DEVELOPMENT OF A FRAMEWORK FOR AREA-BASED EXPLOSIVE TRACE DETECTION USING DEEP TRANSFER LEARNING

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FEBRUARY, 2024

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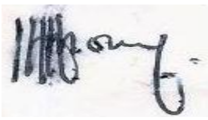
A Thesis Submitted in Partial Fulfilment of the Requirements for the Award of the Degree of Doctor of Philosophy (Ph.D.) in Artificial Intelligence at the Africa Centre of Excellence on Technology Enhanced Learning , National Open University of Nigeria

DECLARATION

I, **Monday Fredrick OHEMU (ACE21140003)** hereby declare that the project work entitled: **DEVELOPMENT OF A FRAMEWORK FOR AREA-BASED EXPLOSIVE TRACE DETECTION USING DEEP TRANSFER LEARNING** is a record of an original work done by me, as a result of my research effort carried out in the Africa Centre of Excellence on Technology Enhanced Learning, National Open University of Nigeria under the supervision of

____  ____19/02/2024___

Student's Signature & Date

CERTIFICATION / APPROVAL

This is to certify that this study was carried out by **Monday Fredrick OHEMU** with Matric Number **ACE21140003** at the **Africa Centre of Excellence on Technology Enhanced Learning**, National Open University of Nigeria, under my supervision.

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DEDICATION

This thesis is dedicated to Almighty God for His mercy and love that has brought me to this level and to late Mr. Raymond Akor for his encouragement and support in my academic pursuit

ACKNOWLEDGEMENTS

I would like to extend my deepest appreciation to my esteemed supervisors, Prof. Ambrose A. Azeta and Prof. Ibrahim Adeyanju for entrusting me with the pursuit of my PhD in a subject that is particularly close to my heart. Without their unwavering guidance and support, my journey through this challenging academic pursuit would have been futile. I am eternally grateful for their encouragement, and commitment to my success. Their mentorship has been instrumental in helping me achieve my academic dreams, and I will always treasure their invaluable contribution to my academic and professional development.

My gratitude also goes to the staff and management of ACETEL, particularly the Centre Director, Prof. Grace Jokthan, AI program Coordinator Prof. Greg Onwodi, the ICT Director, Ibrahim Abubakar, the head of Admin, Udochukwu and to all my lecturers who impacted me to make this programme possible.

My lovely wife stood by my side throughout this journey and believed in me, Thank you. I say thank you to all my family members, Augustine, Francis, Edward, Regina and the Akors. I appreciate the encouragement friends like Moses Anthony, Dr. Obasi Chukwuemeka, Francis Sylvanus and Senior Friends like Dr. Julius Olajire, Dr. Innocent Oguche.

Finally, I will like to thank my class mates, 2020/2021Pioneer set of PhD Artificial Intelligent ACETEL-NOUN, Rexcharle, Dere, Bayole, Ganfather, Keture, it was wonderful working with you people.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
CNN	Convolution Neural Network
CV	Computer Vision
DCNN	Deep Convolution Neural Network
DTLETD	Deep Transfer Learning for Explosive Trace Detection
ETD	Explosive Trace Detection
DNN	Deep Neural Network
GC	Gas Chromatography
HMX	Octahydro- 1,3,5,7 –tetranitro- 1,3,5,7 –tetrazocine
IED	Improvised Explosive Device
IOT	Internet of Things
KNN	K-Nearest Neighbor
MS	Mass Spectrometry
NLP	Natural Language Processing
RDX	1, 3, 5-triazacyclohexane
TNT	2,4,6- Trinitrotoluene
WSN	Wireless Sensor Network

ABSTRACT

Terrorism and the proliferation of explosives has caused serious damage in public places and has become an issue of serious security concern across the globe. Most public places such as airports, trains stations, government institutions and facilities are being targeted, thereby endangering the safety of people's life and facilities. It is essential to protect these target areas from explosions and terrorist attacks, without necessarily exposing human security personnel to such danger. In an attempt to solve the aforementioned problem several approaches such as animals have been engaged. However, machine learning models have been proven to provide better solutions. The accuracy of machine learning model depends on large volume of data although some specific type of training has its own setbacks, since obtaining large volume of data for such training may be cumbersome. The need to develop systems that can easily adapt with less data and little training knowledge has become inevitable. The focus of this work is to develop a framework for area-based explosive trace detection using deep transfer learning. The model used was adapted from deep learning technology trained with large explosive trace data set that were collected from sensor network. The dataset was converted to a 2D data using serial data to image generator. The model was developed from a base model known as GasNet and classified explosive gas within an area base on the concentration of Carbon (C), Hydrogen (H), Oxygen (O), and Nitrogen (N) gases and was able to classify the gas combinations as either explosive or not. The developed model called deep transfer learning for explosive trace detection (DTLETD) was tested and validated using 10% of the explosive trace dataset with the transfer learning model taking less time of about 92 seconds to train against a training time of about 1287 seconds for Convolutional Neural Network (CNN) base model. The transfer learning model converged faster with nearly zero losses for both training and validation. The model also recorded an accuracy of 99.7%, with an average AUC value of about 0.89. The outcome has a precession of 96% against 98.2% accuracy and AUC of 1 that was recorded with the base model. The system was able to adapt with good performance to the new data within little time using few datasets. This research was able to achieve its objective of developing a framework for area base explosive trace and was able to improve the accuracy of explosive trace detection through the development of machine learning based model that utilizes the Deep Transfer Learning (DTL) approach.

CHAPTER ONE
INTRODUCTION

1.1. BACKGROUND OF THE STUDY

Attacks on people and sensitive places in the form of terrorism has become a global challenge that is making organizations such as academic institutions, security agencies and the government to do whatever it takes to secure people and essential infrastructures. Recently, explosive-based attacks on essential equipment, students, personnel and government have become rampant because explosive form of weapons is easy to manufacture and deploy and can cause serious destruction (Al-mousawi & Al-mousawi, 2019). This has made development of various kinds of explosives for destroying innocent people and properties very common. The area of interest includes learning institutions, airport, government properties and military base which can be monitored through sensor network. The sensor network which comprises different types of sensors is designed and deployed continuously to detect and identify explosive traces within specific treat locations in an environment. Trace elements, compounds, or chemical residues associated with explosives, such as TNT (trinitrotoluene), RDX (hexahydro-1,3,5-trinitro-1,3,5-triazine), known as the Royal Demolition Explosive or PETN (pentaerythritol tetranitrate) can be detected. This information collected in real time by the sensor network can be process either by the sensor note or by a remote server using advanced algorithm for data analysis. This has led to the development of Artificial intelligent (AI) based system to accurately detect explosives before causing havoc in an environment. This will eliminate the manual ways of screening by human security system to monitor and secure target environment that further expose human being to potential attacks in volatile areas (Wongwattanaporn, 2021). This work focuses on how to effectively use AI based technology to secure and effectively monitor target environment identified as terrorist potential attack area using sensor networks system.

Two known methods that have been deployed in explosive detection are bulk explosive detection method and trace explosive detection method. Meanwhile, the bulk explosive method uses method such as X-rays and other electromagnetic imaging method such as the recent computer tomography. This method is based on visual, optical and thermal characteristics of explosive substances that requires advance image processing applications for implementation of thermo-optical sensors in achieving better result. Contrary to the bulk explosive detection methods, the trace explosive detection approach is based on chemical property traces of explosive materials (Kishore et al., 2019) with most high explosives having the general formula of C_a H_b N_d O_k, where the subscript a, b, d, k are numbers of atom associated with each element. The sample containing oxidizer (O) and the fuel (C, H) of different degree before explosive will be formed, as in the case of RDX (Cyclotrimethylenetrinitramine, C_3H_6 N_6O_6) (Pai, Peng; Xiaojin, Zhao;Xiaofang, Pan;Wenbin, 2018) (Royal Society of Chemistry, 2011). Since each chemical has distinctive characteristics that may alter its environmental composition by altering some chemical or physical characteristic in the environment. Special sensors are designed to observe these changes often associated to wireless sensor network (WSN) system applied for the detection of explosives substances. The main properties considered for explosive detection procedure includes the chemical characteristic, mechanical nature and physical nature of the material. The chemical nature of the explosive substance does change the chemical nature of the material in its environment, resulting in alteration in environmental composition of the surrounding. Sensors that have either chemical or physical ability to detect these changes are usually used to respond to these chemical and mechanical changes. It should be noted that the mechanical nature of substances are physically related to the motion of substances such as pressure and speed of these explosive substances and are easily detected using mechanical sensors (Al-mousawi & Al-mousawi, 2019)

The focus of current technological advancement in the study area is towards early detection of explosive and the trace detection method which is a faster approach, since at certain pressure and temperature, solid and liquid substances yield vapours that depends on the quantity of that vapours to produce a volatility of a substance. A suitable approach of sampling of the gas and analytical methods in the presence of particular substance makes early detection possible depending on the level of concentration of the substance. The possibility to detect the vapours of interest is directly determined by how volatile the substance maybe (Wasilewski & Gębicki, 2021). Early detection of explosive substance that could possibly be used is beginning to take preference in detection approach. In this approach used for early detection, substances that could be used to manufacture explosives with emphasis mainly on trace of such substances within the areas that are meant to be explosive free are been explored. It has been established that IED are types of bonds commonly used by terrorist and they are made up of certain chemicals (Wang et al., 2019).

1.2. Problem Statement

Terrorism and the proliferation of explosives has caused serious damage in public places and has become an issue of serious security concern across the world (Obasi et al., 2023), with most public places such as airports, trains stations, government institutions and facilities being targeted, thereby endangering the safety of people and facilities. How can these target areas be safe from explosions and terrorists attack without necessarily exposing human security personnel to such danger? In an attempt to solve the aforementioned problem several approaches have been used such as animal Chuen *et al.,* (2020), chemicals ions Adegoke & Nic Daeid, (2021) Hao *et al.,* (2022), mechanical devices, X and gamma rays, neutrons(Al-mousawi & Al-mousawi, 2019) and electronics nose-based Liu et al., (2019). These methods have been developed to be intelligent and effective in monitoring wild area and have a short range of detection. Also, these approaches sometimes result in bulky instrument for detection that become too noticeable, such visibility could make terrorists to attempt to beat the solutions provided (Wongwattanaporn, 2021). Since the explosive trace properties cannot be identified or detected by the human senses, an artificial intelligent based system can be deployed to detect the presence of explosive trace within an environment with high accurately. Sensor network are able to sense explosive trace properties and represent same as numeric values that can serve as input to another system (Al-Mousawi & Al-Hassani, 2018). This is based on the ability of the sensor to track the chemical and physical characteristics of the traces that these explosives emit to the surrounding environment. These substances can be traced by Artificial Intelligent (AI) based wireless sensor network (WSN) that are highly sensitive. The accuracy of the sensor network is very paramount to have a sensitive robust system. Explosive trace substance data are scarce as a result of privacy and ethical concern, which will make deep transfer learning (DTL) approach one of the best techniques to solve this study's problem statement.

The DTL model was based on sensor output labeled from a time-series data collected other source trained for deep neural network (DNN). The DTL was used to learn the general behavior of time-series data before transferring it to another DNN that is developed for the purposed of explosive trace detection. Peculiar features of explosive traces are usually extracted through the normal traditional method of feature extraction which has now been overshadowed by an automated approach of feature learning such as the DNN (Huang *et al.*, 2020; Fisher et al., 2020).

Various types of sensors network can be utilized in collecting different gaseous component together with the physical properties of the environment. In this research, sensor-based data of explosive trace were collected at various location within an environment, and used to developed the machine learning model based on DTL.

