

**INCIPIENT PARTIAL DISCHARGE
DETECTION IN ELECTRICAL EQUIPME
BASED ON ULTRASOUND USING DEEP
LEARNING APPROACH**

BY

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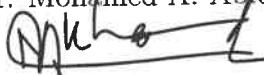
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Dedication to
My beloved parents, my brothers, my wife and my little child

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First and foremost, all praises and thanks are for ALLAH SWT alone, who provided me with the required knowledge to successfully complete my MSc degree in electrical engineering at King Fahd University of Petroleum Minerals (KFUPM). Peace and blessings be upon the greatest man ever, the last and the final Prophet, Muhammad (peace be upon him), upon his family, his companions, and all those who follow him until the day of judgment. I extend my sincere appreciation to my thesis advisor, Dr. Fahad Al-Ismail. Your mentorship and expertise have been pivotal in shaping my research and refining my ideas. Your dedication to my academic growth and your unwavering belief in my abilities have motivated me to push beyond my limits. I am truly grateful for your patience in answering my countless questions and for the countless hours you have devoted to reviewing and providing constructive feedback on my work. To my family, I cannot express enough gratitude for your endless love, support, and encouragement throughout this arduous journey. Your unwavering belief in me and your constant encouragement have been my pillars of strength. Your patience in dealing with my long hours of study, late nights, and occasional moments of stress is truly appreciated. I am forever grateful for your sacrifices and the unconditional support you have given me.

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TABLE OF CONTENTS

ACKNOWLEDGMENTS	vi
LIST OF TABLES	x
LIST OF FIGURES	xi
LIST OF SYMBOLS	xiii
LIST OF ABBREVIATIONS	xv
ABSTRACT (ENGLISH)	xvii
ABSTRACT (ARABIC)	xix
CHAPTER 1 INTRODUCTION	1
1.1 Thesis Motivation	4
1.2 Thesis Objective	5
1.3 Thesis Organization	6
CHAPTER 2 LITERATURE REVIEW	8
2.1 Partial Discharge Definition and Types	8
2.2 Partial Discharge Detection Methods	11
2.2.1 Detection Methods	11
2.2.2 Previous Works	12
2.3 Artificial Intelligence Based Partial Discharge Detection	15

CHAPTER 3	SYSTEM MODELING	17
3.1	Partial Discharge Data Acquisition	17
3.2	Partial Discharge Signal Preprocessing	24
3.3	Convolution Neural Network Architecture	31
3.3.1	Network General Layers	31
3.3.2	Hyperparameter Tuning	33
CHAPTER 4	PROPOSED APPROACH AND RESULTS	36
4.1	Single-Phase CNN For Fault Classification	36
4.2	Double-Phases CNN For Fault Classification	40
4.3	Enhanced Single-Phase CNN using Bayesian Optimization	43
4.4	Benchmark with Pretrained Models	45
CHAPTER 5	CONCLUSION	48
APPENDIX A	PROOFS	49
APPENDIX B	SUPPLEMENTARY MATERIAL	50
REFERENCES		51
VITAE		60

LIST OF TABLES

2.1	Recent researches on PD detection based on acoustic emission and ultrasound	16
4.1	Number of collected samples for healthy and faulty equipment	36
4.2	Number of collected samples for each type of PD	37
4.3	Selected Parameters for CNN	37
4.4	Output Parameters for Single-Phase CNN	38
4.5	Output Parameters for Double-Phase CNN	41
4.6	Hyperparameters Tuning for CNN	44
4.7	Optimal parameters for CNN	44
4.8	Comparison between Single-phase and optimized models CNN	44

LIST OF FIGURES

2.1	Types of Partial Discharge	10
2.2	Partial Discharge detection methods	12
3.1	Partial Discharge model	19
3.2	Partial Discharge simplified model	19
3.3	Piezoelectric ceramics basic behavior	21
3.4	working principle of the detection system	22
3.5	Modern PD Detector Circuit	22
3.6	Samples of The Inspected Equipment	23
3.7	time series waveform of random samples	24
3.8	Arcing common pattern	26
3.9	Looseness common pattern	27
3.10	Corona common pattern	27
3.11	Tracking common pattern	28
3.12	Flow chart for identifying PD type	28
3.13	STFT concept	30
3.14	CNN General Structure	33
4.1	CNN architecture	38
4.2	Output from all convolution layers	39
4.3	Confusion matrix for Single-Phase validation accuracy	39
4.4	Accuracy and loss function for Single-Phases model	40
4.5	Accuracy and loss function for Double-Phases model	42
4.6	Confusion matrix for Double-Phase validation accuracy	43

4.7 Function evaluations throughout the iterations 44

4.8 Confusion matrix for Optimized Double-Phase validation accuracy . . . 45

4.9 Benchmarking the percentage accuracy of proposed models with pre-
trained models 47

LIST OF SYMBOLS

b_{ij}	Biases of neural network
q	Apparent Charge
c	Velocity of Acoustic Wave
p	Medium Density
C_m	Elasticity of the system
e_k	Error function
u_c	External force on the void wall
R_m	friction losses
$\mathcal{D}$	Dataset
φ'	Derivative of hidden function
X	Impedance of the capacitance
L_m	Inductance of the mechanical equivalent circuit
k	The kernel or covariance
η	Learning rate of the neural network
m	mean value
Y_k	Observed values of output layer

P	Medium Pressure
V_v	Voltage across the void
V	Voltage source
ω_{ij}	Wights of neural network

LIST OF ABBREVIATIONS

AE	Acoustic Emission
AI	Artificial Intelligence
ANN-BP	Artificial Neural Network-Backpropagation
BO	Bayesian Optimization
CNN	Convolution Neural Network
DC	Direct Current
DCNN	Deep Convolutional Neural Network
DE	Differential Evolution
DGA	Dissolved Gas Analysis
DL	Deep Learning
DNN	Deep Neural Networks
FFT	Fast Fourier Transform
GA	Genetic Algorithm
GB	Gradient Boosting
GIS	Gas Insulated Switchgear
GP	Gaussian Process

HFCT	High Frequency Current Transformer
HP	Hyperparameters
HVDC	High Voltage Direct Current
IEC	International Electrotechnical Commission
KNN	K-Nearest Neighbor
LSTM	Long-Short-Term-Memory
MFCC	Mel Frequency Cepstral Coefficients
ML	Machine Learning
MLP	Multilayer Perceptron
PCA	Principal component analysis
PD	Partial Discharge
PMS	Preventive Maintenance Schedule
PSO	Particle Swarm Optimisation
ReLU	The Rectifier Linear Unit
RF	Random Forest
RNN	Recurrent Neural Network
RTF	run-to-failure
STFT	Short-Time Fourier Transform
SVM	Support vector machines
UHF	Ultra High Frequency

THESIS ABSTRACT

NAME: Abdulaziz Hamoud Alshalawi

TITLE OF STUDY: Incipient Partial Discharge Detection In Electrical Equipment Based On Ultrasound Using Deep Learning Approach

MAJOR FIELD: Electrical Engineering Department

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Electrical equipment is prone to different types of Partial Discharge failures that are vary between minor and severe level. In this thesis, Three developed models for Convolution Neural Network (CNN) is proposed to detect and classify four electrical equipment faults which are Arcing, Corona discharge, Tracking and Looseness and distinguish them from normal equipment situation. The model is developed to extract the maximum information from each recorded signal waveform through multiple features including Short-Time-Fourier-Transform (STFT) in addition to Mel Frequency Cepstral Coefficients (MFCC) phase and magnitude. Notably, the resulting models exhibited an impressive overall accuracy of more than 92%, which is particularly significant considering the inherent presence of noise in the real-world samples obtained

as representative field failures. The model is further improved by optimizing the model using Bayesian Optimization which results better overall validation accuracy of 94% and improved classification of each PD type. These findings underscore the robustness and effectiveness of the CNN model in accurately identifying PDs, despite the intricate challenges associated with real-world data.

ملخص الرسالة

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عنوان الدراسة:

إكتشاف أعطال التفريغ الكهربائي الجزئي في المعدات الكهربائية بناء على

الموجات الصوتية باستخدام تقنيات التعلم العميق

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قسم الهندسة الكهربائية

تاريخ الدرجة العلمية: ديسمبر 2023

المعدات الكهربائية بطبيعتها معرضة للعديد من أنواع التفريغ الجزئي للتيار الكهربائي و التي قد تتفاوت ما بين التأثير المحدود كإرتخاء التوصيلات و التي حين إكتشافها لا تكلف الكثير لإصلاحها . لكن بعض أنواع الأعطال تعتبر ذات كلفه صيانة عالية و التي تصل في بعض الأوقات لاستبدال المعدة. في هذا البحث، تم تطوير ثلاث نماذج مختلفة لاكتشاف هذه الأعطال و تصنيفها عن طريق التعلم العميق و هذه الأعطال المدروسة في هذا البحث هي تفريغ الإرتخاء، و الأقواس الكهربائية، و ظاهرة كورونا و أخيرا تشجر العوازل. نماذج التعلم العميق تقوم المطورة تقوم بالتعرف على وجود الخلل ثم تصنيفه بدقة عالية تفوق نسبة 92% و هذه النسبة في وجود الضوضاء الخلفية تكون صعبة للغاية و بالتالي هذه النتائج تعتبر عالية. تم تطوير النموذج أكثر بتحسينه عن طريق استخدام طريقة "بيز" الحسائية و التي نتج عنها تحسين دقة أفضل بنسبة 94% و تحسين دقة التصنيف لكل نوع من الأعطال.

CHAPTER 1

INTRODUCTION

Typically power substation electrical equipment is maintained using either run-to-failure (RTF) or preventive maintenance methods. The RTF approach is straightforward and cost-effective in the short term as it involves waiting for the equipment to break down before taking any maintenance action, however, it is expensive and time-consuming in the long run. On the other hand, preventive maintenance involves spending money on maintenance before equipment failure occurs, thus reducing downtime and costs associated with equipment failures. The maintenance cost of electrical equipment can be reduced from 50% to 33% by only correct implementing of preventive and predictive maintenance, this practice is overlooked in manufacturing and process industry companies [1].

Preventive maintenance is a proactive approach to maintaining electrical equipment, which involves regular inspections and scheduled repairs to prevent potential failures. The benefits of this type of maintenance include extended equipment lifespan, improved safety, reduced downtime, and lower maintenance costs. The sources of a faulty electrical component Can be categorized as direct cause, root cause, and

contributing cause. The direct cause refers to the activity or condition that initiates an event, such as contact failure, overheating, ground fault, and more. The root cause, on the other hand, is the fundamental reason for the breakdown or issue and correcting it can prevent future occurrences. Contributing cause, meanwhile, refers to a series of events that increase the risk of the final event and can amplify the likelihood or severity of it. These contributing causes can be related to equipment aging, inadequate maintenance, poor design, and more [2].

