Higgins, M., Hudson, L. D. *et al.* Strategies in preserving lung health and preventing COPD and associated diseases: The National Lung Health Education Program (NLHEP). *Chest*, 1998. 113(2): S123.

52. Mandy, J. Arterial blood gas analysis. 1: Understanding ABG reports. *Nursing times*, 2008. 104(18): 28–29.

53. Ak, A., Ogun, C. O., Bayir, A., Kayis, S. A. and Koylu, R. Prediction of arterial blood gas values from venous blood gas values in patients with acute exacerbation of chronic obstructive pulmonary disease. *The Tohoku journal of experimental medicine*, 2006. 210(4): 285–290.

54. Levy, M. L., Fletcher, M., Price, D. B., Hausend, T., Halbert, R. J. and Yawn, B. P. International Primary Care Respiratory Group (IPCRG) Guidelines: diagnosis of respiratory diseases in primary care. *Primary Care Respiratory Journal*, 2006. 15(1): 20–34.

55. Vandevoorde, J., Verbanck, S., Schuermans, D., Kartounian, J. and Vincken, W. FEV1/FEV6 and FEV6 as an alternative for FEV1/FVC and FVC in the spirometric detection of airway obstruction and restriction. *Chest*, 2005. 127(5): 1560–1564.

56. Mandal, N. Respirometers including spirometer, pneumotachograph and peak flow meter. *Anaesthesia & intensive care medicine*, 2006. 7(1): 1–5.

57. Sudip, S. Capnography equipment market-global industry analysis, size, share, growth, trends and forecast 2014–2020, 2017.

58. Evans, R. A. and Morgan, M. D. The systemic nature of chronic lung disease. *Clinics in chest medicine*, 2014. 35(2): 283–293.

59. Baughman, R. P., Teirstein, A. S., Judson, M. A., Rossman, M. D., Yeager Jr, H., Bresnitz, E. A., DePALO, L., Hunninghake, G., Iannuzzi, M. C., Johns, C. J. *et al.* Clinical characteristics of patients in a case control study of

sarcoidosis. *American journal of respiratory and critical care medicine*, 2001. 164(10): 1885–1889.

60. Mannino, D. M., Ford, E. S. and Redd, S. C. Obstructive and restrictive lung disease and markers of inflammation: data from the Third National Health and Nutrition Examination. *The American journal of medicine*, 2003. 114(9): 758–762.

61. Cross, D. and Nelson, H. S. The role of the peak flow meter in the diagnosis and management of asthma. *Journal of allergy and clinical immunology*, 1991. 87(1): 120–128.

62. Fried, R. A., Miller, R. S., Green, L. A., Sherrod, P. and Nutting, P. A. The use of objective measures of asthma severity in primary care: a report from ASPN. *Journal of Family Practice*, 1995. 41(2): 139–146.

63. Ismail, Y., Loo, C., Zahary, M. *et al.* The value of routine chest radiographs in acute asthma admissions. *Singapore Med J*, 1994. 35(2): 171–172.

64. Strömberg, T. *Breating pattern by inductive plethysmography in relatidon to bronchial obstruction in asthma*. Ph.D. Thesis. Linköpings universitet. 1993.

65. Ballard, R. D., Kelly, P. L. and Martin, R. J. Estimates of ventilation from inductance plethysmography in sleeping asthmatic patients. *Chest*, 1988. 93(1): 128–133.

66. Moussavi, Z. Fundamentals of respiratory sounds and analysis. *Synthesis lectures on biomedical engineering*, 2006. 1(1): 1–68.

67. Palaniappan, R., Sundaraj, K. and Ahamed, N. U. Machine learning in lung sound analysis: a systematic review. *Biocybernetics and Biomedical Engineering*, 2013. 33(3): 129–135.

68. Memon, B. N., Parkash, A., Ahmed Khan, K., Gowa, M. A. and Bai, C. Response to nebulized salbutamol versus combination with ipratropium bromide in children with acute severe asthma. *J Pak Med Assoc*, 2016. 66(3): 243–6.