In order to realize the purpose of this research, there was need to introduce an Artificial Intelligent model for securing a learning environment with high selectivity and accuracy with the capability to adapt speedily with limited explosive trace data (Yaqoob & Younis, 2021), as a result of restriction in explosive chemical production (Omijeh & Okemeka Machiavelli, 2019). Several others such as traditional machine learning models used to solve similar problem can only detect explosive that have been trained and the deep learning model requires much time and large volume of dataset for training (Wang et al., 2022). A model called Deep transfer learning for explosive trace detection (DTLETD) that can use limited explosive data was designed in this work to accurately detect explosive trace among other chemicals in a learning environment with a reduced training time

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1.3. Aim and Objectives

The aim of this study is to develop a model for area-based explosive trace detection using deep transfer learning. The specific objectives of the study are:

I. To carry out requirements elicitation of area-based explosive trace detection
II. To design a framework for the detection of explosive traces using Deep Transfer Learning algorithm
III. To implement a prototype of the framework for area-based explosive trace detection using deep transfer learning
IV. To evaluate and benchmark the performance of the developed model relative to a current state-of-the-art model

1.4. Research Methodology

Table 1.1 shows the mapping of the objectives to the research methodology with corresponding question to be addressed. The requirement for explosive detection was established through literature and the model for explosive trace detection using deep transfer learning was designed using appropriate design tool. The proposed model was implemented using python and its Libraries. The last objective to evaluate the deep transfer learning model was achieved using confusion matrix.

Table 1.1: The objectives, research methodology, and research questions mapping.

SN	Research objectives	Research Methodology	Research Questions
I	To Carryout requirements elicitation of area-based explosive trace detection	-Literature review -Primary and secondary sources of data.	What are the requirements of area-based explosive trace detection?
II	To design a framework for the detection of explosive traces using Deep Transfer Learning algorithm	-Use of schematic diagram, Visio, draw.io Unified Modelling Language (UML)	How can a framework for the detection of explosive traces using Deep Transfer Learning be designed?
III	To implement the framework for area-based explosive trace detection using deep transfer learning	-Use of Python -Anaconda.Navigator, Jupiter Notebook. -Support Vector Machine. -Libraries: Pandas, Numpy, Sklearn, matplotlib, imblearn, etc.	How can a framework for the detection of explosive traces using Deep Transfer Learning be implemented?
IV	To test and evaluate the performance of the transfer learning model and benchmark with other state-of-the-art model like SVM, KNN, CNN, ImageNet and AlexNet	-Standard machine learning evaluation techniques (Recall, Precision, F1-Score, Accuracy),	How can machine learning models of Deep transfer learning be evaluated to determine the level of accuracy?

1.5. Scope of the Study

This research proposes to detect explosives within an area by using the common trace of explosive material. A deep learning model was be developed to detect the presence of explosive trace from the limited available data collected from sensor array network. This model expected to be accurate, fast in detection and at the same time light weighted to be able to run on edge device. The system was not considered for the bulk type of explosives, however the model can be train to work on bulk-based sensors. The system will be validated using dataset generated from a simulated setup to determine the performance of the developed model. The work will not consider sensor and wireless sensor placement. The developed model is not expected to be used on edge devices, since it's outside the scope of this work.

1.6.Significance of the Study

Explosive-based terrorism has become a known means of carrying out attacks on public places, such as learning environment, train station, airports and sensitive facilities which has caused a lot of damages to lives and properties. The reason for this rise in explosive attacks is because explosive-based weapons can easily be manufactured, deployed and can have multiple effects. The need for protection of public environment and lives has given rise to environmental monitoring system that could quickly detect traces of explosives before causing havoc to lives. The selectivity and accuracy of sensors-based system is of paramount importance to have a system that is reliable in the presence of noise. This work tries to improve the selectivity and accuracy of explosive trace detection through the development of machine learning based model that utilizes the DTL approach. The model can work in a new environment with easy adaptation with limited dataset.

1.7.Definition of terms

- Conventional machine learning: this can be any machine learning approach other than deep learning that passes through the process of separate feature extraction process through which the machine learns
- Deep Learning (DL): it is a branch of machine learning model that uses backpropagation for pattern recognition without manual feature extraction.
- Edge devices: These are devices that serves as entry point into service provider core networks, they connect local area network to an external network for data accessibility everywhere.

- Explosive trace (ET): these are microscopic particles from explosive substances that can change the physical property of an environment.
- Sensor: device that response to variable input within the environment and give corresponding noticeable response that can be read by machines or human beings.
- Transfer Learning (ML): machine learning approach that uses the knowledge gained from a particular task to improve the performance of another related task

1.8.Organization of Thesis

This thesis has different chapters with each chapter contributing to the overall objectives of the work. It has the data acquisition part and the software development part to achieve the aim. Chapter one seeks to introduce the overall work, the aim and objectives, and scope of the research, while Chapter Two provides the detailed review of relevant literatures. Chapter Three covers the research framework, methodology, data used, the machine learning approach and the experimental setup. The experimental results and discussion are covered in Chapter Four. The conclusion is explained in Chapter Five with essential recommendations and possible further research.

CHAPTER TWO
LITERATURE REVIEW

2.1 Theoretical Framework

This chapter describes the basic concepts and theories related to this current research. Concepts discussed include Improvised Explosive Device (IED), explosive trace detection, wireless sensor networks, explosive trace detection, and machine learning approaches for explosive detection with focus on deep transfer network.

2.2 Improvised Explosive Device (IED)

Bombs that are manufactured at home or roadside using certain chemicals are IED whose manufacturing process does not follow the normal military conventional way of producing bombs. IEDs could be used by insurgents and terrorists for suicide mission and mass destructions of targeted areas. Since they are improvised, they can exist in divers' forms that could be like small pipe bomb or a form of sophisticated device that could cause massive destruction to lives and properties IEDs are usual hide in vehicle or carried by human beings, concealed in package; or place by the roadside (Gill et al., 2011). It contains an explosive substance that could be combine with other materials that could blast with the ability rippled destructive effect. These substances can be dynamite, gunpowder, and nitroglycerin, blasting caps, detonating fuses, black powder, and gunpowder. Some other substances could be combustible but not regarded as explosive because they do not emit ionizing, gasoline, oils, etc. are in that categories (Sapir & Giangrande, 2009). Some explosive chemical and compound are commonly available and can easily be accessible within most countries, civilian therefore easily manufacture IED illegally to cause civic unrest in the society(Wilkinson et al., 2007). IED can be used in any place, it can be dropped by the road side, brought into military barrack and area localized target.

Principally, IEDs is made up of an initiator, a detonator, an explosive charge, and a casing or collection of projectiles (such as ball bearings or nails) that produces lethal fragments upon detonation. In reality, it consists diver kinds of substance such as artillery or mortar rounds, aerial bombs, and some varieties of fertilizers, compound like TNT. It could as well contain radiological, chemical, or biological part to increase their lethal and psychological effect

(Mansoor, 2018). The effect of the IED mostly depend on the explosive used, those target at structure will have higher explosive to generate much more effect.

Explosives bombs can basically be classified into three main categories according to (AL-Mousawi & K. AL-Hassani, 2018). The first category is the military bomb which are said to be of a high standard in preparation and so need special intervention from governments. The manufacturing procedure is very complex and it requires high cost because of special devices involved that makes these types of bombs not readily available. The commercial or industrial bombs are the types of bombs that are used in the industry for process such as to detect metals and destruction of hard metallic substances. These categories are always developed in scientific laboratories. The third category is the improvised explosive devices that are mostly used by terrorists for unlawful attacks this is because it is easy to produce since the material for its production are readily available and as no special equipment is also required to manufacture it. This form of explosive can be of two categories with the first been an IEDs and the second category is the mobile type that like car bombs (AL-Mousawi & AL-Hassani, 2018).

Most commonly used approaches in explosive trace detection approach are sensor-based detection, Gas Chromatography (GC), Mass Spectrometry (MS), and Mobility Spectrometry (MS). The vapor and particulate emission are what the trace explosion detection approach utilizes for its detection. Different vapours are emitted from explosive particles such are used for research in explosive detection obtained from RDX, TNT and other explosive materials that include nitro aromatics, nitroaminies, nitroesters, acid salt, ammonium picrate, and organic peroxides. RDX is associated with the vapour nitroamines while the TNT is associated with nitro aromatics. Nitro amines for vapour trace explosive detection are associated with the explosives such as RDX: 1, 3, 5-triazacyclohexane, HMX: Octahydro- 1,3,5,7 –tetranitro-1,3,5,7 –tetrazocine and NQ: Nitro guanidine. Explosives associated with nitroaromatics include TNT: 2,4,6- Trinitrotoluene, TNB: 1,3,5- Trinitrobenzene, DNB: 1,3- Dinitrobenzene, 2, 4 DNT: 2,4 – Dinitrotoluene, 2, 6 –DNT: 2, 6 –dinitrotoluene, Tetryl: Methyl-2, 4, 6-trinitro-phenylnitramine, 2AmDNT: 2-amino-4, 6 – dinitrotoluene, 4AmDNT: 4-amino-2, 6 – dinitrotoluene, NT: Nitrotoluene (3 isomers), NB: Nitrobenzene and EGDN: Ethylene glycol dinitrate. Ammonium nitrate and urea nitrate are related to acid salt. Nitroesters are associated with NG: Nitroglycerin (glycerol trinitrate) and PETN: Pentaerythritol tetra nitrate. Picric acid relted exlsoive materials are AP/PA: Ammonium 2, 4, 6-trinitrophenoxide/2, 4, 6-

trinitrophenol while organic peroxides are TATP: Triacetone tripede and HMTD: Hexamethylene triperoxide diamine.

Most of the component used in manufacturing of IED products can be found with the description is shown in table 2.1. Most of these explosive components for the manufacture of IED can easily be found in medical stores and that makes the production easy.

Table 2.1: Common Explosive Component (AL-Mousawi & AL-Hassani, 2018).

SN	EXPLOSIVE SUBSTANCE	NATURE/WHERE TO BE FOUND	EXPLOSIVE IDENTITY
1.	Hydrogen peroxide	Can be found at chemist or pharmaceutical shop	IED
2.	Acetone	Can be found at polish remover, also as part plastic substance	IED
3.	Mercury	Can be found in dental stores in a form of toxic substance.	IED
4.	Ethyl alcohol	Can be called ethanol as well and can be found in medical shops.	IED/ military
5.	Methyl alcohol	Very flammable substance and can be used as antifreeze, can be called methanol and used as wood alcohol	IED
6.	Hexamine	This chemical substance removed from the white cool, white cool available on big stores.	IED
7.	Sodium acid	Available in medical store	IED
8.	Sodium nitrate	Known as Soda Niter, can be found at the agriculture stores	IED
9.	Ammonium nitrate IED	Available at agriculture stores	IED
10.	Potassium nitrate	Also known as nitrate, available at agriculture stores	IED

11.	Lead nitrate	Compound can be found at agriculture shops	IED
12.	Barium nitrate	Chemical compound can be found at agriculture stores	IED/ military
13.	Urea	Known as carbamide, available at the agriculture shops	IED
14.	Sodium carbonate	It is used to make papers and glasses, known as sal soda washing soda, and soda ash. Available at supermarkets	IED
15.	Sodium bicarbonate	A white soluble compound used in baking powder, known as baking soda, soda bicarbonate. Available at supermarkets	IED
16.	Ammonium hydroxide	Sometimes called ammonium water, can be found in supermarkets	IED / Military
17.	Potassium chlorate	Known as bleaching agent, chemical compound can be found at the supermarkets	IED
18.	Sulphur acid	Used as a vehicle's battery filler, known as battery acid	IED / Military
19.	Nitric acid	Available at the gold shops, known as aqua fortis	IED
20.	Aluminium powder	Available in painting store	IED
21.	Citric acid	A weak water-soluble acid. Can be found at the supermarkets	IED
22.	Acetic acid	The colourless pungent liquid widely used in the plastic manufacturing can be found at the supermarket.	IED
23.	Potassium permanganate	Used as a water cleaner, used in oxidising and bleaching agent, known as permanganate of potash,	IED
24.	Nitrobenzene	Oily high toxic water, used for screen cleaning, used to manufacturing aniline	IED
25.	Glycerin	Available in the medical store	IED / Military
26.	Petroleum Jelly	A semisolid mixture of hydrocarbons obtained	IED

		from petroleum, known in the market as (Vaseline), can be found in medical shops	
27.	Charcoal	This chemical element can be found at the leftover of wood burning	IED
28.	Hydrazine hydrate	Can be found on sponges	IED