A Preventive Maintenance Schedule (PMS) determines when maintenance should be performed on equipment or devices within an organization within a specific time frame. The PMS aims to improve both efficiency and reliability, reducing operating expenses and increasing indicators such as expected energy reserves, available energy, and probability of load. The challenge of PMS lies in determining the optimal sequence of maintenance procedures for each component over the planning horizon [3].

PMS is usually utilizing monitoring tools and methods to determine the state of the equipment and decide if farther action is required or not, such as Dissolved Gas Analysis for transformers [4] [5], Power Quality Analyzer [6] that is used for all equipment, Infrared Thermography [7] for substations, and Ultrasound detectors for medium and High voltage equipment.

Ultrasound detectors are specialized devices used to detect sound waves that operate at frequencies above the audible range of human hearing (i.e. 20 KHz). They have found widespread applications in a variety of fields, including medical imaging, industrial testing, and security systems. The tools use electronic means to convert ultrasound frequencies into audible sounds via heterodyning. The sounds are then

heard through headphones or viewed as intensity levels on a screen. These sounds can be received in two ways: airborne, such as leaks or electrical emissions, which are detected by a scanning module, and structure-borne, such as those produced by bearings or leaks in valves, which are picked up by a wave-guide or contact module [8].

one of the applications of ultrasound device is to detect Partial Discharge (PD) defects in different kind of electrical equipment such as transformers, motors, cables, switchgears and breakers. As per the International Electrotechnical Commission (IEC) standard 60270 [9], “ Partial Discharge (PD) is a localized electrical discharge that only partially bridges the insulation between conductors and which may or may not occur adjacent to a conductor.” and it has several forms including internal and surface discharge, corona discharge and tracking. PD can be caused from manufacturing, during mobilization and installation, aging, deterioration and mechanical stress while in service [10].

In this thesis, Optimized developed Convolution Neural Network (CNN) has been utilized to classify several electrical equipment faults such as arcing, corona discharge, tracking and looseness to distinguish them from healthy equipment situation. In chapter II, related work will be explored and discussed of how electrical failures are detected and how Machine learning is applied to enhance the detection and classification. In chapter III, System model will be discussed and in IV the proposed approach will be explained and efforts to collect the data and techniques applied will be illustrated.

1.1 Thesis Motivation

The reliable operation of electrical equipment is significantly reliant on the condition of its insulation system. Dielectrics are available in gaseous, liquid, or solid states, and the insulation material may undergo different types of electrical, mechanical, thermal, chemical, and radiation stresses during use. The combination of these factors can result in permanent deterioration of the insulating characteristics, leading to reduced lifespan. Partial Discharge detection accuracy is big challenge for industry since the behavior of failure for each type is different than the others, which require expertise to observe and differentiate between different types. In addition, one main practical challenge that hinder the detection is noise associated with environment around the equipment and from the detector itself, on contrary lab experiments will not address this challenge as main challenge for CNN to achieve high detection accuracy.

Due to the aforementioned factors, the need for condition monitoring is significantly increasing in industry. Many methods and techniques to uncover PD in early stages have been proposed but there is still need for more studies to improve overall outcomes. The main focus on this thesis is to investigate PD early detection and diagnosis specifically Arcing, Looseness, Corona and Tracking since these are very common problems in the industry. Most of the recent studies focus on investigating specific type of electrical equipment such as transformer or switchgear and most of the studies have been conducted in lab environment which usually tend to be ideal cases for PD behavior. However, in this paper, the study includes different cases from different equipment such as transformer, motors, switchgears, controlgears and

breakers. In addition, the study samples are taken from actual industry environment where noise are inherent in most of the cases.

In addition, Convolution Neural Network (CNN) has been proposed in this study to classify all previous mentioned faults without human intervention. The proposed model is optimized using Bayesian Optimization method to improve the accuracy and reduce the loss function in addition to reducing the computation time. In addition to the proposed model, three additional pretrained models that are well known in the literature for their accuracy have been examined to be benchmarked with proposed models which are VGG (developed by Google), OpenL3 (Self-supervised L3-Net) and YamNet (developed by Dan Ellis). The details of pretrained models are elaborated more in Chapter 4.

1.2 Thesis Objective

The main objective of this thesis is to diagnose PD in many kinds of electrical systems and automatically classify the failures based on the ultrasound signals. Since each PD failure produce a unique ultrasound pattern, it is of a good utilization to use CNN to classify the failures without human intervention.

The thesis objectives can be summarized as follows:

1. A comprehensive literature review on PD detection and detection methods.
2. Proposing Convolution Neural Network (CNN) to classify different types of PD for a wide range of equipment and voltage levels.

3. Achieve high precision in the detection of PD in the presence of high level of field noise.
4. Optimizing the developed CNN algorithm using Bayesian Optimization technique.
5. benchmark the proposed model with pretrained state-of-the-art models (VGG, OpenL3, YamNET) and achieve higher accuracy in PD detection.

1.3 Thesis Organization

This thesis is organized in five chapters. The chapter's contents are described below:

- **Chapter 1:** introduce the problem by giving the reader an overview on Partial Discharge phenomena. After that, thesis motivation and objectives are discussed.
- **Chapter 2** is discussing the literature review on PD including the physics of the phenomena to understand the source of the problem. Then, PD detection methods are discussed in addition to advantages and disadvantages of all methods. Additionally, Artificial Intelligence methods that are used for detection are discussed.
- **Chapter 3** presents the PD modeling and detection method used to collect the data in addition to the techniques used to preprocess the signals before feeding them to the Convolution Neural Network. CNN architecture is also discussed in addition to the optimization method.

- **Chapter 4** shows the proposed methods to tackle the detection and classification of the signals in addition to the results of each model. Benchmark with pretrained models are also provided.
- **Chapter 5** concludes the work in this thesis by showing the most important finding and results.

CHAPTER 2

LITERATURE REVIEW

2.1 Partial Discharge Definition and Types

PD can be defined as the existence of a tiny vacancy in a solid insulator or a small gas bubble in a liquid insulator causes changes in the electric field distribution within the material. The dielectric constant of the void or gas bubble is lower than that of the surrounding insulating material, resulting in a higher electric field strength inside the void or gas bubble than the surrounding insulating material. In general, the occurrence of PD is a result of the local accumulation of electrical stress in specific areas of electrical insulation [11] [12].

PD can arise in a wide range of equipment that utilize different insulation materials and structures, including gas-insulated, oil-insulated, and solid-insulated devices. Any imperfection in the insulation may result in the emergence of PD. The nature of PD may differ depending on the equipment with distinct structures and insulation materials. PD can take place due to any of the following causes [13][10]:

1. rise of electric field intensity due to over stress.
2. deterioration of the insulating material with age.
3. local overheating which usually implant voids and bubbles.
4. poor manufacturing which might introduce impurities in the insulation.
5. bad installation or termination that accelerate insulation failure.

PD can take different forms and different names but as per IEC 60270 Partial Discharge is a general name for all forms which include Corona discharge, surface discharge and internal discharge [14]. Corona discharge can not be used interchangeably with the other two types as per IEC 60270 since corona usually take place in gaseous mediums only. Corona discharge is an electrical discharge that occurs due to the ionization of air in the vicinity of a high-voltage electrode. Surface discharge is a type of electrical discharge that takes place along the surface of a dielectric material, and it frequently occurs at the interface of two different materials [15]. Internal discharge is an electrical discharge phenomenon that takes place within dielectric materials having low strength. This discharge is initiated by various factors such as the presence of cracks, contamination, air voids, and trees [16]. These factors contribute to the emergence of internal Partial Discharge.

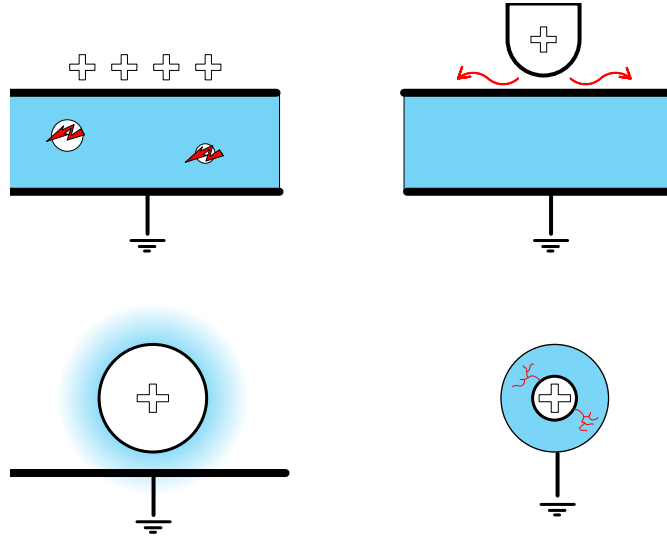


Figure 2.1: Types of Partial Discharge

In figure 2.1, several forms of PD are illustrated. In the upper left of the figure, internal discharge is shown where several voids are present in the insulation medium which usually develop higher potential than the surrounding insulation medium. If PD is not repair then it will stress the insulation to develop a new for which is tracking (below right) In the upper left of the figure, surface discharge is shown and it can take different forms and names, e.g looseness can generate surface discharge that can be developed to arc flash if it is left disregarded for long periods. Corona only take place in gaseous mediums as it can be shown in the below left of the figure as it is represented by the blue cloud around the conductor.

2.2 Partial Discharge Detection Methods

2.2.1 Detection Methods

The methods employed for the detection of Partial Discharge can be classified into two categories: conventional and unconventional methods. The conventional method is a well-established electrical technique that adheres to the IEC-60270 standard for PD measurement. It involves measuring the Apparent Charge q across the terminal of the test object. Partial Discharge detection methods can be classified into two categories: conventional and unconventional methods. The conventional method, which is based on measuring the apparent charge (q) across the test object's terminal, adheres to the IEC-60270 standard for PD measurement. However, it cannot be utilized on-site due to electromagnetic interference. In contrast, unconventional methods, including acoustic, Optical, Ultra High Frequency (UHF), and High Frequency Current Transformer (HFCT), detect high-frequency PD signals and are immune to electromagnetic interference.

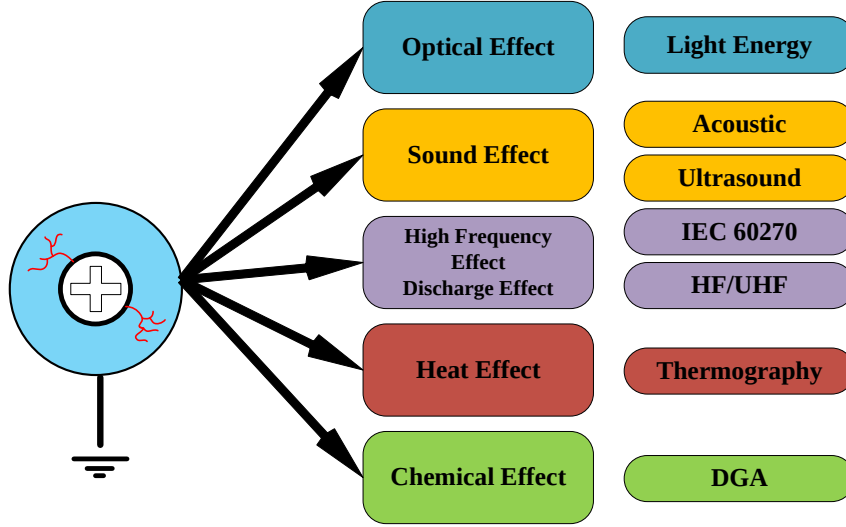


Figure 2.2: Partial Discharge detection methods

2.2.2 Previous Works

Electrical equipment is prone to different types of failures that vary between minor and severe level, e.g. wiring looseness is usually considered as minor and usually is not expensive to be fixed. Other failures are considered severe and cost the organizations huge maintenance cost to repair or sometimes to replace such as Tracking.