69. Pedersen, S. E., Hurd, S. S., Lemanske Jr, R. F., Becker, A., Zar, H. J., Sly, P. D., Soto-Quiroz, M., Wong, G. and Bateman, E. D. Global strategy for

the diagnosis and management of asthma in children 5 years and younger. *Pediatric pulmonology*, 2011. 46(1): 1–17.

70. Kwan, A. M., Fung, A. G., Jansen, P. A., Schivo, M., Kenyon, N. J., Delplanque, J.-P. and Davis, C. E. Personal lung function monitoring devices for asthma patients. *IEEE Sensors Journal*, 2014. 15(4): 2238–2247.

71. Li, S.-H., Lin, B.-S., Tsai, C.-H., Yang, C.-T. and Lin, B.-S. Design of wearable breathing sound monitoring system for real-time wheeze detection. *Sensors*, 2017. 17(1): 171.

72. Yu, C., Tsai, T.-H., Huang, S.-I. and Lin, C.-W. Soft stethoscope for detecting asthma wheeze in young children. *Sensors*, 2013. 13(6): 7399–7413.

73. Oletic, D., Arsenali, B. and Bilas, V. Low-power wearable respiratory sound sensing. *Sensors*, 2014. 14(4): 6535–6566.

74. Pramono, R. X. A., Bowyer, S. and Rodriguez-Villegas, E. Automatic adventitious respiratory sound analysis: A systematic review. *PloS one*, 2017. 12(5): e0177926.

75. Aydore, S., Sen, I., Kahya, Y. P. and Mihcak, M. K. Classification of respiratory signals by linear analysis. *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE. 2009. 2617–2620.

76. Emrani, S. and Krim, H. Wheeze detection and location using spectro-temporal analysis of lung sounds. *2013 29th Southern Biomedical Engineering Conference*. IEEE. 2013. 37–38.

77. Alang, T. A. I. T., Singh, O. P. and Malarvili, M. Time-frequency analysis of wheezing sound to differentiate asthmatic and non-asthmatic condition. *2016 6th IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*. IEEE. 2016. 193–198.

78. Lin, B.-S., Wu, H.-D. and Chen, S.-J. Automatic wheezing detection based on signal processing of spectrogram and back-propagation neural network. *Journal of healthcare engineering*, 2015. 6(4): 649–672.

79. Jin, F., Sattar, F. and Goh, D. Y. Automatic wheeze detection using histograms of sample entropy. *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE. 2008. 1890–1893.

80. Hashemi, A., Arabalibeik, H. and Agin, K. Classification of wheeze sounds using cepstral analysis and neural networks. In: *Medicine Meets Virtual Reality 19*. IOS Press. 161–165. 2012.

81. Lin, B.-S. and Lin, B.-S. Automatic wheezing detection using speech recognition technique. *Journal of Medical and Biological Engineering*, 2016. 36(4): 545–554.

82. Wisniewski, M. and Zielinski, T. P. Application of tonal index to pulmonary wheezes detection in asthma monitoring. *2011 19th European Signal Processing Conference*. IEEE. 2011. 1544–1548.

83. Hashemi, A., Arabalibiek, H. and Agin, K. Classification of wheeze sounds using wavelets and neural networks. *International conference on biomedical engineering and technology*. IACSIT Press Singapore. 2011, vol. 11. 127–131.

84. You, B., Peslin, R., Duvivier, C., Vu, V. D. and Grilliat, J. Expiratory capnography in asthma: evaluation of various shape indices. *European Respiratory Journal*, 1994. 7(2): 318–323.

85. Yaron, M., Padyk, P., Hutsinpiller, M. and Cairns, C. B. Utility of the expiratory capnogram in the assessment of bronchospasm. *Annals of emergency medicine*, 1996. 28(4): 403–407.

86. Lee, D. I., Jin, Y. H. and Lee, J. B. Capnographic Monitoring for Acute Asthma in the Emergency Department Setting. *Journal of the Korean Society of Emergency Medicine*, 2001. 12(3): 305–311.