These explosive chemicals can either be pure individual/single explosive or mixture of two or more chemical to produce the explosive. The single explosives can also be referred to every explosive compound that its unimolecular decomposition reaction may produce an explosion. Thy are pure compound that are consist of various atoms chemically bonded which can be of two categories of compound of either inorganic or organic as a result of the chemical compound (Zapata & García-Ruiz, 2021). Figure 2.1 show a comprehensive classification of explosive chemical. The pure individual explosive which is divided into organic and inorganic contain peroxide, nitro, organic azides, Halogen amino compound and other organic explosives, while the inorganics explosive contains the non-metal and metal explosives. The most common chemical found in this classification are TNT class, TATP class or the nitroguanidine (with one atom of carbon) while the TNT has seven atom of carbon and TATP has nine carbon atom. Others are the peroxides, Nitro explosive, Ammonium nitrate (NH_4NO_3), Chlorate-based explosives etc.(Zapata & García-Ruiz, 2021). Knowing these chemical constituents can the narrow the detections of the explosive trace to the response base on the sensor response to these chemicals. Majority of high explosives substance are described by this formula $C_a H_b N_c O_d$, it contains both oxidiser (O) and the fuel (C, H). Some of this substance can also have low sensitivity and that will demand high sensitivity sensor to be able to detect explosive trace using such (Jimenez & Navas, 2007). Most common explosive are nitrate base but the hydrogen peroxide has become popular because of terrorist. The approach appropriate for direct explosive traces detection in the form vapour that can detect explosive concentrate at below 1 ng/L.(Jimenez & Navas, 2007)

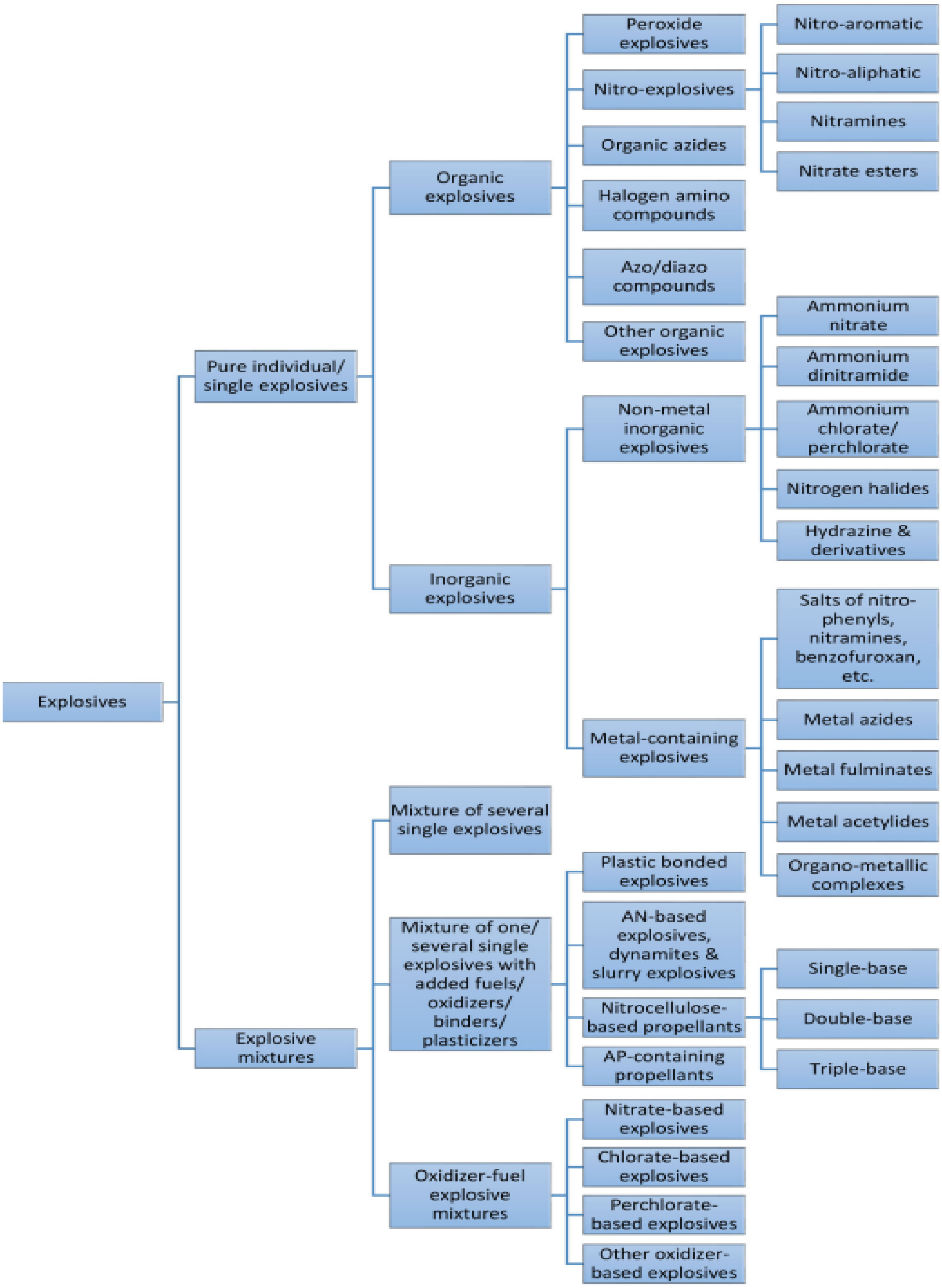

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Figure 2. 1: Classification of Explosive Chemicals (Zapata H & García-Ruiz, 2021)

2.3 Explosive Trace Detection Methods

Generally, explosive detection approach can be categories in two ways, the trace detection method which focuses on vapor/particles that could lead to actual explosive and the bulk detection method which find actual explosive. Figure 2.2 shows the two methods of explosive detection which are the bulk detection and the trace detection method. While our interest id on the trace detection approach, we shall give brief insight into the bulk detection approach.

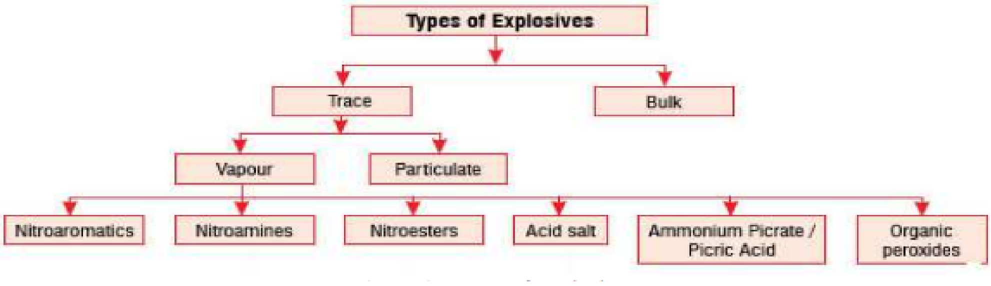

Figure 2.2: Explosive Detection Methods(Zafar et al., 2017)

2.3.1 Bulk detection method

The bulk explosive detection approach tends to detect explosives that are obvious to human that is big in size but sometimes maybe concealed, this approach tries to use high penetrating capacity system to clearly detect explosive presence. This methods of detection can either be imaging-based methods or nuclear-based methods(Kishore Kumar & Murali, 2016). The bulk detection approach apart from image target could also targets high nitrogen, oxygen content and high bulk density of the explosive substance (Marshall & Oxley, 2009).

Imaging approach such as various X-ray methods like single- energy X-ray, dual-energy X-ray, and computed tomography approach are employed for the bulk detection of the explosive. Most bombs have unique spatial features and specially shaped metal components like wires, detonators, and batteries. These components allow some level of discrimination from the background due to explosive dielectric constants for X-ray and microwave imaging approaches. The reflection, absorption, and scattering for various explosives in a set of spectral bands can be classified, and this information can be used as a data base for image analysis.

There are several imaging techniques that utilizes radiation with wavelengths from the range of radio waves to gamma rays(Kishore Kumar & Murali, 2016). Some method found in these techniques involve the use of X-Rays, Infrared, Terahertz and Microwaves. Another important method is the nuclear based approach that includes the use of thermal neutron analysis, pulsed fast neutron analysis, nuclear quadrupole resonance. Each method has its own advantages. In these detection methods screening of personnel in sensitive places, screening cars and items in the ship. Hidden bombs are searched to ensure protection of lives and infrastructure. One of main concern in deploying these methods is health issue(The National Research Council, 2004).

2.3.3 The Trace Detection methods

Explosives can also be detected in a form of trace associated with the explosive. In this methods vapour/chemical emitted from explosive or explosive particles within the surrounding is used to detect the presence of explosive (Kumar et al., 2019). These explosives could exist either as a vapour or particulate form. If it appears as a vapour, it is found in the air but if it is in particulate is in a form of the residue of explosive material that adheres to surfaces of the object premise (Kishore Kumar & Murali, 2016).

In the trace detection approach, efforts are being made to track the chemical properties of the explosive substances and also its physical properties within the surrounding environment. Any of these chemicals has the ability to effect changes within the surroundings and this will greatly affect the properties of the environment (Al-mousawi & Al-hassani, 2017). The basic property used in explosive trace detection system is the chemical signatures of the explosive that easily alter many chemical constituents within the vicinity of its presence, this sudden in the surrounding of interest can be detected using chemical sensors like electronics nose. The other properties of consideration is the mechanical properties and physical properties *(Al-mousawi & Al-hassani, 2017).* The physical and mechanical properties are physical and all are related to how the explosive moves, the speed of movement and pressure, these properties are handled by mechanical sensor.

The vapour component is referred to as the gas molecules released from either solid or liquid explosive material. For proper detection of this trace some other information that are very important are the explosive concentration in the air known as vapour pressure, the frequency of explosives material in the environment, air flow in the environment , etc. The particulate are the tiny explosive substance that are like a form of leftover on the surface of object or human being that have made contact with the explosive through any means. The vapour sampling requires no contact while the particulate sampling requires direct contact to remove explosives material particles from a contaminated surface. This different form of explosive trace makes the detection system to have advantages and disadvantages in its approach (Thiesan et al., 2005). To overcome the setback, one of the best approaches is to consider the specific chemical from the target compound in the material that is used to manufacture explosives rather generalized property. This help in reducing the probability of false alarm compared to bulk detection methods which focus on the typical property (Marshall & Oxley, 2009).

The three main categories of explosives are the Nitro aromatic explosives, Chlorate based explosives and the Peroxide based explosives. The traditional form of explosive detection has not been so effective because these techniques of detection of are large and terrorists can easily notice them and try to beat them(Zafar et al., 2017). Hence the need to use detection system that are not visible to human eyes and are economical to be set up in public places. Explosive detection evolution shows some natural beings like animal are efficient sensors for detecting explosive traces in an environment. Like the dogs could be trained on particular explosive material so well that anytime they smell the fragrancen of such material in the environment they can alarm their handler for the presence of explosive material. The limitation is that when dogs are tired of smelling they become ineffective. Honey bees are said to be most effective sensors used like the trained dogs but very difficult to harness and are not commercially available. Also considering the fact that some methods such as X-ray are visible and take more time to detect explosive (Zafar et al., 2017), the Wireless Sensor Network detection method has become a better method.

Automated means of detecting explosives is unavoidable in the present reality because of how frequent terrorist have started attacking and causing alarming destruction in sensitive's environment so it is necessary to have a workable intelligent system that could provide relevant information for needful actions against explosive based attacks (Kishore Kumar & Murali, 2016),. At a certain temperature, solids and liquids release vapour to the environment, the amount of vapour released can be used to determine the nature of that substance. The sample of this vapour are is collected without making contact with the surface of the material, sampling and analysis are air-borne. Since some explosive substance do not evaporate easily as a result material that depend on the vapour pressure hence, sampling strategies are very important due to the usually small amount of vapor- phase explosives material emitted from solid explosives material.