Over time, the Direct Current (DC) cable experiences the effects of a DC electric field during transmission, causing a buildup of electrical charges on the insulation surface. This leads to an increase in local electric field strength, causing partial discharging. As the insulation's ability to withstand electricity decreases, it becomes easier for discharge channels to form, ultimately causing the insulating material to break down. A correlation model was established to study the relationship between partial discharge ultrasonic waves and the amount of discharge in a DC cable. This model aims to analyze the mechanism of partial discharge and the ultrasonic properties

of the cable [17].

High Voltage Direct Current (HVDC) cable system is also prone to partial discharges. In [17], a relationship between partial discharge ultrasonic waves and the amount of discharge in a DC cable was established through a study of the partial discharge mechanism and ultrasonic properties of the cable. The experimentally determined partial discharge repetition rate and magnitude for various insulation defects, along with the ultrasonic characteristic data, was used to develop a Sagnac fiber detection system. The impact of varying the length of fiber sensing probes on the sensitivity of partial discharge signals was studied using the frequency distribution characteristics of partial discharge. The results of the measurements indicated that the accuracy of determining the location of partial discharge points was within ± 80 m.

Unpleasant discharges are not limited to DC cable, their effect can be extended to the insulators that carry the DC cables. When an insulator is faulty, it can no longer effectively insulate and can result in power system failures. To maintain the reliability of the electric power system and meet the standards set by inspection agencies, it is crucial to regularly inspect and ensure the proper functioning of insulators. The article presents the results of a laboratory study on predicting faults in distribution insulators. The study [18] involved applying 13.8 kV to a contaminated insulator and using an ultrasound detector connected to a computer to collect data. The data was then analyzed using a hybrid deep learning technique called wavelet Long-Short-Term-Memory (LSTM) for time series prediction.

Transformers are crucial components of power systems as they act as intermediaries

between energy sources and consumers. Any malfunction in transformers can disrupt the usage of electrical energy, which can lead to significant costs in terms of downtime. Therefore, it is essential to detect any potential problems in transformers to prevent hazardous conditions and minimize the expenses associated with downtime. Typically, faults in transformers arise due to either electrical or thermal stresses, which cause damage to the insulation material in transformers. In oil-filled transformers, the insulation consists of cellulose and oil, and the decomposition of the insulation leads to the creation of gases that can dissolve in the oil. By analyzing the dissolved gases in the oil, known as Dissolved Gas Analysis (DGA), it is possible to diagnose any faults in oil-filled transformers. effectively [4]. Traditional techniques for measuring partial discharge in transformers, including the pulse current method, high-frequency current method, and dissolved gas analysis method, are useful for identifying the onset of insulation degradation. However, these methods cannot accurately detect and determine the location of the PD sources within the transformer. these problems have been investigated in [19], [20] utilizing intelligent techniques such as hybrid Differential Evolution (DE) algorithm and the Particle Swarm Optimisation (PSO) algorithm and the results showed high accuracy of detection and localization.

Gas Insulated Switchgear (GIS) is another major part of electrical system which is also prone to PD issues. In [21], Deep Convolutional Neural Network (DCNN) has been utilized to accurately recognize partial discharge in complex data sources within GIS. The DCNN has shown high recognition accuracies when applied to PD pattern recognition, surpassing traditional machine learning algorithms. This method is particularly effective in handling complex and noisy data sources, which are commonly

encountered in GIS. By training the DCNN on large datasets, it is possible to improve the accuracy of PD recognition, which is vital in detecting and diagnosing insulation failures in GIS. Overall, the use of DCNN in PD recognition has shown promising results in improving the accuracy and reliability of PD detection in GIS applications.

2.3 Artificial Intelligence Based Partial Discharge Detection

Automated fault recognition of electrical equipment is a crucial research area, particularly in industries where equipment breakdowns can have a significant impact on production capacity and employee safety. Neglecting active Partial Discharge in power cables, for instance, can lead to arc flash, resulting in dangerous consequences when the cables are damaged. Identifying faults is necessary to prevent further equipment damage and maintain a healthy production environment. Automated fault recognition has been carried out through many techniques including Machine Learning (ML) and Deep Learning (DL). Below is a benchmark of many research efforts on PD utilizing Artificial Intelligence (AI) based on Ultrasound data:

Ref	Equipment	AI method	Accuracy
[16]	Outdoor Insulator	ANN-BP	85%
[22]	oil-filled submarine cable terminal	ANN-BP	96%
[23]	Power Transformer	KNN/SVM	98%
[24]	High Voltage Bushing	KNN/ANN/SVM & others	95%
[25]	Power Transformer	PCA/KNN	94%
[26]	Power Transformer	GB/RF/SVM& others	>90%
[27]	Power Transformer	IFA	high
[28]	XLPE Cable	CNN	96%
[29]	Transformer Insulation	CNN	88%
[30]	Power Transformer	CNN/DNN/RNN	89-93%
[31]	PD simulator	CNN	74-86%
[32]	Oil Paper Insulation	KNN/MLP& others	92-99%
[33]	Insulation for Transformers	ANN	95%

Table 2.1: Recent researches on PD detection based on acoustic emission and ultra-sound

CHAPTER 3

SYSTEM MODELING

3.1 Partial Discharge Data Acquisition

Electrical methods for detecting partial discharge (PD) are not always effective due to excessive electromagnetic interference, which can be difficult to control in field settings. Discrimination based on time or frequency domain characteristics is often necessary, and specialized PD couplers may need to be designed into the apparatus. Acoustic PD detection is advantageous in many situations because it is immune to electromagnetic interference, does not vary in sensitivity with test object capacitance, and can often provide location information for PD sources in complex systems. Acoustic methods can also be applied from enclosures in situations where electrical methods would require installation of PD couplers within the apparatus.

Acoustic discharge detection involves the detection of mechanical signals produced by a discharge event. The discharge generates a mechanical wave that travels through the insulation, which can be detected using a specialized sensor. The output from the sensor can be analyzed using conventional data acquisition systems. The signal

detected is influenced by various factors, including the source of the discharge, the sensor, and the detection apparatus, and can take various shapes.

When sound travels through a medium, it creates a disturbance that propagates through the medium. This disturbance causes local changes in pressure P and density p , which in turn cause molecules to move and create a wave motion. In liquids, the disturbance leads to compression and rarefaction of the medium and can be described by general differential equation of acoustic wave motion [34]

$$\nabla^2 p = \frac{1}{c^2} \frac{\partial^2 p}{\partial t^2} \quad (3.1)$$

where $\nabla^2 p = \left(\frac{\partial^2 p}{\partial x^2} + \frac{\partial^2 p}{\partial y^2} + \frac{\partial^2 p}{\partial z^2} \right)$, c represents the velocity of the acoustic wave.

there are several graphical modeling of PD, one of the well known models is the Whitehead's three capacitance circuit model [35]. In order to represent the void within an insulation material, a circuit model with 3 capacitances is used. In this model, C1 and C3 are used to denote the capacitance of the insulator that is still present and runs parallel to C4 and C5. On the other hand, C4 and C5 are utilized to represent the capacitance of the insulator that is in series with the void. The remaining capacitance, C2, completes the circuit. This circuit model is depicted in Figure 3.1.

The model can be simplified by using three capacitance equivalent circuit as demonstrated in figure 3.2. C1 and C3 are the capacitances of the remaining insulator that are connected in parallel with C4 and C5 and represented by C1 in figure 3.2. On the other hand, C4 and C5 represent the insulator capacitance that is connected

in series with the void C2, and replaced with C3 in the simplified model.

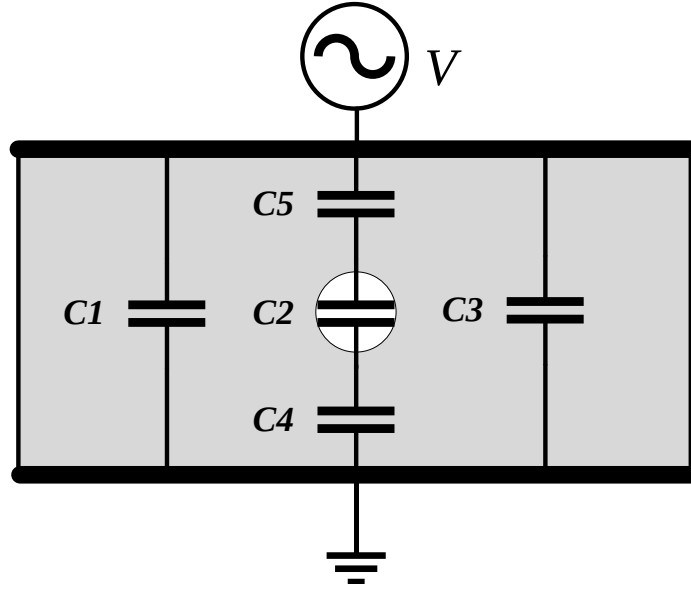


Figure 3.1: Partial Discharge model

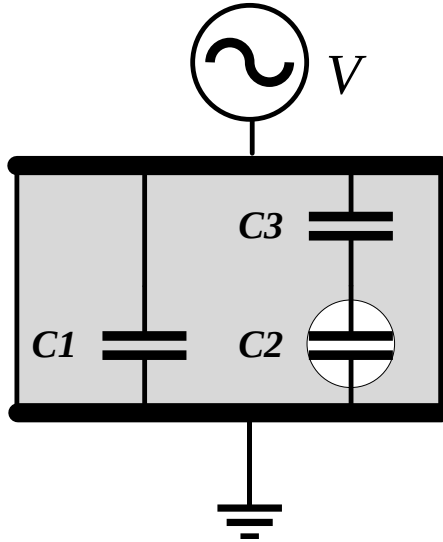


Figure 3.2: Partial Discharge simplified model

Before PD occurrence, the voltage across the void (V_v) is equal to

$$V_v = \frac{X_{C3}}{X_{C2} + X_{C3}} V \quad (3.2)$$

V is the voltage from the source, X represents the impedance of the capacitance.

When partial discharge (PD) happens, the electric field force acting on the void from the outside suddenly disappears, causing the void to lose its equilibrium state. As a result, the bubble starts to vibrate due to the elastic force acting on it. This phenomena can be expressed using the following equation:

$$L_m C_m \frac{d^2 u_c}{dt^2} + R_m C_m \frac{du_c}{dt} + u_c = 0 \quad (3.3)$$

where L_m is the inductance of the mechanical equivalent circuit; C_m represents the elasticity of the system; R_m represents the friction losses; and u_c is the external force on the void wall.