87. Fletcher, R. Volumetric capnography: the early days, 2004.

88. Liu, J.-M., Hu, H.-C., Shi, M.-H., Yang, W.-L., Zheng, W. and Wang, Y.-M. The significance of volumetric capnography in assessment of asthmatic acute exacerbation staging. *Zhonghua jie he he hu xi za zhi= Zhonghua Jiehe he Huxi Zazhi= Chinese Journal of Tuberculosis and Respiratory Diseases*, 2008. 31(3): 186–190.

89. Druck, J., Rubio, P., Valley, M., Jaffe, M. and Yaron, M. 415: Evaluation of the Slope of Phase III from the Volumetric Capnogram as a Non-Effort Dependent Surrogate of Peak Expiratory Flow Rate in Acute Asthma Exacerbation. *Annals of Emergency Medicine*, 2007. 50(3): S130–S131.

90. Herry, C., Townsend, D., Green, G., Bravi, A. and Seely, A. Segmentation and classification of capnograms: application in respiratory variability analysis. *Physiological measurement*, 2014. 35(12): 2343.

91. Corbo, J., Bijur, P., Lahn, M. and Gallagher, E. J. Concordance between capnography and arterial blood gas measurements of carbon dioxide in acute asthma. *Annals of emergency medicine*, 2005. 46(4): 323–327.

92. Langhan, M. L., Zonfrillo, M. R. and Spiro, D. M. Quantitative end-tidal carbon dioxide in acute exacerbations of asthma. *The Journal of pediatrics*, 2008. 152(6): 829–832.

93. Nagler, J. and Krauss, B. Capnography: a valuable tool for airway management. *Emergency medicine clinics of North America*, 2008. 26(4): 881–897.

94. Truchot, J., Gayet, A.-R., Philippon, A.-L., Chauvin, A., Malka, J., Vicaut, E. and Plaisance, P. End tidal carbon dioxide monitoring in acute asthma: a prospective pilot study in emergency department patients. *European Journal of Emergency Medicine*, 2019. 26(6): 412–416.

95. Nik Hisamuddin, N., Rashidi, A., Chew, K., Kamaruddin, J., Idzwan, Z. and Teo, A. Correlations between capnographic waveforms and peak flow meter measurement in emergency department management of asthma. *International journal of emergency medicine*, 2009. 2(2): 83–89.

96. Howe, T. A. Use of capnographic waveform indices in monitoring nonintubated asthmatic patients within the emergency department. *Master Degree Thesis*, 2001.

97. Almeida, C. C., Almeida-Júnior, A. A., Ribeiro, M. Â. G., Nolasco-Silva, M. T. and Ribeiro, J. D. Volumetric capnography to detect ventilation inhomogeneity in children and adolescents with controlled persistent asthma. *Jornal de pediatria*, 2011. 87: 163–168.

98. Kazemi, M. and Malarvili, M. Investigation of capnogram signal characteristics using statistical methods. *2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences*. IEEE. 2012. 343–348.

99. Kazemi, M., Imarah, N. I. and Malarvili, M. Assessment on methods used to detect asthmatic and non-asthmatic conditions using capnogram signal. *Journal Teknologi (Sciences & Engineering)*, 2013. 62(1): 93–100.

100. Kazemi, M., Krishnan, M. B. and Howe, T. A. Frequency analysis of capnogram signals to differentiate asthmatic and non-asthmatic conditions using radial basis function neural networks. *Iranian Journal of Allergy, Asthma and Immunology*, 2013: 236–246.

101. Kazemi, M. and Teo, A. H. New prognostic index to detect the severity of asthma automatically using signal processing techniques of capnogram. *Journal of Intelligent Procedures in Electrical Technology*, 2016. 7(26): 53–63.

102. Pertzov, B., Ronen, M., Rosengarten, D., Shitenberg, D., Heching, M., Shostak, Y. and Kramer, M. R. Use of capnography for prediction of obstruction severity in non-intubated COPD and asthma patients. *Respiratory Research*, 2021. 22(1): 1–9.