2.4 Machine Learning Approach in Explosive Trace Detection (ETD)

Machine learning (ML) is subset of Artificial Intelligent (AI) makes machine to receive data, analysis them and make decision without or with minimal human intervention, it's a trainable assistant system adapting to individual user's objectives, the system can be trained to achieve what the user intended it to achieve (Díaz-Ramírez, 2021). Machine can also be trained to scan environment. As research in ML keeps progressing, we have seen recent development in intelligent systems that make systems to behave like human with capacity that enables systems to do the work of human beings (Shrestha et al., 2021). This makes ML learning finds application is several fields like security. The development of a capacity-based systems that can solve advanced problem is generally referred to as artificial intelligence (AI), these systems used analytical approach algorithms to predictions, generate rules, give answers, recommendations, or similar outcomes in solving problems. This relieves humans of their burden and the risk of doing certain task by transferring their knowledge into a machine-accessible form and allow the development of an intelligent systems that will work efficiently (Díaz-Ramírez, 2021).

The fundamental concept of AI shall briefly be discussed for clarity and since Ai is not an entity, its relationships and differences with ML algorithm, Artificial Neural Networks and Deep neural networks shall be expressed. The Venn diagram in figure 2.3 shows the relationship between them. Generally, AI is the compound word that represent all technique that makes computers to learn how to be intelligent as human beings in reproducing whatever it learnt and making decision in solving complex tasks with minimal human intervention.

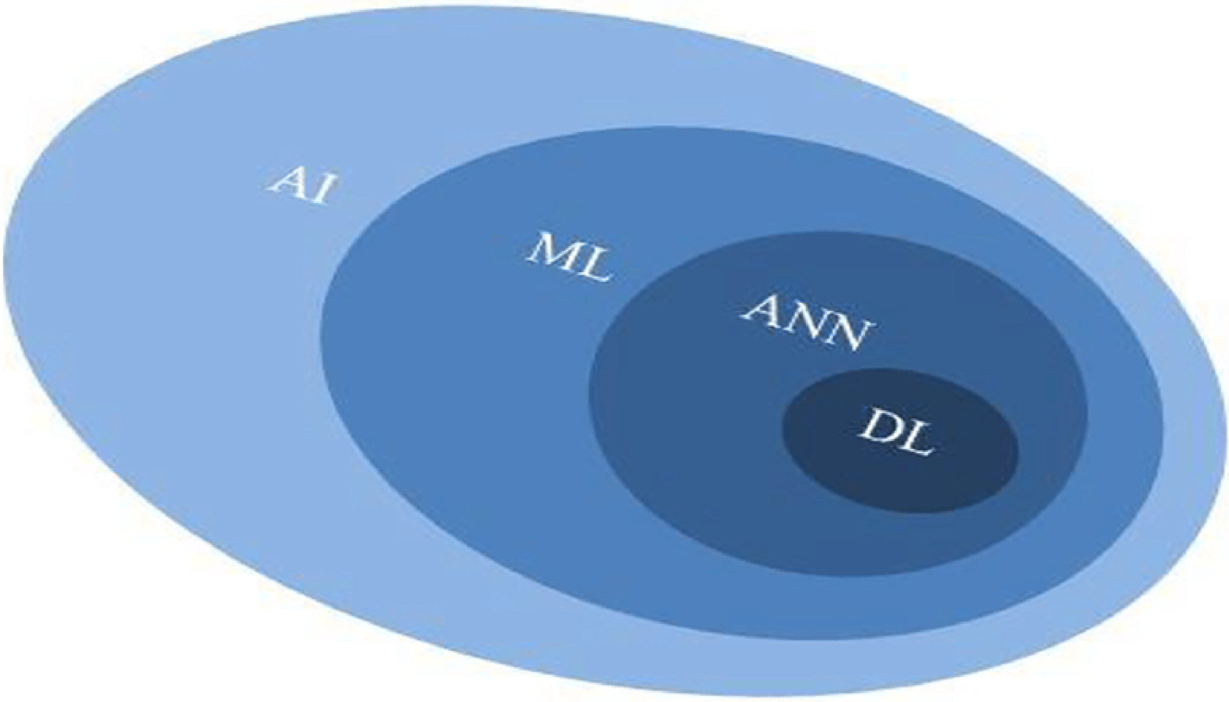

Figure 2.3: Relationship between AI, ML and DL (Aljojo et al., 2022)

AI research in the first stage is interested in hard-coded expressions that follow a set of rules that a computer can understand and carry out a logical decision. This is referred to as knowledge-based system and this is found to have limitations of not being able to handle complex task that ML approach has to solve (Díaz-Ramírez, 2021). ML is referred to computer program whose performance keeps improving as it keeps learning through experience with respect to assignment and certain performance measures (Jordan & Mitchell, 2015). It target how to automate assignment by using analytical approach to build performance cognitive tasks to detected object. It does that with the help of algorithms that keep learning from the task training data that makes the machine to have in-depth understanding of complex patterns even when fresh programming is not involve. When the system learns from pools of data that relate to classification, regression, and clustering, ML seems to be very reliable and perform that task with repeatable decision. ML model have gained success in several application area like image recognition, natural occurrence predations, natural language processing (NLP), etc. (Díaz-Ramírez, 2021). Generally, ML is divided into three types which are; supervised learning, unsupervised learning, and reinforcement learning. The supervised learning is majorly used in several applications that electronic markets.

Machine learning algorithm has some limitations such as inability to handle large volume of data (big data). Its approach focuses mainly on hand encrypted features which demand that the system carefully learn those feature and extract them before taking decision based on these and these will take a lot of time. This model also has another limitation known as vanishing gradient and over fitting that tends to reduce the performances of the training models (Aljojo et al., 2022). These limitations are what leads to the emerging of Deep learning (DL), DL can handle complex data efficiently without experiencing the drawback of ML and this has made DL more acceptable than the traditional ML algorithm.

2.4.1 Traditional Machine Learning Concept

A group of methods and algorithms known as "traditional machine learning" were created prior to the development of deep learning. These algorithms are frequently used for many machine learning tasks, such as classification, regression, clustering, dimensionality reduction, and more. They are primarily based on mathematical optimization and statistical concepts. These are some of the fundamental ideas and techniques of conventional machine learning. Experience generates the matching algorithm model, and machine automated learning is truly the process that generates the algorithm model. Machine learning researches these learning algorithms (Zheng, 2023). The process of creating new things, reasoning with insufficient knowledge, digesting current big data trends, and replicating human thought processes are all included in the production of learning algorithms. Currently, supervised learning algorithms, unsupervised learning algorithms, and semisupervised learning algorithms comprise the majority of classical machine learning algorithms. Regression and classification algorithms are the two main categories of supervised learning algorithms. Using continuous functions to match input and output variables is known as regression. The matching of discrete categories and input variables is known as classification. Unsupervised learning implies that the final product is unknown beforehand. For instance, clustering allows us to extract a unique structure from the data. In unsupervised learning, there is either no label or just one label (Sarker, 2021) A learning strategy called semisupervised learning combines supervised and unsupervised learning. There are two types of data in machine learning: marked data and unmarked data. Learning may be made more accurate and efficient by using semisupervised learning.

A binary classification algorithm that supports both linear and nonlinear classification is called support vector machine (SVM). It is now commonly used in regression and classification and supports multivariate classification after evolution. It effectively resolves nonlinear, small sample, and high-dimensional issues and resolves the issues raised by conventional approaches. Experiments demonstrate that this approach excels in various domains and has grown to be an essential component of the machine learning community.

SVM is essentially a decision-making tool that classifies sample data; its true purpose is to solve. The classification problem is converted into a quadratic programming problem by first determining the maximum classification interval and then identifying the ideal classification hyperplane. The element problem is converted into a dual problem and subsequently into a convex quadratic programming problem by applying the Lagrangian optimization technique. In order to solve the optimization problem in this procedure, relaxation variables must be added if the sample points are linear and indivisible. The kernel function is utilized to solve the problem if the sample is nonlinear (Sarker, 2021).

With its strong classification performance, support vector machines (SVMs) have taken the machine learning world by storm since their invention.

Support vector machines are effective in high-dimensional spaces and can behave differently based on different mathematical functions. In high- or infinite-dimensional space, they construct a hyper-plane or set of hyper-planes. Intuitively, the hyper-plane, which has the greatest distance from the nearest training data points in any class, achieves a strong separation since, in general, the greater the margin, the lower the classifier's generalization error:(1) Gaussian radial basis kernel function; (2) Polynomial kernel function; and (3) Linear kernel function(4) The kernel function sigmoid

Another traditional machine learning approach is the K-nearest neighbors (KNN), it is referred to as a "lazy learning" method. It said to be "instance-based learning" or non-generalizing learning algorithm. It retains all instances corresponding to training data in n-dimensional space, rather than concentrating on building a generic internal model. KNN use similarity metrics, such as the Euclidean distance function, to classify new data points using existing data (Barupal & Fiehn, 2019). The k closest neighbors of each point vote with a simple majority to determine the classification. Accuracy is dependent on the quality of the data, but it is rather resilient to noisy training data. The most significant problem with KNN is determining the ideal number of neighbors to take into account. KNN is useful for regression as well as classification.

There are other traditional machine learning algorithm that can used for detection and classification of explosive trace data with appropriate parameter selection.

2.4.2 Deep Learning Approach in Explosive Trace Detection

The Deep Learning algorithms will record better perform whenever larger dataset is to be considered because it eradicates the challenge of vanishing gradient and overfitting which is a serious problem with traditional ML. It can bring out hidden information that are very relevance in large volume of dataset(Alom et al., 2019). Neural Networks (NN) is associated to ML, and that is where DL evolved from and since its emergence it has proved to be outstanding in almost all application domain. Deep Learning utilizes deep architectures or hierarchical learning approach, it is a subset of ML that became so pronounced from 2006 onward. Learning is a process that tries to estimate the system parameters so that the learned algorithm could carry out assigned task. The Artificial Neural Networks (ANN) uses the weight matrices as the parameter and it is made up of many layers in between the input and output layer that made it possible for non-linear data processing units with hierarchical architectures to be available for exploitation of feature learning and pattern classification (Schmidhuber, 2014).

DL has become so popular because of various successes it has recorded in complex data in object recognition detection and segmentation, image classification and localization, face and speech recognition and so on. In addition to these, DL is better intense of feature engineering, and feature extraction (Díaz-Ramírez, 2021). These advantages make DL the best model for explosive trace detection. Deep learning has become a strong analyzing model when dealing with high volumes of information that is generated through sensor network especially in an environment polluted with high level of noise and complex situation that make the conventional machine learning techniques difficult to be apply (Li et al., 2018). This problem can be easily solve by deploying Deep learning approach is seen as the best appropriate method since explosive traces has to be precisely detected in a complex and noise environment. The deep learning model with many layers can be scaled down to find sufficient features that can be applied to edge device.

2.4.3 Deep transfer learning for Explosive Trace Detection

DL tries to focus on reduction of training time of data especially when considering the cost implication of nonlinear data. Extensive training datasets is hard to retrieve in certain cases leads to the introduction of deep transfer learning (DTL). With DTL a pre-trained model for a certain assignment can be applied on a simple edge device like a cellphone that is limited in processing power and need reduced training time. Its developments has led to an intuitive and high level of AI based systems because DTL sees learning as a continuous process (Iman & Arabnia, 2022).

In DTL, the model is first trained on one task, then the knowledge obtained from that model is used on another task or related task to reduce learning cost. A large amount of label data is necessary for accuracy in DL model and most time to get this dataset is very difficult and expensive, with the DTL higher accuracy can be gotten from small amount of trained dataset. There is also the need of reducing the processing power in ML models for it to work effective on edge devices like handsets, hence transfer learning is necessary.