The PD ultrasonic wave in the medium is affected by two primary factors. The first factor is the electric field force that occurs during the discharge process. The second factor is the pressure wave that results from the expansion of the void or bubble due to the heating of the discharge arc [36].

Acoustic Emission (AE) is a phenomenon that occurs in solid materials, in which elastic waves propagate either within the material or on its surface. To detect AE waves during testing, sensors are attached to the surface of the solid material if the sensor is structure borne. The sensors convert the detected waves into electrical signals, typically using piezoelectric ceramics. This conversion process allows the signals to be analyzed using conventional data acquisition systems. Piezoelectric is a group of materials that practice a phenomenon where they exhibit a reversible relationship between mechanical stress and electric field. This behavior is depicted in Figure 3.1,

where a cylindrical piezoelectric element with electrodes on both ends is shown. When a voltage is applied to the element through the electrodes, it either expands or contracts in response to the voltage. Conversely, when the shape of the piezoelectric element is changed by an external force, it generates a voltage. Hence, the piezoelectric element can convert mechanical energy into electrical energy, and vice versa, which is referred to as the piezoelectric effect. Materials that exhibit this property are called piezoelectric materials. Piezoelectric ceramics are one such type of piezoelectric material [37].

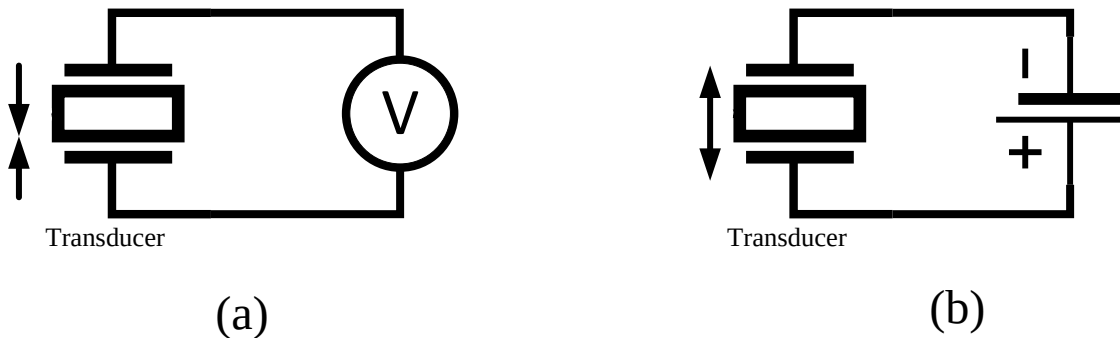


Figure 3.3: Piezoelectric ceramics basic behavior

During the AE event, the AE wave generated within a solid material travels through different materials until it reaches the AE sensor made of piezoelectric ceramic. The AE wave deforms the piezoelectric ceramic, producing a voltage signal known as the AE signal. This signal is transmitted through a cable and preamplifier, then the filter will remove external signals. After that, it will be amplified again to be detected by a measuring instrument as shown in figure 3.4.

The modern PD acoustic detectors are based on a concept called Superheterodyne. Figure 3.5 shows a circuit of a similar detector that was used to collect the data used

in this research. The signal will be detected through the transducer then it will be amplified before the mixer. In the mixer, multiplying the original signal with local oscillator frequency will generate new two signals with a frequencies that are equal to the summation of the original frequencies and the difference of the two original frequencies. The resultant signal with a lower frequency will be audible and will be passed through the filter, the other signal with higher frequency will be filtered out. The resultant signal will be amplified for the final stage before producing the sound for the user [38].

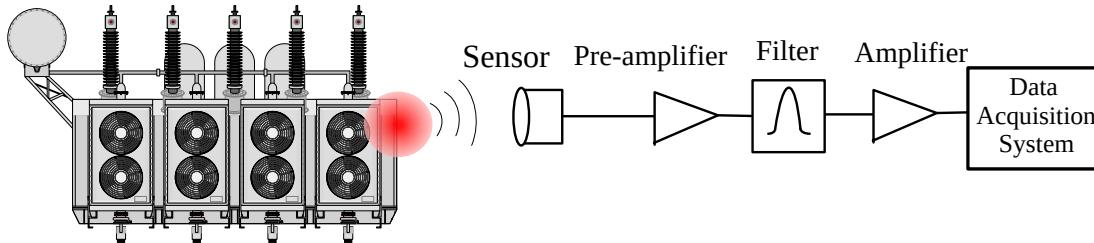


Figure 3.4: working principle of the detection system

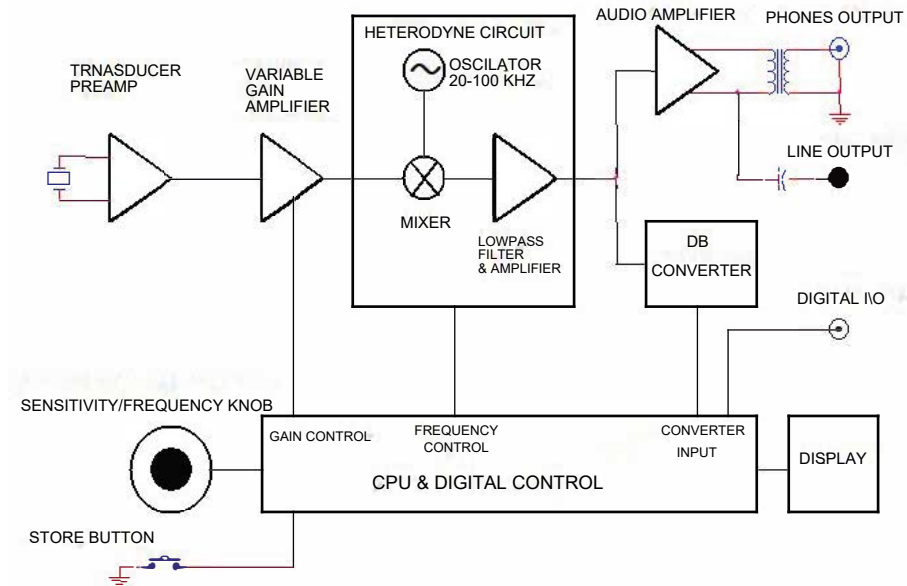


Figure 3.5: Modern PD Detector Circuit



(a) Transformer



(b) Switchgear



(c) Controlgear



(d) Motor

Figure 3.6: Samples of The Inspected Equipment

3.2 Partial Discharge Signal Preprocessing

The AE signal waveforms can exhibit a wide range of variations, but they can usually be categorized into specific patterns based on their visual appearance. Although all signals can be categorized as PD, each equipment failing due to PD can produce slightly different waveform. Also, some forms of PD appear on some equipment but not in all, such as tracking can not be seen in transformers internal winding.

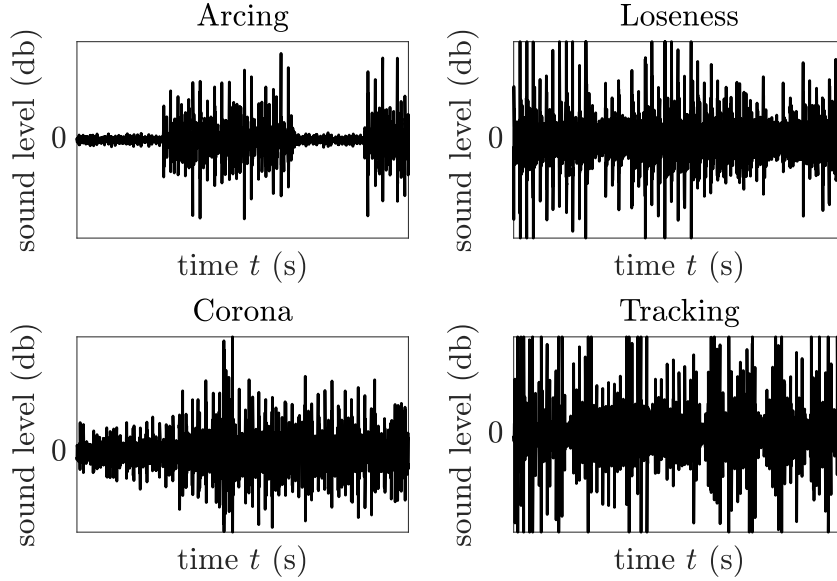


Figure 3.7: time series waveform of random samples

all collected samples have been classified into 5 classes; four represents the state of the failure and one represent the healthy state of the equipment. The four classes that represent the failure type are shown in figure 3.7 . Time domain waveforms are usually investigated to identify the type of failure, but in some cases we refer to Frequency waveform to farther assist the waveform, because corona in some cases looks similar

to tracking but if frequency domain in corona is inspected it can be noticed that the system frequency multiples usually have higher components than other frequencies. The noise level existed is considerable and it might affect the recognition of fault, however adding the step of removing the noise each time we need to classify the fault is not significant for the final accuracy so it is not considered in this work.

The collected samples are diverse that cover a wide range of electrical equipment such as power transformers, switchgears, controlgears, motors, and cables. The collected samples have been processed and classified manually based on general patterns that are usually recognized during the inspection. The frequency response of any waveform is produced by taking the Discrete Fourier transform of time domain waveform as in equation 3.4 [39], then the negative spectrum of the signal will be removed by taking the absolute value of the signal.

$$Y(k) = \sum_{j=1}^n X(j)W_n^{(j-1)(k-1)} \quad (3.4)$$

where $W_n = \exp(-2\pi i)/n$

Arcing waveform is usually recognized as an off and on burst of waves, that is due to the fact that the loose wire or cable start to build the voltage until the breakdown and then it will emit a high frequency sound wave as can be seen in figure 3.8. The frequency domain show clear components at system frequency and around three times the system frequency, however this pattern is not necessary to be seen all arcing waveforms.

During the event of equipment looseness, the time domain waveform tend to form

small triangles of wave burst and the frequency waveform usually has frequency components more than arcing waveform which is again not necessary a multiple of system frequency as depicted in figure 3.9.

In case of corona, the time domain waveform produce peaks on system frequencies which clearly can be observed by investigating the frequency spectrum. Corona produce frequency components on the system frequency and system frequency multiples as it can be seen in figure 3.10. in contrast, tracking waveform is very random and produce high sound intensity with random frequency components which clearly can be seen in figure 3.11.