103. Cracco, O., Degrugilliers, L., Rames, C., Bécourt, A. and Bayat, S. Change in capnogram waveform is associated with bronchodilator response and asthma control in children. *Pediatric Pulmonology*, 2019. 54(6): 698–705.

104. Singh, O. P., Palaniappan, R. and Malarvili, M. B. Automatic Quantitative Analysis of Human Respired Carbon Dioxide Waveform for Asthma and Non-Asthma Classification Using Support Vector Machine. *IEEE Access*, 2018. 6: 55245–56.

105. Leturiondo, M., de Gauna, S. R., Ruiz, J. M., Gutiérrez, J. J., Leturiondo, L. A., González-Otero, D. M., Russell, J. K., Zive, D. and Daya, M. Influence of chest compression artefact on capnogram-based ventilation detection during out-of-hospital cardiopulmonary resuscitation. *Resuscitation*, 2018. 124: 63–8.

106. Kazemi, M. and Malarvili, M. Analysis of Capnogram using linear predictive coding (LPC) to differentiate asthmatic conditions. *Journal of Tissue Science and Engineering*, 2011. 2(5): 1000111.

107. Betancourt, J. P., Tangel, M. L., Yan, F., Diaz, M. O., Otaño, A. E. P., Dong, F. and Hirota, K. Segmented wavelet decomposition for capnogram feature extraction in asthma classification. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, 2014. 18(4): 480–8.

108. Putra, I. P., Brusey, J., Gaura, E. and Vesilo, R. An event-triggered machine learning approach for accelerometer-based fall detection. *Sensors*, 2018. 18(1): 20.

109. Bangira, T., Alfieri, S. M., Menenti, M. and Van Niekerk, A. Comparing thresholding with machine learning classifiers for mapping complex water. *Remote Sensing*, 2019. 11(11): 1351.

110. Antoniou, A. *Digital signal processing: signals, systems and filters*. McGraw-Hill. 2005.

111. Madisetti, V. Digital Signal Processing Fundamentals, 2010.

112. Rangayyan, R. M. and Reddy, N. P. Biomedical signal analysis: a case-study approach. *Annals of Biomedical Engineering*, 2002. 30(7): 983.

113. Blanca, M. J., Arnau, J., López-Montiel, D., Bono, R. and Bendayan, R. Skewness and kurtosis in real data samples. *Methodology*, 2013. 9(2): 78–84.

114. Oh, S.-H., Lee, Y.-R. and Kim, H.-N. A novel EEG feature extraction method using Hjorth parameter. *International Journal of Electronics and Electrical Engineering*, 2014. 2(2): 106–110.

115. Pachori, R. B. and Patidar, S. Epileptic seizure classification in EEG signals using second-order difference plot of intrinsic mode functions. *Computer methods and programs in biomedicine*, 2014. 113(2): 494–502.

116. Khair, U., Fahmi, H., Al Hakim, S. and Rahim, R. Forecasting error calculation with mean absolute deviation and mean absolute percentage error. *Journal of Physics: Conference Series*. IOP Publishing. 2017, vol. 930. 012002.

117. Navascués, M. and Sebastián, M. V. Time domain indices and discrete power spectrum in electroencephalographic processing. *International Journal of Computer Mathematics*, 2009. 86(10-11): 1968–1978.

118. Asuero, A. G., Sayago, A. and Gonzalez, A. G. The correlation coefficient: An overview. *Critical reviews in analytical chemistry*, 2006. 36(1): 41–59.

119. El-Badawy, I. M., Aziz, A. M., Omar, Z. and Malarvili, M. B. Correlation between different DNA period-3 signals: An analytical study for exons prediction. *Proceedings of the 2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*. IEEE. 2017. 1123–1128.

120. Fawcett, T. An introduction to ROC analysis. *Pattern recognition letters*, 2006. 27(8): 861–74.

121. Wang, R. and Tang, K. Feature selection for maximizing the area under the ROC curve. *2009 IEEE International Conference on Data Mining Workshops*. IEEE. 2009. 400–405.