To define a transfer learning using mathematical notation, let define what domain and task are. Say D is a domain that has two parts, made up of feature space X while $P(X)$ is marginal distribution. The Domain, $D = \{X, P(X)\}$. Where X is a symbol that shows the instance set and is

$$X = \{x|xi \in X, i = 1,...,n\}. \quad (2.1)$$

A task denoted as T with decision function f is made up of a space y, that is expressed as T = {Y, f}. f which is the decision function is to be learnt and generated from the dataset.
Certain machine learning algorithm usually gives the predicted conditional distributions of instances. This will yield,

$$f(X_j) = \{P(y_k|X_j)|y_k \in y, k = 1,...,|y|\}. \quad (2.2)$$

In essence, a domain is viewed and records the instances with or without the label data. For instance, say D_S is source domain that corresponds to source task, T_S that is always viewed through the instance-label pairs, that results in, $D_S = \{(x, y)|X_i \in X^S, y_i \in y^S, i = 1,...,n^S\}$; the target comprises of instances that is not labelled either any of few number of labeled instances.

The TL, when assigned certain observations that corresponds to $m^S \in N^+$ of the source domains and tasks, that implies $\{(D_{Si.}\ T_{Si})|i = 1,...,m^S\}$, and some observations relating to $m^T \in N^+$ target domains and tasks $\{(D_{Tj.}\ T_{tj})|j = 1,...,m^T\}$, what transfer learning does is that the knowledge gained from the source domains is been used to improve learned decision functions f^{Tj} $(j = 1,....,m^T)_{Si.}\ T_{Si})$ on the target domains. If $m^S = 1$, we will have a single-source transfer learning scenario else it referred to as multisource transfer learning. m^T is the total sum of the TL assignment. Some research tend to make $m^T \geq 2$. The current transfer learning approach focuses more on scenarios where $m^s = m^T = 1$ (Zhuang et al., 2020)

DTL is not exactly same as semi-supervised learning, Multiview learning, i.e multitask leaning and another feature of the semi supervised learning is that the same dataset forms data source and target data. In this case the target data will not have labels, but Multiview learning approach differs because more than one datasets are utilized so as output of the task could be improved by the result obtained from another task. Like in video dataset, image data and audio data are separated. In the multitask transfer learning task are interconnected for the purpose of boosting each other while the transfer of knowledge happens the same time between all the tasks involved (Iman & Arabnia, 2022).

When we are considering the DTL, the interest is the target domain, and the knowledge needed for the target data is has been gotten from source data so, the is no need of running both the source and target data concurrently to obtain the necessary result (Iman & Arabnia, 2022). In the classification of DTLs groups based on label-setting three classes are considered; the transductive, inductive, and unsupervised approach. The transductive focuses on labeling the source data alone, inductive labels both source and the data of interest (target data) but in some cases none of the data is labeled it becomes unsupervised deep transfer (Zhuang et al., 2020). Another way to look at DTL approach is based on the aspect is been applied and this can be categorized into four which are: the instance-based, the feature based, parameter-based or network-based, and relational-based or adversarial-based. Instance-based transfer learning uses selected parts of instances sometimes all the instances in source data and apply different weighting approach on the target data to obtain result. In the case of Feature-based method instances or what is called features are mapped from both source and target data to form another homogenous dataset for result. The feature-based could be based on asymmetric approach of transfer learning or symmetric mode of transfer learning. While the Asymmetric approaches transform the source features to match the target ones, the symmetric approaches attempt to find a common latent feature space and then transform both the source and the target features into a new feature representation (Iman & Arabnia, 2022).

2.4.4 Edge-Computing Based Explosive Trace Detection

In edge-computing based system can be deployed to monitor the environment of interest against explosive trace, sensor network collect the ET information live and tries to communicate the information to edge computing server that will carry out expected data operation and analysis. This will result in reducing system energy consumption and network bottleneck (Fang et al., 2020). Edge computing is a modern technology that tends to minimizing the time the application will complete and the energy consumption of data transmission by distributing cloud resources closer to where data generation (Fang & Ma, 2021). The 'Edge' means to make computing device closer to the source of data. It is the distributed framework where data is processed as close to the originating data source possible and this tries to eliminate any form of delay in processing the output results. The processing of the data, storage and the networking get closer to the user.

Edge computing finds real application in WSN and this can be used to monitor the presence of ET in the environment. All the heavy ML model can be deployed in the cloud and the trained model can be deployed on the edge for real time prediction.

2.5 Sensor Network for Explosive Trace Monitoring

Sensor network compose of several sensors interconnected to monitor physical condition of an environment in real time, such condition could be temperature, pressure, pollutant sound, vibration or motion and explosive to produce sensory data that can be interpreted. The sensors can form an array or sometimes are connected through a wireless means called wireless Sensor network (WSN). The information gathered by the WSN is usually passed to the sink or base station which serves as an interface where human gets information from the network, which maybe through direct connection, satellite, internet, edge device or any type of wireless link (Fong, 2017).

A typical WSN contains several sensor nodes that can communicate with one another using radio signals. The sensor (radio) node consists of microcontroller, radio transceivers, power modules and external memory. The node can both serve as data originator and also data router. it receives what is sensed from the sensor and send it to the access point (sink node) (Suganya et al., 2019). The sink communicates with end user directly or through any wireless means. The sensors are used to capture the variable within the environment but convert this variable to electrical signal. The access point sent the data through the internet to the server where we have the evaluation software. The challenge of deploying entity nodes in WSN are lack of resource associated with it, there is limitation of speed of response, storage space, and channel bandwidth and these are areas researchers have tried to address lately. When Global Positioning System (GPS) and certain model are used on the WSN location and positioning information can be obtained (Matin & Islam, 2018). Figure 2.4 show a typical WSN with multiple sensors, sink and user. Multiple user and sink could be in cooperated depending on the coverage area.

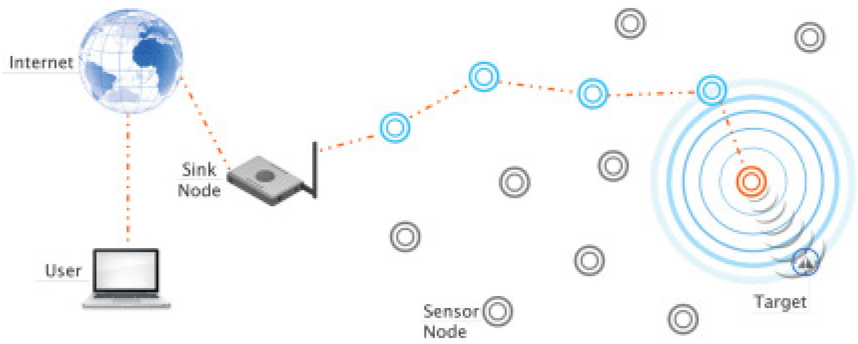

Figure 2.4: Typical WSN architecture (Matin & Islam, 2018)

When detection area to be considered is in a large public place, WSN must be deployed to cater such environment for adequate monitoring. With the help of WSN, a localized area can be monitored live using AI base system, data are collected, aggregated and forwarded to the server. When the defined characteristic is analyzed, prediction of explosive presence will be possible. Array of sensors forming WSN will be adequate to monitor the environment against the presence of explosive traces (Simi & Ramesh, 2011).

There are many types of sensors used for detecting system, Table 2.2, shows most sensor used for detection of explosive, all these sensors can be connected in different modes. The sensors that can easily be seen are those of thermal, photoreceptors, mechanical, chemical and physical sources. Table 2.2 is a descriptive table and characteristics of sensors according to (AL-Mousawi & K. AL-Hassani, 2018). The operation and description of the sensor will determine the quantity of the explosive it will be used to sense. We have different types of sensors ranging from chemical sensors, electrochemical sensors, and chromatography sensors and more, they are known based on the kind of sensing work they perform. Even though there are several types of explosives in existence that does not mean the same number of sensors are required. Explosives have some common features like geometry, material density, elemental composition, and vapor emissions that could clearly classify explosive for proper choice of sensor. For geometry properties, image shape is used. When explosive density becomes the focus, it is believed that explosive is denser than other material. Another class is the vapour emission feature that senses vapour samples and analyze those (Kishore Kumar & Murali, 2016)

Table 2.2: Sensors and their Characteristic Properties (AL-Mousawi & AL-Hassani, 2018)

S/N	SENSOR TYPE	FEATURES OF SENSOR	ENVIRONMENTAL CHARACTERISTICS
1.	Piezoresistive pressure sensors	Membrane-in-cooperated in the sensor instrument that causes resistive changes leading to pressure power	Pressure power applied on sensor
2.	Capacitive pressure sensors	The effect of pressure on the surface of the sensor causes deflection and noticeable change in capacitance	
3.	Optical Pressure Sensor	The sensor response to laser light from optical fibre cable that produce noticeable change of colour in response to pressure changes.	
4.	Resistive and capacitive accelerometers	A Piezoresistive is connected to the sensor deflectable cantilever that response to any alteration in resistance to yield movement	Acceleration force presenting by velocity
5.	Piezoelectric accelerometers	This is piezoelectric types of sensor that yield charges when sensing materials is stranded	
6.	Electromechanical temperature sensors	Respond through the effect of temperature on the sensor material that yield electromechanical motion that could be interpreted in specific area.	Temperature and Heat

7.	Resistive temperature sensors	Effect of temperature on resistance result in same effect of sensor data variations due to the resistance effect.	
8.	Thermistors	This sensor type has resistor with deflectable material that is changed with slight changes in temperature	
9.	Resistive temperature detectors (RTDs) sensor covers larger temperature range	This sensor make use of metal oxide and resistive temperature detector to bring a noticeable changes in the environment, it consist of pure metal	
10.	Humidity sensors the substance volume	Calculate the ratio of water vapours	Vapours in substance
11.	Resistive Humidity Sensors	Calculate the resistive variations in a known medium	
12.	Chemical sensors	The sensor contains sensitive indicating transducer and membrane that could respond to chemical substance.	Chemical components and materials
13.	Interdigital transducer sensors	Very sensitive layer using dielectric between electrodes, the dielectric properties in sensitive layer are changed according to the substance interaction	
14.	Conductivity sensors as gases	Highly Sensitive layer that conduct flow of current and relate with chemical materials.	
15.	Optical chemical sensors	The sensor has a layer that easily deflect in the form of optical waveguide, that quickly respond when there is contact	

		between the substance chemical and chemical substance that is of interest	
16.	Piezoelectric chemical sensors	Gives rise to an electrical charge on crystalline when it is being stressed	
17.	Radiation sensors	Monitors level of radiation to detect beta and gamma in the material	Everything associated with radiation
18.	Geiger-Müller counter	Made up of conductors that response to the level of radiation.	
19.	Quartz fibre dosimeter	Calculate and report rate of radiation received over time from a device.	
20.	Film badge	Dosimeter calculates the rate of radiation level coming the material to the sensing element	
21.	Thermoluminescent Dosimeter Measuring Magnetic Sensor	Calculate rate of radiation from visible light in the material, it make use of magnetic field sensor.	Magnetic field
22.	Light and brightness sensor Gyroscope sensor	Consist of up of basic optical operation that have operate like structural and logical form	light level and colours degree rotation ratio circuits

2.5.1 Communication of Sensor Network for Explosives Trace Detection System

The means of data transmission between sensors in WSN does not need any form of cable connection but by use of wireless medium. One of the limitations of this means of communication is its limited range, so the sensors and nodes must be placed in locations that are not far from each other to effectively transmit data. This radio frequency range must be carefully identified depending on the type of application because each application has its specific frequency range. The applications could be industrial, health and scientific applications (ISM bands)(AL-Mousawi & AL-Hassani, 2018).

The area under consideration where the Sensor nodes are evenly placed is referred to as sensor field. The node gather data within a sensor field and transmit this data to where it can be processed within wireless sensor network system by utilizing multiple hop arrangement. Passing information from the sensors to the processor is done through the internet or via the satellite communication medium. The sink is the connecting link between sensor nodes and the processing unit. (AL-Mousawi & K. AL-Hassani, 2018). Whenever information is to be shared between the sensor fields, it will be done by the Base station, while information sharing among sensor nodes ad-hoc network comes into play. In the design of WSN large bandwidth is always been considered for adequate space for smooth data transfer.