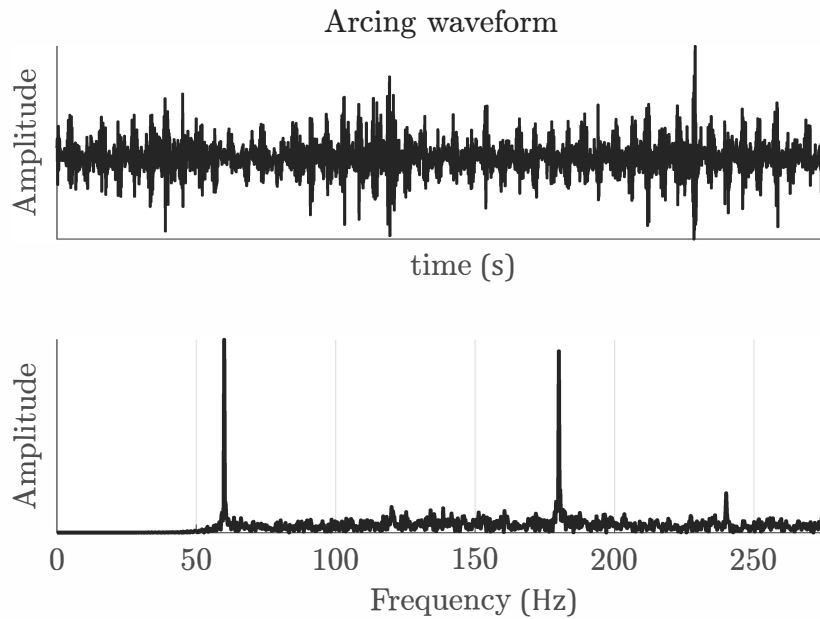


Figure 3.8: Arcing common pattern

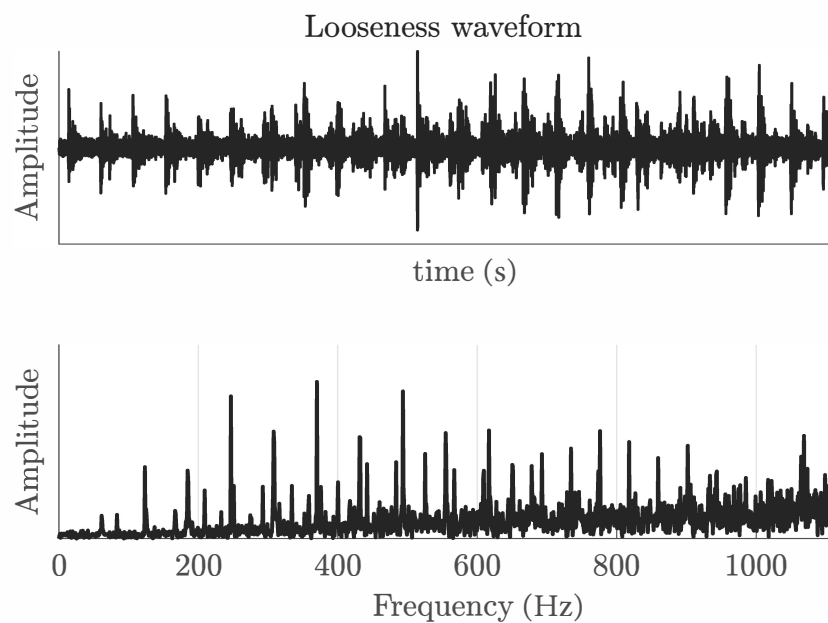


Figure 3.9: Looseness common pattern

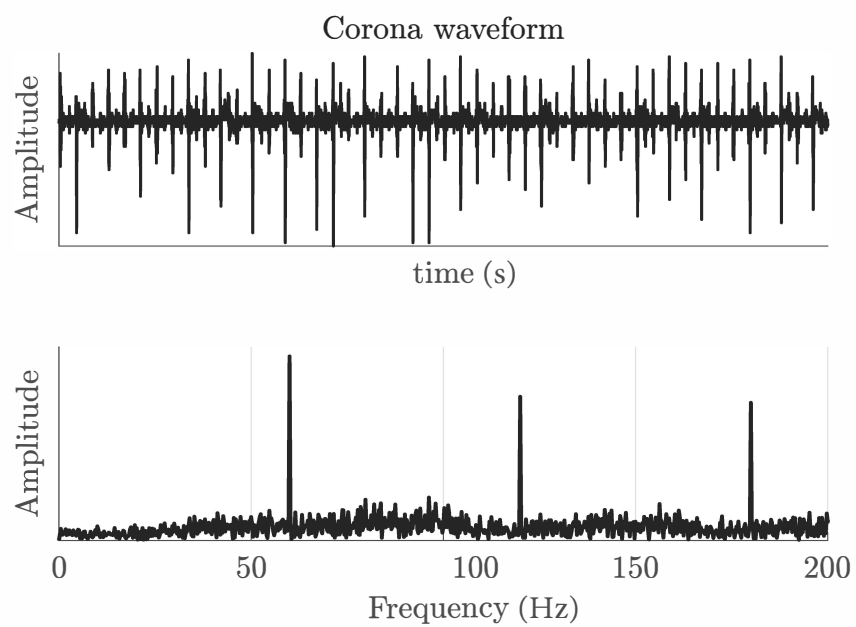


Figure 3.10: Corona common pattern

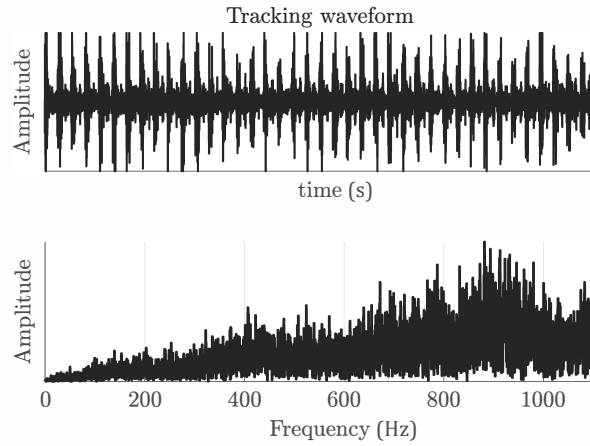


Figure 3.11: Tracking common pattern

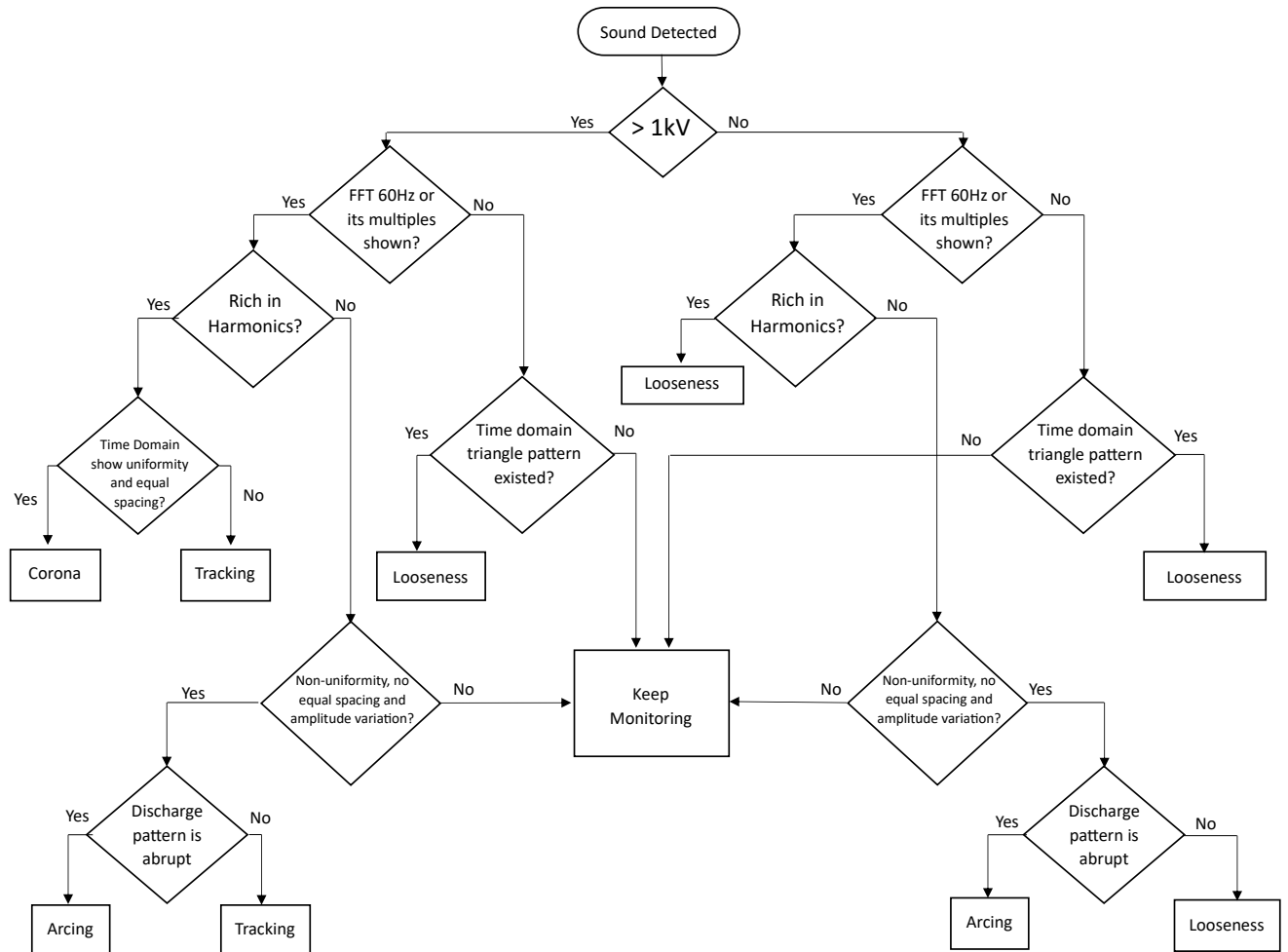


Figure 3.12: Flow chart for identifying PD type

After processing the signal, the data need to be prepared for Convolution Neural Network by converting the waveform into pictures. This step is very important since CNN accept input pictures only,hence three features will be extracted from the signals and then will be converted into pictures. First of all, Fast Fourier Transform (FFT) will provide an information of the complete signal at once, but instead Short-Time Fourier Transform (STFT) will be implemented to preserve the time information. STFT is simply breaking the audio signal into small segments [40] and takin FFT of each segment as per the below illustration 3.14 [41].