122. Chen, X. and Wasikowski, M. FAST: a roc-based feature selection metric for small samples and imbalanced data classification problems. *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*. 2008. 124–132.

123. Thiese, M. S., Ronna, B. and Ott, U. P value interpretations and considerations. *Journal of thoracic disease*, 2016. 8(9): E928.

124. Dorey, F. In brief: The P value: What is it and what does it tell you?, 2010.

125. Chandrashekar, G. and Sahin, F. A survey on feature selection methods. *Computers & Electrical Engineering*, 2014. 40(1): 16–28.

126. Guyon, I., Gunn, S., Nikravesh, M. and Zadeh, L. *Feature extraction: foundations and applications*. Physica-Verlag, Springer. 2006.

127. Pliego Marugán, A. and García Márquez, F. P. Advanced analytics for detection and diagnosis of false alarms and faults: A real case study. *Wind Energy*, 2019. 22(11): 1622–1635.

128. Yeh, S. T. Using trapezoidal rule for the area under a curve calculation. *Proceedings of the 27th Annual SAS® User Group International (SUGI'02)*, 2002.

129. Blum, A. L. and Langley, P. Selection of relevant features and examples in machine learning. *Artificial intelligence*, 1997. 97(1-2): 245–271.

130. Cristianini, N. and Shawe-Taylor, J. *An introduction to support vector machines and other kernel-based learning methods*. Cambridge university press. 2000.

131. Kotsiantis, S. B., Zaharakis, I. and Pintelas, P. Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*, 2007. 160(1): 3–24.

132. Tharwat, A. Parameter investigation of support vector machine classifier with kernel functions. *Knowledge and Information Systems*, 2019. 61(3): 1269–1302.

133. Berrar, D. Bayes' theorem and naive Bayes classifier. *Encyclopedia of Bioinformatics and Computational Biology: ABC of Bioinformatics; Elsevier Science Publisher: Amsterdam, The Netherlands*, 2018: 403–412.

134. Song, Y.-Y. and Ying, L. Decision tree methods: applications for classification and prediction. *Shanghai archives of psychiatry*, 2015. 27(2): 130.

135. Breiman, L. Random forests. *Machine learning*, 2001. 45(1): 5–32.

136. Azar, A. T., Elshazly, H. I., Hassanien, A. E. and Elkorany, A. M. A random forest classifier for lymph diseases. *Computer methods and programs in biomedicine*, 2014. 113(2): 465–473.

137. Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., Yen, N.-C., Tung, C. C. and Liu, H. H. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society of London. Series A: mathematical, physical and engineering sciences*, 1998. 454(1971): 903–995.

138. Lei, Y., Lin, J., He, Z. and Zuo, M. J. A review on empirical mode decomposition in fault diagnosis of rotating machinery. *Mechanical systems and signal processing*, 2013. 35(1-2): 108–126.

139. Krishnan, S. and Athavale, Y. Trends in biomedical signal feature extraction. *Biomedical Signal Processing and Control*, 2018. 43: 41–63.

140. Wang, X. and Zhong, Y. Statistical learning theory and state of the art in SVM. *The Second IEEE International Conference on Cognitive Informatics, 2003. Proceedings.* IEEE. 2003. 55–59.

LIST OF PUBLICATIONS

Journal with Impact Factor

1. El-Badawy, I. M., Singh O. P. and Omar, Z. Automatic classification of regular and irregular capnogram segments using time- and frequency-domain features: A machine learning-based approach. *Technology and Health Care*, 2021. 29(1): 59–72. (Q4, IF: 1.285).
2. El-Badawy, I. M., Omar Z. and Singh, O. P. An effective machine learning approach for classifying artefact-free and distorted capnogram segments using simple time-domain features. *IEEE Access*, 2022. 10: 8767–8778. (Q2, IF: 3.367).

Indexed conference proceedings

1. El-Badawy, I. M., Omar Z. and Singh, O. P. Cooperative classification of clean and deformed capnogram segments using a voting approach: A trade-off between specificity and sensitivity. *Proceedings of the 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE. 2022. 389-393. (Indexed in Web of Science)