2.5.2 Explosive Sensor communication models

The mode of communication for Wireless sensor nodes is through the radio units. A particular node is linked wirelessly with another node to both transmit and receive data between each other. Mathematical model can be used to express the connectivity and transmission between the two sensor nodes. One of common communication model employed is the disk connectivity model proposed by (Fong, 2017), he said communication between sensor nodes are only possible within a disk and that it occurs within the range of the radius, the radius of its communication range is called communication hub and that is the range two sensors could communicate. This focus of this model is to use geometric approach to analyze network connectivity which is quite simple in analysis but has limitation and not quite realistic because there is not clear boundary between the successful and unsuccessful communication.

Within a particular distance the attenuation of a wireless signal is a function of path loss and shadowing within that path referring to as path loss is express as to be the random fluctuations in signal strength. Through empirical measurements it was established that shadowing have proved to have zero-mean normally distributed random variable with standard deviation (SD) δ_{ϵ} (Fong, 2017). Environment varies in nature so most radio propagation models combines both analytical and empirical approaches determining path loss shadowing. The popular model is the radio propagation approach, by this log-normal shadowing path loss model which is given according to (Fong, 2017) as:

$$PL(d) = PL(d_r) + 10\gamma log_{10}\left(\frac{d}{d_r}\right) + \epsilon \tag{2.3}$$

PL is the path loss between transmitter and receiver, distance between transmitter-receiver is denoted as d, while d_f is a reference distance and γ is the signal decay rate or what we call path loss exponential, then ϵ is a zero-means Gaussian distributed random variable that has SD of δ_{ϵ} (dB) that expresses the shading effects.

At distance d, the output power of the transmitter less the $PL(d)$ is the received signal strength P_r. That is express as:

$$P_r(d) = P_t - PL(d) = P_t - PL(d_f) - 10\gamma log_{10}\left(\frac{d}{d_f}\right) - \epsilon \tag{2.4}$$

For a given value for which $\gamma = 2$, $\delta_{\epsilon} = 4$, $PL(d_f) = 15dB$, $d_f = 1$, and for an output power

$P_t = 0\ dB$, the CC2420 IEEE 802.15.4, with 2.4GHz, the analytical propagation model is shown in Figure 2.4.

From equation (2.4), $P_r(d) \sim N(P_t - PL(d_f) - 10\gamma log_{10}\left(\frac{d}{d_f}\right)\delta_{\epsilon}\ ,)$. Since $P_r(d)$ is a Gaussian, that information from sensor 1 get to sensor 2 as expected is expressed as a function of probability the two sensors , $s_i\ and\ s_j$ located at distance d from each other is given as:

$$\rho[P_r(d) > SS_{min}] = Q(\frac{SS_{min} - \left(P_t - PL(P_f) - 10\gamma log_{10}\left(\frac{d}{d_f}\right)\right)}{\delta_{\epsilon}}) \tag{2.5}$$

Where $SS_{\epsilon mim}$ is referred as the minimum acceptable signal strength and Q is is the complementary cumulative distribution function of a standard Gaussian, so

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_{x}^{\infty} e^{-\frac{t^2}{2}}dt \tag{2.6}$$

Figure 2.5 is the channel path through which the signal is transmitted, it is observed that the strength of the signal fades with distance. Figure 2.6 shows the formulated connectivity indicating how some area that supposed to receive connection are being discarded with receiving power less than $SSmin$ while some other area receives power more than what is expected, i.e., beyond the connectivity range receive of $SSmin$. The main limitation is that there is no clear separation to determine the successful and unsuccessful communication among the sensors (Fong, 2017).

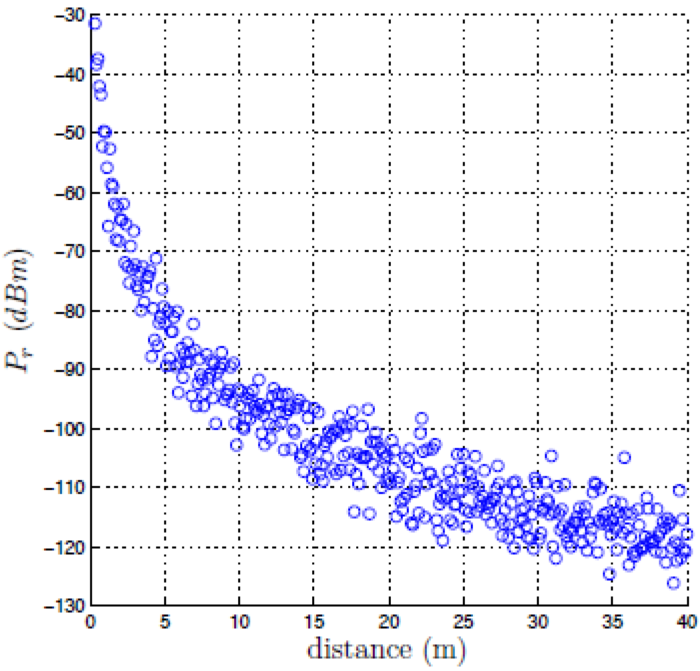

Figure 2.5: Channel Model, $\gamma = 2, \delta_{\epsilon} = 4$, and $P_t = 0\ dBm$ (Fong, 2017)

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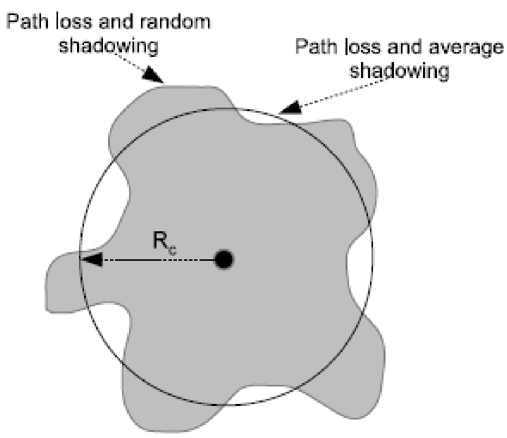

Figure 2.6: Connectivity model (Fong, 2017)

2.5.3 WSN for Explosive Trace Detection Deployment

The major challenge in deploying WSN is where to place the sensor for effective coverage within the area of interest to be surveyed and for this to be possible a careful optimization approach is used to achieve the design objective (Fong, 2017). The coverage objective is how to make sure the sensors are well arranged to maximize the area of interest and in achieving this the sensors must not be place too close or very far from each other. This will enable the sensing capacity to be fully maximized. For better performance on data acquisition in the localized area good deployment cannot be compromised. According to (Mao et al., 2019), two types of deployment approach are being employed which are deterministic and random deployment. In the deterministic approach the environment in question is familiar, the network functionality is rclaerly fixed and the sensor nodes are clearly placed in space. Mathematical model that are often transform into a linear programing problem or static optimization problem are being used to implement this. The hexagonal grids are usually used for nodes deployment when maximum network coverage and eff/ective connectivity is of great interest.

It was observed that deterministic model proved effective solution to deployment problem but it is oversimple and too perfect. However, when harsh environment is to be considered and also when large deployment is becoming difficult the random deployment will be the best option (Mao et al., 2019). One of the setbacks of the Random deployment method is the inability to guarantee full coverage, however, its cost effectiveness is a great advantage and when there is no strict coverage requirement it becomes a better choice. Some tines redundant nodes are introduced to achieve desired coverage.

Focusing on optimization object, the deployment of nodes is divided into three base deployment methods; coverage-based, network connectivity-based, and energy efficiency-based deployment. High result operation of the WSN is determined by how well the network is well represent in the target area. Node deployment of sensor network is greatly improved the performance and coverage of the sensors. (Mao et al., 2019).

2.6 Internet of things (IOT) Application in monitoring Explosive Trace

Environment of interest can be monitored and this process which is known as the process of capturing of values of data of interest in an outside environment. This approach can be used to acquire and grade the data even if it's a large volume of data (big data) using Internet of Things Technology (Cunin et al., 2018). When we connect and attach sensors to communicate with the ‘various things’, AI application can be used to enable these devices to share real-time data without human interventions. The IOT makes the society to be smart and flexible in adaptation and connect the digital technology with real-world. The different sensors that monitor environmental quality can be connected to IOT system to operate autonomously. Figure 2.7 shows IOT with different connection that can be anywhere, any environment and anytime. Whatever is sensed is transmitted and the output is viewed through web application or in some cases edged devices. The communication is through wireless means with appropriate communication protocol.

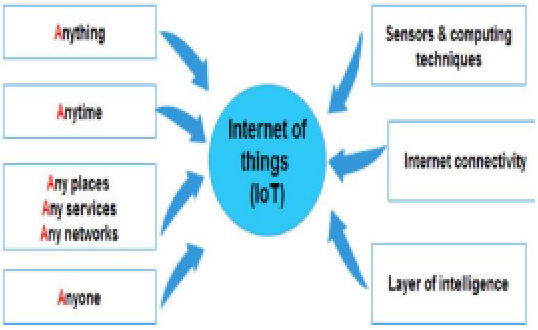

Figure 2.7: Concept of IOT in monitoring (Haji & Sallow, 2021)

Data collected by IoT environmental monitoring sensors in this case explosive traces within a wild area of interest. The environmental properties can be connected with a single cloud-based environmental system through the use of Wireless Sensor Network (WSN). When an IoT component fused with ML system can register, characterize, track, and analyze elements in a specific environment (Haji & Sallow, 2021)

2.6 Related Works

In this section, worked carried out such as biological means, analytical method, technological mean ranging from stand-alone sensors, sensor arrays, wireless sensor network and Artificial Intelligent (AI) approach in explosive trace detection will be reviewed.

2.6.1 Animal olfactory Systems

Chuen *et al.,* (2020) has shown that animal’s methods have proved to exceed technological approaches in explosive trace detection especially for the fact that it can detect multiple traces of explosive concurrently and this is what sensor array network technology is finding difficult to achieve. Animal such as dogs, rats, pigs and honeybees are used to detect explosive traces**.**

Even though several animals are being used, dogs are commonly been used. In demonstrating the efficacy of dogs in explosive trace detection.

Command & Belvoir, (1978) shows a study that demonstrated the explosives trace detection by dog-handler teams which was carried out by Nolan and Gravitte, the teams were trained to detect landmines. The dogs recorded averaged detection of location accuracy of over 80% with several teams averaging 90% correct location. Further studies were carried out on this to examine the efficacy of detection teams, the training was improved and maintenance protocols developed by various agencies to validate the result scientifically. When the explosive was free from contamination and negative controls such as interfering samples, it resulted in improved accuracy of the detection. Another well-accepted work administered by the North American Police Work Dog Association that recorded about 91.6% accuracy on target odors was recorded in (Frost, 1990). The test was conducted on six different explosive odor classes over four of five different search areas. Although this publication was not peer-reviewed but was reviewed by panels of recognized experts before adoption. Sensitive and trained dogs were used by military during World war II to detect explosive and since then civilians began to used it for detection of drugs and explosive (Furton & Myers, 2001). Some of putative olfactory receptors from the dog detection have been cloned with subsequent characterization of some of the molecules. It has been shown that smell is the mechanism through which dog uses to detect explosive as dogs with defected sense of smell do not perform well in detection task. The Department of Defense program, which uses 500 explosive detection canines worldwide and has a proficiency requirement of at least 95% detection rate for the targets (known explosive odor standards) used and 5% or less nonproductive rate (alerts to distracter odors), is one specific example of how the reliability of explosive detection canines is repeatedly substantiated. (Thiesan et al., 2005). Among behavioral factors evaluated are type and duration of search, alertness of the team, responsiveness of the dog to the handler, and, the handler's skill in observing the behavior of the dog and interpreting those observations. Detection becomes more challenging since a living thing must be involved for accurate detection rather than relying solely on instrumental approaches. The U.S. Congress asked the Treasury Department to set standards for bomb-sniffing canines with the Bureau of Alcohol, Tobacco, and Firearms (ATF), suggesting the contentious standard of 100% accuracy on 60 tests. This move brought attention to the long-debated canine standards for bomb dogs. (Thiesan et al., 2005). Gazit et al., (2003), worked on implementation of a device that is used for operational research. The device aimed at assisting the handlers of sniffer dogs by the police to compare the effectiveness of the dog in detecting explosive. The device was able to improve the efficiency of search in such operations. The device is to identify whether dogs utilized as a part of hunt are capable sniff or not. Those devices are incorporated with system that associates in remote recognition and investigation of explosives. While dog detection of explosive seems very good, adverse environmental conditions can easily affect it (i.e. high temperatures, long search times) and more prone to operator influence. The scientific knowledge acquired through the instrumental devices is generally more acceptable because it can be proved scientifically. For dog explosive detection calibration standards cannot be able to run and identify the specific explosive to make alert specific to the explosive type because the detector dog teams use sequential calibration (Thiesan et al., 2005). Dog training is quite costly because it takes a lot of time and effort to train them well. Animals are generally only useful for a few hours a day and have a tendency to become fatigued and distracted. This is a downside to their utilization. When they simultaneously detect explosive odors from multiple sources, they can become confused (Liu et al., 2019).