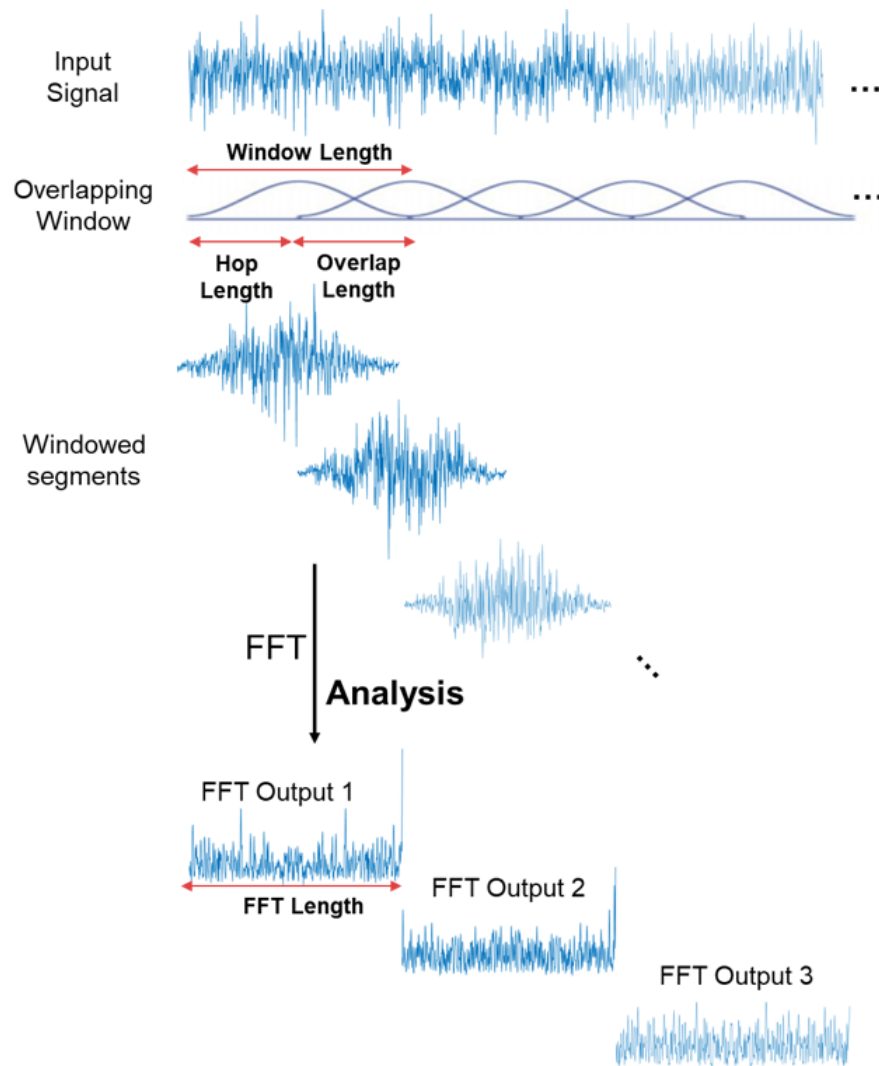


Figure 3.13: STFT concept

After Completing the STFT, we start constructing the signal into spectrogram where the signal is converted into a usable picture for CNN.

3.3 Convolution Neural Network Architecture

A Convolution Neural Network (CNN) is a deep learning model that was inspired by the visual system of living organisms. This type of neural network has multiple layers and is commonly used in computer vision and natural language processing. Its ability to automatically learn and extract features from images and texts has made it a popular choice for various fields. CNNs use convolutional layers that apply filters to input data to extract meaningful information. The extracted features are then fed into fully connected layers that classify or predict the output. CNNs have been successfully applied to various tasks such as image classification, object detection, and natural language processing [42].

3.3.1 Network General Layers

CNN comprises several layers that function as building blocks. In the following section, more elaboration on some of these building blocks will be discussed and their respective roles in the CNN architecture.

Convolutional layer: Mathematically, the convolution $(x*w)(a)$ of functions x and w is defined in all dimensions as

$$(x * w)(a) = \int x(t)w(a - t)da \quad (3.5)$$

The convolutional layer is a crucial element in CNN architecture that plays a vital role in generating an output feature map by convolving a set of convolutional kernels

or filters with the input image [43].

Pooling layer: Pooling layers are an essential component of CNN architectures, which enable sub-sampling of the feature maps obtained after convolution operations. They reduce the size of the feature maps by extracting dominant features in each pool step while maintaining the most important information [44].

Activation Function: In a neural network, the activation function plays a crucial role in mapping the input to the output. The input is obtained by calculating the weighted sum of the neuron's input, and the bias is added if applicable. The activation function determines whether the neuron will activate or not for a given input by generating the corresponding output. Essentially, it transforms the input to the output, allowing for more complex decision-making and non-linearity in the neural network. The Rectifier Linear Unit (ReLU) is a widely used activation function in CNNs. It is designed to convert all negative input values to zero while maintaining positive values. This function is computationally inexpensive compared to other activation functions. Mathematically, ReLU is represented as:

$$f(x)_{ReLU} = \mathbf{max}(0, x) \quad (3.6)$$

Fully connected layer: Typically, the final layers of a CNN architecture used for classification consist of fully-connected layers. Each neuron in a fully-connected layer is connected to every neuron in the previous layer. The last fully-connected layer serves as the output layer, which produces the classification result of the CNN architecture

[45]. Fully connected layers can be modeled using the below general equations:

$$\omega_{ij}(t+1) = \omega_{ij}(t) + \eta x_j \varphi' \sum_k^L (e_k \omega_{ki}) \quad (3.7)$$

$$b_{ij}(t+1) = b_{ij}(t) + \eta \varphi' \sum_k^L (e_k \omega_{ki}) \quad (3.8)$$

The above equation is used to update weights ω_{ij} and biases b_{ij} which is derived from the least mean square method of observed Y_k and predicted $\hat{Y}_k$ outputs:

$$I = \frac{1}{2} \sum_k^L (Y_k - \hat{Y}_k)^2 \quad (3.9)$$

η represents the learning rate of the training process, φ' represents the derivative of internal parameters in the hidden layers, e_k is error function between observe and predicted values.

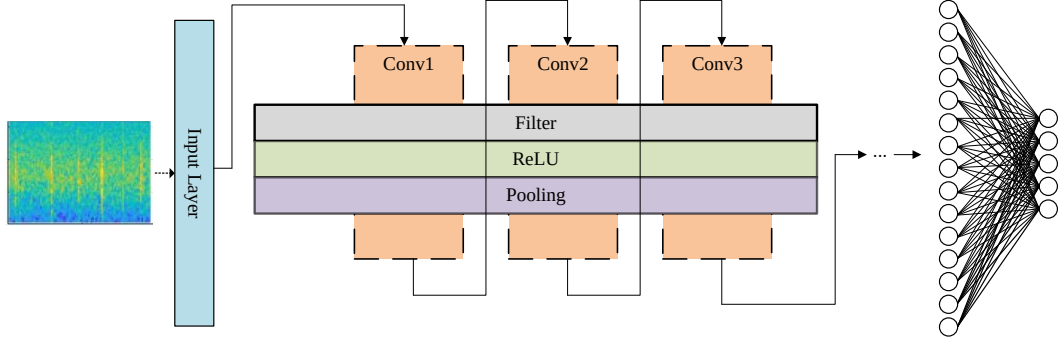


Figure 3.14: CNN General Structure

3.3.2 Hyperparameter Tuning

There are great number of hyperparameters that can be tuned within CNN architecture. e.g. filter size, number of convolution layers, learning rate, input picture size

and number of fully connected neurons. Tuning of these parameters can be done with trail and error, however there are more robust methods that improve the architecture accuracy and reduce the loss in more efficient way such as Bayesian optimization method [46].

Bayesian optimization is an algorithm used to solve global optimization problems by leveraging Bayes Theorem, which means that the posterior probability of a function M given the evidence E is proportional to the likelihood of E given M multiplied by the prior probability of M :

$$P(M|E) = \frac{P(E|M)P(M)}{P(M)} \quad (3.10)$$

Global optimization is a complex task that involves finding the input parameters that can minimize or maximize a given objective cost function:

$$X^* = \underset{x \in X}{arg \ Min} \ f(x) \quad (3.11)$$

Typically, the objective function is characterized by non-convexity, nonlinearity, high-dimensionality, noise, and high computational cost, making it difficult to analyze. Bayesian optimization is an effective approach to address these challenges, as it is able to efficiently and effectively explore the parameter space to identify the optimal set of parameters that can yield the best results [47], [48].

Bayesian Optimization (BO) is unique in terms of constructing a probabilistic model of $f(x)$ and then exploit a bounded set of X to proceed with the next evaluation

of $f(x)$, keeping updates of the uncertainty integrated. When the evaluations of $f(x)$ is cheap, existing global optimization models e.g. Genetic Algorithm (GA) can work perfectly, however in the case of deep learning for example the evaluations is very expensive. Since the objective function is unknown and expensive to evaluate, Gaussian Process (GP) is often used to approximate $f(\mathbf{x})$ based on some observe data of inputs and outputs in dataset $\mathcal{D}_{1:t} = \{\mathbf{x}_{1:t}, f(x)_{1:t}\}$:

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')) \quad (3.12)$$

$\mathcal{GP}$ will estimate the objective function by returning the mean m at the sampled point and variance (or kernel) k of the normal distribution [49]. After fitting the priors the next step is to update utilizing new observation, the method used to update based on new observation is call acquisition function. The charter of the acquisition function is to explore for the optimum (based on maximization or minimization). If the search is for minimization, then the acquisition will trade of the lowest mean value areas with high uncertainty areas looking for the global minimum value [50]. There are several methods to implement acquisition functions such as *Expected Improvement*, *Probability of Improvement*, *Lower Confidence Bound* and *Upper Confidence Bound* [51].

CHAPTER 4

PROPOSED APPROACH AND RESULTS

4.1 Single-Phase CNN For Fault Classification

The main objective of the model is to classify any detected fault during the equipment operation so the maintenance crew can take action to rectify the issue. Sometimes, the rectification limited to cleaning the equipment, but other times the rectification involve shutting down the whole process and taking the equipment out of service for extended periods. The ultrasound data is collected from different equipment at different locations and times which reflect the diversity of the data collected as it can be seen in Table 4.1 and Table 4.2.

Equipment Condition	Collected Samples
Faulty Equipment	1824
Healthy Equipment	1732

Table 4.1: Number of collected samples for healthy and faulty equipment

PD Type	Collected Samples
Arcing	356
Corona	442
Looseness	506
Tracking	520

Table 4.2: Number of collected samples for each type of PD

The architecture of the network and the main parameters are shown below in table 4.3 and figure 4.1:

Parameter	Selected Value
Number of layers	22
Input layer size	$86 \times 86 \times 3$
1 st Convolution Layer size	$86 \times 86 \times 32$
2 nd Convolution Layer size	$43 \times 43 \times 64$
3 rd Convolution Layer size	$21 \times 21 \times 128$
4 th Convolution Layer size	$21 \times 21 \times 128$
1 st pooling Layer size	$43 \times 43 \times 32$
2 nd pooling Layer size	$21 \times 21 \times 64$
3 rd pooling Layer size	$10 \times 10 \times 128$
Fully connected layers/ (neurons in each layer)	2 / (512)-(5)
Max Epochs	20
Mini-Batch size	32
Training-Validation-Testing percentages	70% - 15% -15%
Validation frequency	10
Initial learning rate	0.001
Learning rate drop factor	0.1
learning rate drop period	15

Table 4.3: Selected Parameters for CNN

The selection of CNN parameters for this proposed method is based on trail and error in addition to inspecting the network performance with parameter tuning. The four convolution layers in this proposed model can learn several features that is extracted from the acoustic signals e.g. timbral and pitch information that is usually extracted from Mel Frequency Cepstral Coefficients (MFCC) and FFT. Figure 4.2 shows leaned features after each convolution layer, each convolution layer will capture

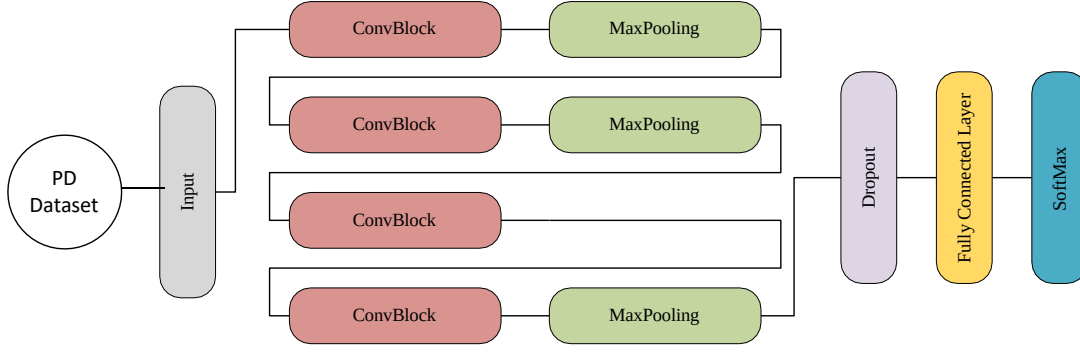


Figure 4.1: CNN architecture

certain picture features like edges and colors. First picture in figure 4.2a, clearly shows the learnable features as mostly colors while as the layers go deeper the the learned features turned to be more detailed and complex such as textures and edges.