Under this biological approach used for explosive trace and some harmful chemicals detection Rodacy *et al.*, (2002). The honeybee's colony was used to cover a wider area that has different media such as land, water, air and plant, as they will be moving they came in contact with pollutants in the air,on plant and water that were in gaseous form, particulate or liquid form. These contamination are used to train the bees, in the process chemical such as 2,4,6-trinitrotoluene (TNT) have been used. Honeybees have been used to collect sample as well as locating contaminated areas and also to indicate anomalies in the area. In the experiment they setup sugar-water feeder closed to honeybee's colony and positioned explosive trace substances very close to it. The honeybees did not only got attracted to the sugar-water but also the explosive odor so that anywhere such substance is present in the future there will gather there thereby detecting explosive traces. In their work they achieve an accuracy of 98%. (Girotti et al., 2013) in their work Honeybees was used as biosensors since pesticides could affect their usage, they are then used to collect contaminant within the environment. Once there is changes in the environment, honeybee will behave differently and that can be a sign to predict explosive substance. (Bajić, 2014) tried to solve the challenge of locating the explosive trace through honeybees localization since honeybees has been accepted for explosive trace detection in a wild area. In their work they used methods such as
lidar, microwave dipole and detecting the third harmonic of the radar waves, and also using spectral features to detect the honeybees. Methods such as electro optical sensors, use of long

distance thermal camera combined with digital image processing have equally been deployed, in this case UAV was used. Although honeybees training is less and could cover more areas in detection of explosives trace like TNT, C4 and TATP explosives at parts-per-trillion levels but weather and night condition can easily affect the operation of the honeybees and may not also be deployed in areas where human beings are present (Chuen To et al., 2020)

Poling *et al.*, (2011) proposed the use of trained pouched rats for explosive like chemical detection. The training was carried out in a metal cage that has a small hole in the underneath and a pot was presented with a sample that has some small drop of about a 100ng per microliter of 2,4,6-trinitrotoluene (TNT). The person carrying out the training made a click sound and present mouthful of mashed bananas mixed that was mixed with crushed rat chow through a plastic syringe and the rat will smell through the nose for sometimes. When this positive training was ended the discriminative training was done where the trainer will serve the rats food along with the TNT sample by the hole and this will be done relatedly for several times until the rats only response when TNT sample is present with the food. They carried out the test using 34 rats with each rat covering 186,800 m2 and false alarms rate per 100m^2 was 0.33 per 100 m2. While this has the advantage of portability and been less expensive, training takes much time and rats are not readily been available.

2.6.2 Analytical Approach for Explosive Trace Detection

Due to abilities of unique nature of the chemical constituents of explosive substances it is possible to analyze explosives contents as that was presented by the work of Wasilewski *et al.*, (2021). The method has aided in instruments design and development of the strategy aimed at detection of explosives trace with these systems. This method that is referred to as chromatographic includes the thin layer chromatography, gas chromatography (GC), high pressure liquid chromatography (LC), capillary electrophoresis, and ion chromatography; then spectroscopic or spectrometric methods such as infrared, ion mobility spectrometry (IMS), mass spectrometry (MS) are used. Shahraki et al., (2018) suggested using a negative ion mobility spectrometer in conjunction with an ionization source to detect explosives. In the investigation, explosive trace was detected using negative ion base thermal ionization operating in the air. In order to detect the mobility particle of typical explosion compounds like TNT and RDX in air, the ionization was enhanced by doping a chlorine chemical for the negative ion. It was determined that IMS is a highly regarded and frequently used technology in the majority of US airports for the detection of traces of nitro-organic explosives on carry-on luggage and bags. One challenge is that since most explosives yields negative ions and most operated in the negative mode failed to detect trace on certain compounds e.g. TATP traces. To solve this problem of IMS not able to detect certain traces from some compound, Crocombe *et al.*, (2021) proposed the dual-tube IMS that could detect both negative and positive ions. Under IMS, sample vapors are often transformed into ions at atmospheric pressure, and the characteristics of those ions under mild electric fields are their gas phase nobilities. However, the vapor concentration dependency of the ion mobility spectrum and the seemingly erratic response caused by memory and humidity effects impeded the quick development of IMS and (Gary & Eiceman, 2006) has solved this problem earlier by developing an in-field analyzer that can best be represented by the handheld Chemical Agent Monitor. This development has made IMS to be found in most of the airport for screening against explosive substance. (Smith et al., 2020), developed flexible drift tube IMS system that is not expensive, the system that was constructed using a single printed circuit board was used to analysis common explosive substance such as RDX, TNT and PETNT and was found to have a detection limit of few nomogram and this make IMS device to be close to the substance meant to be screened. This had earlier been established by the work of (Mokalled et al., 2014), where qualitative analysis of a real explosion residue and explosive sample taken from a suspect was carried out and the explosive material and trace were identified successfully. It recorded a detection of explosives at Nano-gram levels and about six seconds response times, even with the little advantage of high speed in detection because it took only few seconds to detect explosive traces, its low selectivity was a serious drawback.

Evans-Nguyen *et al.,* (2021) proposed a fieldable Mass Spectrometry (MS) system used for security application. The system works based on membrane inlet systems and hybrid gas chromatography and the system recorded fast detection and also an improved selectivity. (Yinon, 2007) reported that the use of Mass Spectrometry (MS) for detection of explosive trace was based on the masses of the atoms and the molecule of the explosive substance. The mass to charge radio (m/e) is determine from the time and space of the charged substance in a force field. Since ions have difference m/e ratio they recorded different time of flight. A system was proposed to detect traces of explosive residues on aircraft boarding. The work focuses on how to detect traces of explosive residue on passengers that may had made contact with explosive substance and such substance would have been left on their body. An investigation of the quantities of explosive residues on previously used boarding cards was conducted. The residues are detected by the system prior to the passenger entering the aircraft and are transmitted by touch to the boarding pass. A triple quadrupole mass spectrometer (MS/MS) was used to collect the generated vapors, which were then observed using selective reaction monitoring (SRM). Corona discharge is used to ionize the material. One of the produced ions is chosen to enter the collision cell and react with the nitrogen molecules there, producing a series of product ions. Precursor adduct ions are seen for RDX, PETN, and NG when an additive, such as dichloromethane, is added to the MS. Every hour, the system could process one thousand boarding passes. This result is based on a background investigation into the levels of explosive residues on two thousand boarding passengers. According to Yanon (2007), an explosive detection personnel portal is a walk-through system for quickly screening staff members for traces of explosives at locations like airports or federal buildings. This is an additional application of IMS in explosive detection. A mass spectrometer detector was used in the construction of the Syagen Guardian MS-ETD Portal (Grove et al., 2019). The following explosives were found: Tetryl, ammonium nitrate fuel oil (ANFO), triacetone triperoxide (TATP), hexamethylene triperoxide diamine (HMTD), RDX, HMX, PETN, EGDN, NG, and TNT.. Analysis time is less than 15s. MS recorded improvement in selectivity but its huge devices that are very expensive is required for large scale deployment of sensors in the wake of ever-increasing terror attacks prevailing in different part of the world was a limitation (Kishore et al., 2019).

Adegoke & Nic Daeid, (2021) proposed a method for explosive trace detection called "colorimetric optical Nano sensors for trace explosive detection using metal nanoparticles" The system is based on the work of Almog & Zitrin, (2009) that color reactions leads to the production of product that can be identify by its colour and this is a form of chemical reaction that is used to know the type of compound in used. So when you treat explosive compound with the right reagent can produce a unique colour that can be used to identify the constituent elements. Several system like Fluorescent and colorimetric sensors for selective detection of TNT and TNP explosives in aqueous medium proposed in Junaid *et al.*, (2022) have been developed based on this technology. The sensor based colorimetric system was able to respond to TNP and TNT substance very rapid. The fluorescence colorimetric methods is found to be one of the pronounce technique in detecting explosive trace. Fluorescence quenching methods remain the most popular technique. The major limitation of colorimetric method is the use of color reactions for the analysis of explosives that lies in their low specificity, some non-explosive chemical may produce the same colour and that is why colorimetric approach is combine with system to obtain the best result. It could only effectively work for specific explosive or particular explosive compound designed to detect, for a wider range of field operation multiple colorimetry sensors have to be designed.

Remote detection of explosive trace using Raman Technology was presented by Hao *et al.,* (2022)**.** The technology was based on focusing of Laser Beam. They used two enhanced Raman spectroscopy methods to improve the low sensitivity observed in existing Raman Technology to detect explosive trace from Distance. In their method that used convex lens to converge the laser beam while collecting the Raman signal, the plasmonic spray was used to prevent Raman scattering along the surface. This enhanced approach achieved remote Raman detection up to thirty (30) meters different types of explosive with about 1 μg/cm2 of consecration. It was and improve version of Raman technology that was based on exciting a sample with a monochromatic light like laser, the explosive chemical composition radiate light at different frequency that can be differentiate from the from what exist in the environment. Raman spectroscopy is then used to collect the Roman spectra scattered light of the sample from a distance as a means of detecting substance that contain explosive trace (Gares *et al.*, 2016). This system involve the user of different types of laser that is hazardous to human safety especially the safety of the eyes. According to (Regis *et al.*, 2018) Another setback of the Raman technology is that fluorescent do interferes with its operation or when strongly absorbing substance is being used. Its operation fails on metals and it does not cover large area

2.6.3 Electronics Nose for Explosive Trace Detection

It was discovered that the usual electronic nose components are a chemical sensor array and an artificial neural network according to Liu et al., (2019). This array of sensors has unique properties that allow it to detect explosive traces of the target fragrance. Explosive traces are identified via an adaptive pattern recognition study of the signatures using techniques like artificial neural networks, and the pattern recognition process allows the identification of a particular explosive. According to Peveler *et al.* (2016), many electronics noses in array, such as a fluorophore array, were utilized for explosive chemical detection and discrimination. A quick reaction was achieved from a tiny amount of sample after array units were combined into a single multichannel platform. Using quantum dots as fluorescent probes, the multichannel platform detects and distinguishes between five explosives: TNT, DNT, Tetryl, PETN, and RDX. Another illustration was the colorimetric electronic nose, which was exhibited for the vapor phase detection and explosives classification. It was based on a handheld scanner and a cross-reactive array (Askim et al., 2016). With a discriminating error rate of less than 1%, the array consisting of 40 colorimetric response sensors, 16 explosives including conventional explosives, characteristic explosive components, and homemade explosives was able to distinguish between 14 classes. Nonetheless, it is currently generally accepted that electronic noses are insufficient to identify the minute amounts of chemicals that dogs consume. Future developments will aim to expand the system's coverage and improve sensitivity and dependability. This improvement in the e-nose is what (Gradišek et al., 2019) used to utilize a 16-channel e-nose demonstrator that was based on micro-capacitive sensors with functionalized surfaces to measure the response of 30 different sensors to the vapours from 11 different substances, including the explosives 1,3,5-trinitro-1,3,5-triazinane (RDX), 1-methyl-2,4-dinitrobenzene (DNT) and 2-methyl-1,3,5-trinitrobenzene (TNT). In their work they developed a classification model through. Random Forest algorithm that was used to train set of signals, the varied parameters in their test were the concentration and flow of a selected single vapour. The model was able to recognizeand successfully classified the signal pattern of different sets of substances at an accuracy of 96%. Ot shows that the silane monolayers used in their sensors as receptor layers are can identify TNT and similar explosives from among other gaseous substances.