The training and validation plot showed good improvement of the accuracy and loss function with increased number of iterations as it can be seen in Figures 4.4a and 4.4b. Table 4.4 shows the results of CNN model training, validation and final accuracy as well as simulation time:

Output parameter	Result
Training Accuracy	98%
Validation Accuracy	92%
Training loss	0.038
Validation loss	0.23
Number of iterations	1540
Training time	159 sec

Table 4.4: Output Parameters for Single-Phase CNN

The detection of Tracking failure scored the lowest accuracy due to the randomness of signal detected by ultrasound device, while detecting healthy equipment scored the highest accuracy since the produced signal is unique in terms of the wave form and usually don't produce high frequency signals as it can be seen in Fig 4.3.

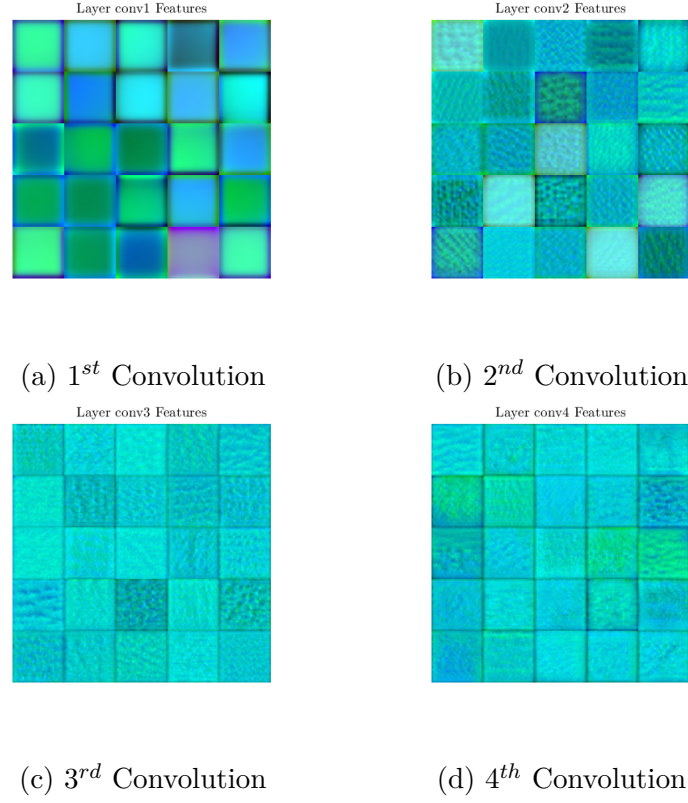
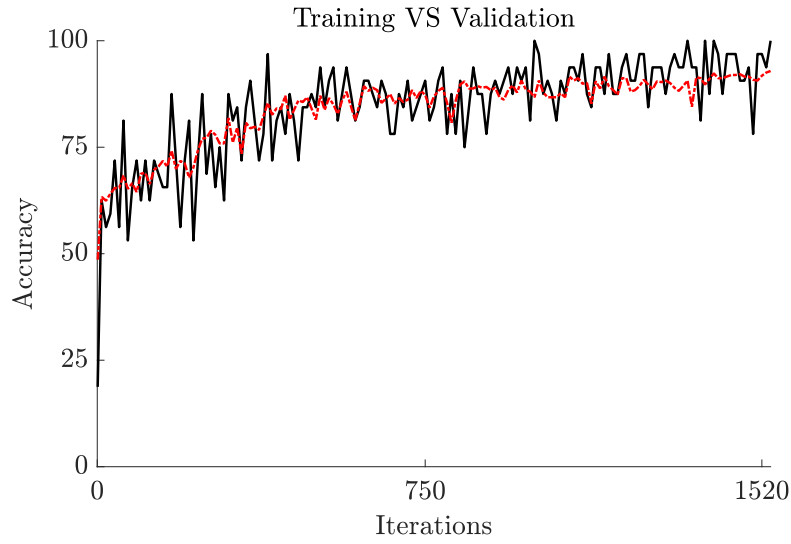


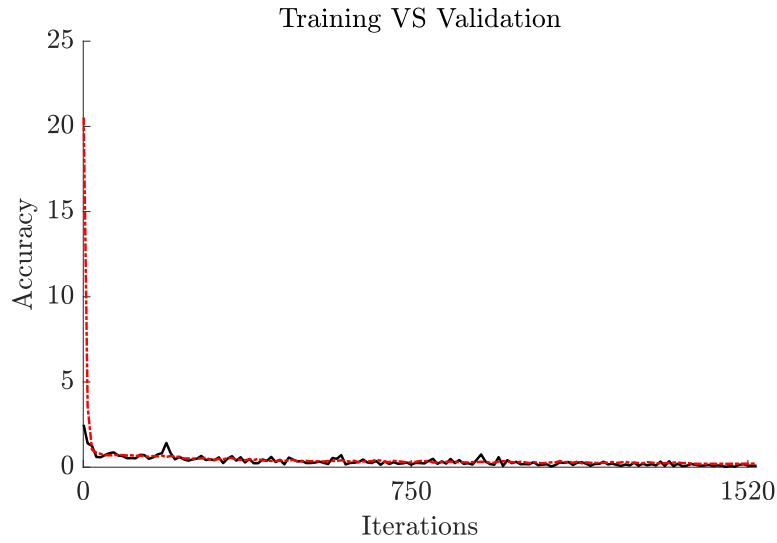
Figure 4.2: Output from all convolution layers

		Confusion Matrix						
True Class	Arcing	44	1			8	83.0%	17.0%
	Corona	3	57		3	3	86.4%	13.6%
	Healthy			260			100.0%	
	Looseness		3	1	67	5	88.2%	11.8%
	Tracking	1	6		7	64	82.1%	17.9%
		Predicted Class						
		Arcing	Corona	Healthy	Looseness	Tracking		

Figure 4.3: Confusion matrix for Single-Phase validation accuracy



(a) Accuracy



(b) Loss

Figure 4.4: Accuracy and loss function for Single-Phases model

4.2 Double-Phases CNN For Fault Classification

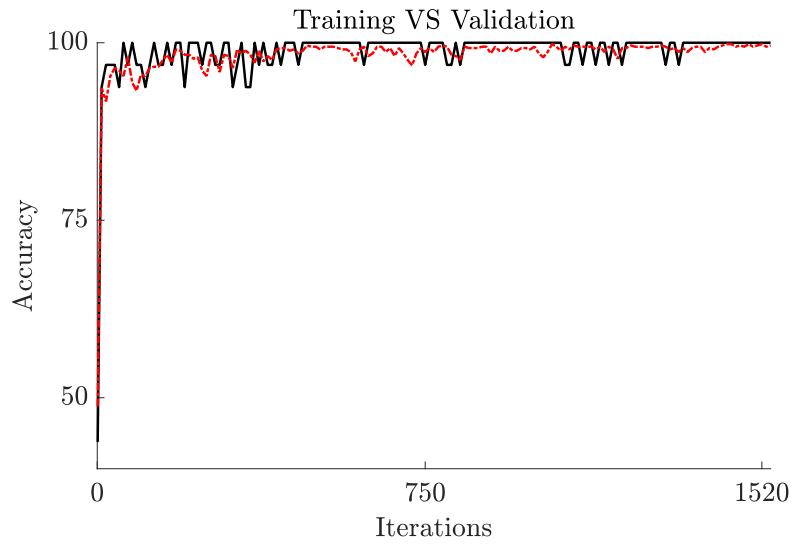
The maintenance crew during the inspection demand the knowledge of one answer as a starting point; is the equipment healthy? in that case, the model can be modified to

answer this question in the beginning, then the model as a second phase can identify the type of the fault. This method allow the model to improve the overall accuracy to a very great percentage.

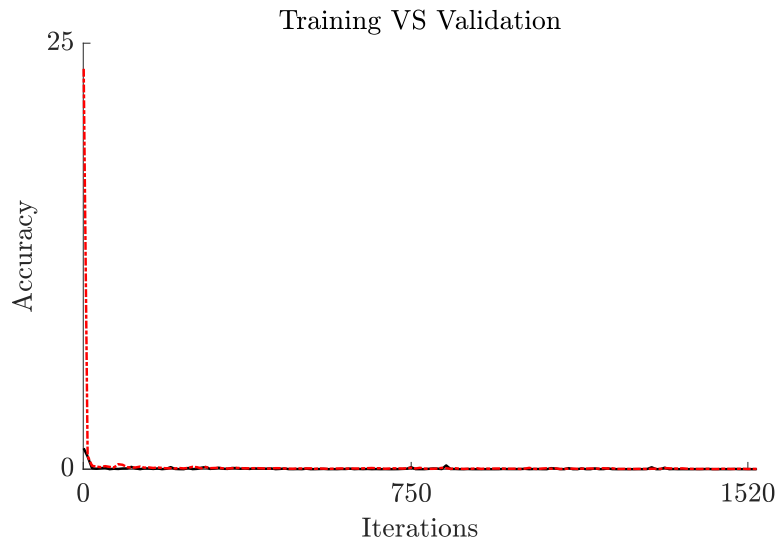
the parameters in single-phase model will be used as they are except of the output classifier since it will be changed to two classifications. The output of the model outperforms the previous single-phase model as it can be seen in table 4.8 and figure figs. 4.5a and 4.5b. The training and validation plot showed a robust convergence after few iterations, which clearly improve the detection of any issue in the equipment.

Output parameter	Result
Training Accuracy	100%
Validation Accuracy	99.62%
Training loss	9.6×10^{-5}
Validation loss	0.016
Number of iterations	1540
Training time	206 sec

Table 4.5: Output Parameters for Double-Phase CNN



(a) Accuracy



(b) Loss

Figure 4.5: Accuracy and loss function for Double-Phases model

All PD failures produce high frequency components that easily can be distinguished from the health "silent" waveforms which clearly indicated in the confusion matrix in Fig.4.6.

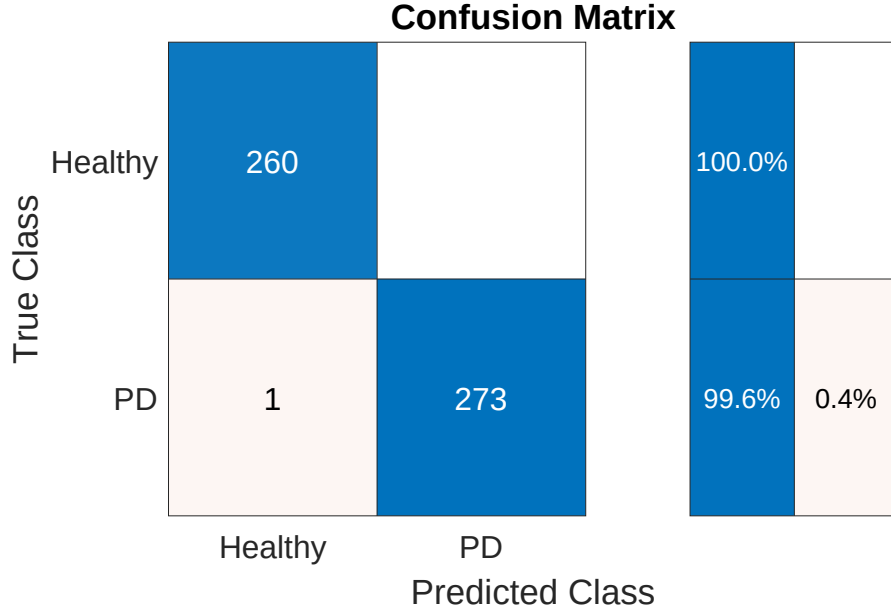


Figure 4.6: Confusion matrix for Double-Phase validation accuracy

4.3 Enhanced Single-Phase CNN using Bayesian Optimization

The goal of the Bayesian optimization technique employed in this research is to minimize the validation classification error, which is set as the objective function. In general, Multiple hyperparameters are decided to be tuned within the selected range in order to achieve the objective function. Four Hyperparameters (HP) are selected in this model to be optimized, *section depth* decide the depth of the model in terms of number of convolution layers in each section. *Initial learning rate* in other side will select The hyperparameters are listed in the below table 4.6. After optimizing the network, table 4.7 shows the outcomes of the optimizer with optimal parameters.

The optimized hyperparameters produced better model with improved accuracy

Hyperparameter	Search range	Scale
Section depth	[1 4]	Integer
Initial learning rate	$[1 \times 10^{-3} \ 1]$	Log
Momentum	[0.8 0.98]	Real
Regularization	$[1 \times 10^{-10} \ 1 \times 10^{-2}]$	Log

Table 4.6: Hyperparameters Tuning for CNN

Hyperparameter	Optimal value
Section depth	2
Initial learning rate	0.0042
Momentum	0.8035
Regularization	1.237

Table 4.7: Optimal parameters for CNN

as well as loss value as per the below table. The objective function progress through the optimization process is shown in figure 4.7

Output parameter	Single-Phase Model Result	Optimized model Result
Validation Accuracy	92%	94%
Validation loss	0.23	0.058
Training time	159 sec	4501 sec

Table 4.8: Comparison between Single-phase and optimized models CNN

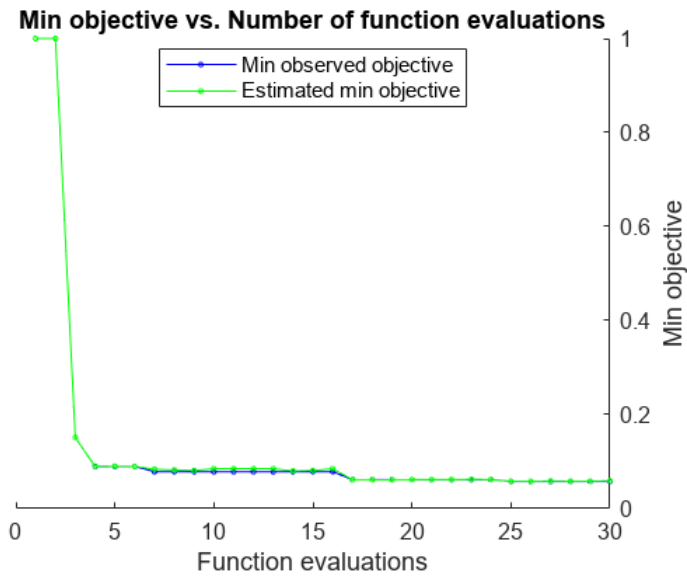


Figure 4.7: Function evaluations throughout the iterations

The overall accuracy is improve as well as the validation accuracy of each PD type when compared with Single-Phase case. Tracking detection accuracy is improved by far when compared to other PD types as it can be seen in Fig. 4.8

		Confusion Matrix						
True Class	Arcing	45			3	5	84.9%	15.1%
	Corona	2	58		1	5	87.9%	12.1%
	Healthy	2		258			99.2%	0.8%
	Looseness		4		68	4	89.5%	10.5%
	Tracking	3	1		3	71	91.0%	9.0%
		Predicted Class						
		Arcing	Corona	Healthy	Looseness	Tracking		

Figure 4.8: Confusion matrix for Optimized Double-Phase validation accuracy

4.4 Benchmark with Pretrained Models

The models developed in the research are not the first models in the field of audio classifications, there are existing models that have been developed for general applications [52]. In order to investigate the performance of the developed model, the same collected data have been trained and validated with latest state-of-the-art audio classification pretrained models and compared with the developed models as shown in figure 4.9. Below is a summary of each model:

- **VGGish** represents a Convolutional Neural Network (CNN) that has been pre-trained by Google. Its architecture takes cues from the well-known VGG networks extensively utilized for image classification tasks. The structure of VGGish encompasses a sequence of convolutional and activation layers, with the possibility of including a subsequent max pooling layer. In its entirety, this neural network consists of a total of 17 layers [53].
- **OpenL3** is a freely available deep audio embedding framework developed as an open-source project. It builds upon the self-supervised L3-Net and introduces enhancements to its architecture. OpenL3 surpasses the performance of VGGish, SoundNet, and even the original L3-Net on various sound recognition tasks [54].
- **YamNet** (Yet Another Mobile Network), abbreviated as YAMNet, is a pre-trained model designed for acoustic detection. It was trained by Dan Ellis using the AudioSet dataset, which consists of labeled data sourced from over 2 million YouTube videos. YAMNet utilizes the depth-wise-separable convolution architecture of MobileNet_v1. This architecture allows for efficient computation and reduces the number of parameters in the model, making it suitable for mobile and resource-constrained environments [55].

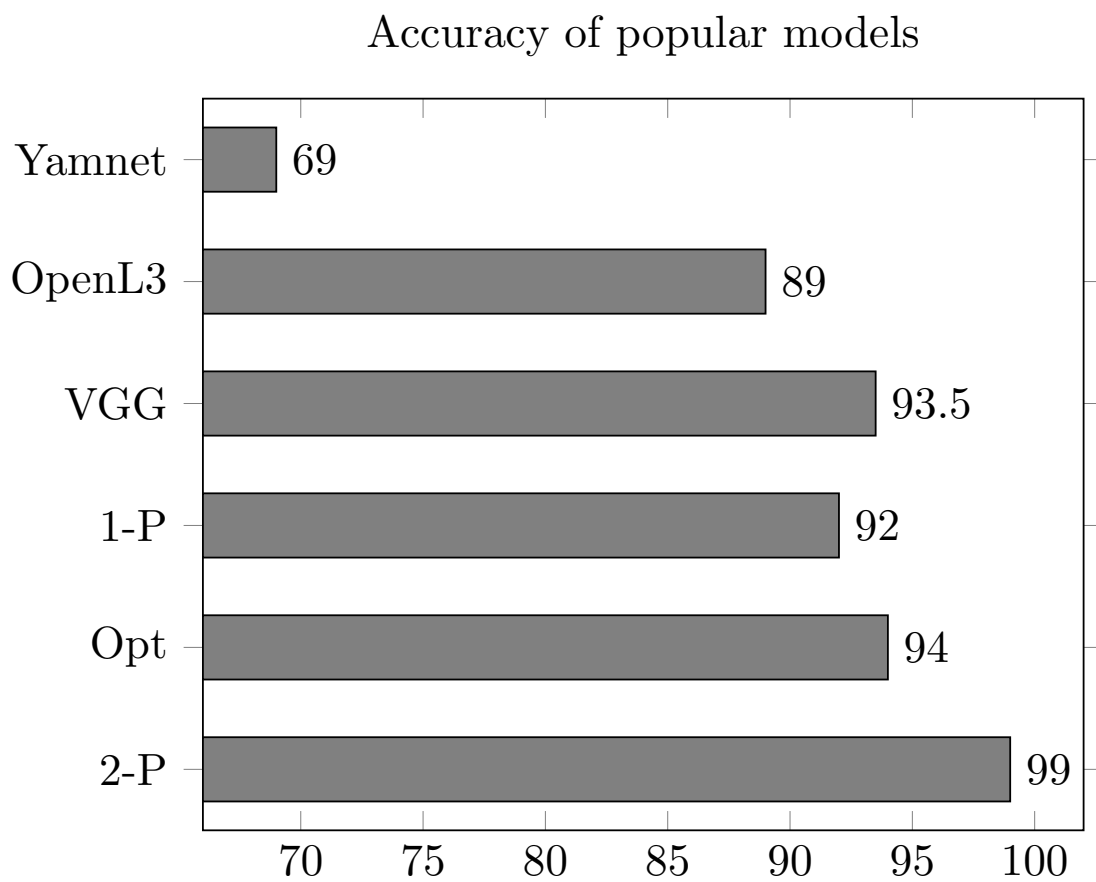


Figure 4.9: Benchmarking the percentage accuracy of proposed models with pretrained models

CHAPTER 5

CONCLUSION

In this work, four different types of PD have been collected of a diverse number of electrical equipment. Each type of PD produce a unique audio signal that is possible to be detected by ultrasound detector. In this work, a general observation on the audio signals have been reported in order to be classified before the preprocessing of the data. After the processing stage, a novel methodology have been implemented to preprocess the data using three different features which are STFT, MFCC and PSD. In the final stage, three different proposed approaches have been discuss which are the Single-Phase CNN, Double-Phase CNN and Optimized Single-Phase CNN. The proposed approaches have showed higher accuracy in comparison with three different pretrained models available on the literature.

APPENDIX A

PROOFS

APPENDIX B

SUPPLEMENTARY MATERIAL

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