(Chowdhury et al., 2008) suggested a portable electronic nose system that uses five Metal Oxide Semiconductor (MOS) sensors that are available for purchase. A microcontroller is utilized to recognize patterns in the MOS sensors. Black tea scent is classified using the feed forward multilayer perceptron (FF-MLP) method in the IC (PIC18F4520). In order to determine the ideal architecture, weights, and biases of the neurons, the MLP is first trained using the backpropagation algorithm with the fingerprint from the sensor array and the corresponding tea tasters' mark in a PC. The samples were collected from various gardens in northeastern and eastern India. After training, the IC is programmed with the computed weights and biases of the neurons, enabling it to function as a portable device that provides the fragrance index for newly discovered tea samples without further processing. When compared to unidentified finished black tea samples, the results show that the ic-based electronic nose system performs on par with the PC-based electronic nose system.

Using 237 completed tea samples, the performance of the microcontroller-based electronic nose was assessed. Of these samples, 4000 patterns were evaluated for testing, while the remaining 60% were utilized to train the BP-MLP neural network model. In contrast to the PC-based electronic nose, which has an accuracy of 85.7%, the microcontroller-based electronic nose obtained values of 83.6%. With a little quantity of tea samples, It was found that the accuracy of the FFMLP microcontroller-based electronic nose is somewhat less than that of the PC-based electronic nose. This could be because the portable version of the microcontroller uses an inbuilt 10-bit ADC, whereas the PC-based electronic nose uses a 16-bit A/D converter. Additional comparable work was completed by (Hasan et al., 2012), In order to detect spoilt meat kept in refrigerators, they created an electronic nose. The beef and fish samples were analyzed by an electronic nose, which then used a support vector machine (SVM) classifier to determine which meat was causing the bad stench. The experiment is run for a week in order to assess. The findings show that the SVM classifier performs well in generalization and allows for an accuracy rate of about 94.5% for both fish and meat. This indicates that SVM is a useful pattern classification method for identifying rotten meat using an electronic nose. With the addition of nano-enhanced sensors and changes in pattern recognition thanks to neural network technologies, electronic sensor work to mimic human nose sensing capability has improved and now can detect and identify minute amounts of explosive chemicals (Mokalled et al., 2014). The challenge of wider coverage has been confronting the Sensor designed for explosive trace Detection and to also have sensors that could detect multiple explosive the same time.

2.6.4 Sensor Network for Explosive Trace Detection

The sensor network technology tries to solve the problem of multiples sensing of explosive trace and also solve the problem of monitoring a localized environment against explosive trace. The sensor network is applicable to all the types of sensor used in detection explosive trace.

So *et al.,* (2009) proposed Laser-based atmospheric trace-gas sensors with great potential for long-term, real-time, maintenance free environmental monitoring in distributed Wireless Sensor Networks (WSN was proposed. A laser based chemical sensing technology with wide-area autonomous wireless sensor networking as the final target was developed. The prototype sensor measures atmospheric oxygen concentration in the form of a battery powered, handheld unit with power consumption <0.3W, sensitivity of 0.02% in 1 sec, weight of <0.4Kg without batteries, low cost, high specificity, and the robustness required for long term sensing applications. A gas plume localization and quantification using a prototype three-node sensor network was demonstrated. The technology is modular and can be used for different environmentally important molecules such as different environmentally important molecules such as CO_2 NO_x, and methane with exceptionally high specificity.

A reliable security threat warning system for public spaces like train stations, enabling security personnel to respond quickly to bomb threats was designed according to Simi & Ramesh, (2010). Using a multi-phase wireless sensor network, the technology offered a means of accurately and quickly detecting explosives in order to decrease, control, and alert people to impending terrorist action. The chemical makeup of explosives was determined using a number of wireless sensor nodes that were integrated with various kinds of sensors. The system dynamically collected data from the sensing nodes using several orthogonal strategies, aggregated the data, and forwarded it to the sink node for additional analysis. In order to verify the suspected items, a mobile node was subsequently added, improving the target tracking system and lowering the frequency of false alarms. In the work of (Simi & Ramesh, 2011) a multi-phase wireless sensor network design solution for monitoring was proposed. In order to lower the amount of false alarms, the system makes use of several wireless sensor nodes that are integrated with various sensor kinds and target tracking mechanisms. In order to respond quickly to bomb threats, this system offers an efficient warning mechanism for security risks in public areas. (Song et al., 2011) conducted research on the development and deployment of a wireless electronic nose (WEN) system that could identify and quantify the quantities of the flammable gases methane and (CH_4 / H_2). Two wireless sensor nodes in the system can function as either a slave or a master node. In slave mode, it consists of a wireless transceiver unit (WTU) that transmits the detection results to the master node connected to a computer, a digital signal processor (DSP) system that processes and samples sensor array data in real time, and a Fe_2O_3 gas sensing array for the detection of combustible gases. A Fe_2O_3 gas sensor type that is resistant to environmental effects is created that is insensitive to humidity. On a DSP, a threshold-based least square support vector regression (LS-SVR) estimator is used for concentration and classification calculations. The findings of the experiments verify that LS-SVR outperforms standard support vector regression (SVR) in terms of accuracy and convergence rate, outperforming artificial neural networks (ANNs). Gas mixture analysis is accomplished efficiently and in real time using the WEN system that was built. The system has limited application to be extended to other types of gases, particularly those associated with explosive trace.

(Rejeti et al., 2019) tried to establish the need to have a simple and effective network that can monitor an area against anti-social element such as explosive actions. They developed a detecting system that can detect explosives reliably and accurately. In their work a comprehensive framework that have all ingredients to detect explosives and integrated them with a wireless sensor network (WSN). It was used to detect RDX and TNT explosives component. Explosive Detection Algorithm (EDA) was developed and proved to be effective. The simulation results shows great improvement over existing methods. Their work was not used to test other types of explosive component to show overall improvement.

In another development, explosive detection in border areas that handles threats from people and detect terrorist activities, they used PIR sensors for detecting person and metal detector was used for detecting explosives respectively, while a camera was used for continuous monitoring of the scenario at a remote station. They studied different technologies involved in the system. They include Bluetooth technology and infrared technology. They implemented a simulation study in Visual Basic using these three technologies (Minni & Siddharth, 2016).

Simi & Ramesh, (2011) designed a reliable security threat warning system for public spaces like train stations, enabling security personnel to respond quickly to bomb threats. By accurately and quickly detecting explosives, the system made use of a multi-phase wireless sensor network to provide a means of mitigating, controlling, and alerting people to impending terrorist action. The chemical makeup of explosives was determined using a number of wireless sensor nodes that were integrated with various kinds of sensors. The system constantly gathered data from the sensing nodes, aggregated it, and sent it to the sink node for additional analysis based on various orthogonal methodologies. In order to verify the suspicious items, a mobile node was added, improving the target tracking system and lowering the frequency of false alarms. Their system could not clearly discriminate against noise.

AL-Mousawi & AL-Hassani, (2018) to address the challenge of wider coverage of the sensor presented a work on wireless sensor network for explosive detection. Utilizing specialized sensors that are compatible with wireless sensor networks is necessary for explosive detection. The three primary axes of wireless sensor systems covered in this study are as follows: the first axis concerns the scalability of wireless sensors in explosives detection technologies. The connectivity and mobility of these networks and sensor are the second axes of the WSN explosives detection system. He discussed the need of using hyper sensor type that contains buddle of sensors for different simultaneous sensing. The challenge in WSN is the issue sensor security and latency, the WSN generally experience delay in transmitting information.

2.6.5 Artificial Intelligent in Explosive Trace Detection

The introduction of AI based technology in explosive trace detection is mainly to enhance the selectivity and sensitivity of the sensors and also try to solve the problem of latency in sensor network to achieve faster respond time. Different work has been done in this field.

Kapitanova *et al.,* (2010), suggested event detection, which is a key element in many applications involving wireless sensor networks (WSNs). We think that the frequently inaccurate sensor readings are too much for sharp values to manage. In their research, they showed that the accuracy of event detection is greatly increased when fuzzy values are used in place of crisp ones. They proved that a fuzzy logic method outperforms a few well-known classification algorithms in terms of detection precision. However, it was that using fuzzy logic has the drawback due to exponentially growing size of the rule-base. Sensor nodes have limited memory and storing large rule-bases could be a challenge. To address this issue, a number of techniques that help reduce the size of the rule-base by more than 70% while preserving the level of event detection accuracy was developed. Mølgaard *et al.,* (2017) offered a data-driven machine learning method for air sampling that uses colorimetric sensor technology to identify precursors of drugs and explosives. Utilized was the sensor technology developed within the framework of the CRIM-TRACK project. Currently, a fully functional portable prototype featuring automated data collection and disposable sensing chips has been created for air sampling. Large datasets of colorimetric data have been produced for several target analytes in laboratory and simulated real-world application scenarios thanks to the prototype's quick and easy sampling process. In order to reliably classify target analytes from confounders present in the air streams, many machine learning algorithms were utilized to leverage the very multi-variate data generated by the colorimetric chip. It was shown that relevant features and a high analyte detection rate can be obtained by combining a probabilistic classifier with a data-driven machine learning technique that uses dimensionality reduction. Moreover, the probabilistic machine learning methodology offers an automatic way to detect measures that are incorrect and may result in inaccurate predictions.

A series of studies concentrating on the amphetamine precursor phenylacetone and the improvised explosives pre-cursor hydrogen peroxide have been conducted to assess the durability of the colorimetric sensor. The investigation shows that, in real-world sampling circumstances, the system can detect analytes in clean air and combined with naturally occurring chemicals. The technology being developed for CRIM-TRACK has the potential to be a useful tool for law enforcement applications such as bomb detection and drug trafficking control.

Deming et al., (2017) carried out a work on feasibility study where an artificial neural network was used to detect person-borne improvised explosive devices (IEDs) from images acquired from a radar array sensor, an infrared (IR) camera sensor, and a passive millimeter-wave camera sensor. The data set was obtained from the U.S. Department of Homeland Security (DHS) Science and Technology Directorate (S&T), and consists of hundreds of images of human subjects concealing various simulated IEDs, and clutter objects, beneath different types of clothing. The network used for detection is a hybrid, where feature extraction is performed using a multi-layer convolutional neural network, also known as a deep learning network, and final classification performed using a support vector machine (SVM). The performance of the combined network is scored using receiver operating curves for each IED type and sensor configuration. The results demonstrate (i) that deep learning is effective at extracting useful information from sensor imagery, and (ii) that performance is boosted significantly by combining complementary data from different sensor types. The focus of the work was not on trace and since images data where used the computational time is high. Their work only considered fabricated IEDs and not the possible properties. Al-mousawi & Al-mousawi, (2019) in their work represented a new direction in detecting magnetic explosives by the use of a wireless sensor network adapted with machine learning. The Improvised Explosives Devices (IED) consider a series threat due to the easy manufacturing. However, the scientific directions heading towards the use of information technology in the development of explosives detection systems. They focused on the type of explosives used is the magnetic explosives which are a type of IEDs that is used in targeting the vehicles. A Magnetic Explosives Detection System (MEDS) is a wireless sensor network system that uses a network of magnetic sensors to detect the magnetic field that emitted from magnetic effector and consider this magnetic field as a possible threat. The experiments of the system show its ability to detect the change in the magnetic field caused by the magnet stacked under the vehicle. The main use of the neural network algorithm in this paper is to determine the highest reading among a series of readings to determine where the threat exact position. Excellent results produced by the neural network algorithm in the MEDS to enable the system from learn and identify the required data type.

Fisher *et al.,* (2020) proposed machine learning approach to improving Trace Explosive Selectivity which they applied to Nitrate-Based Explosives. In the work, machine learning methods were utilized to examine the extent of improvement in IMS selectivity for detection of nitrate-based explosives. The work considered five classes: ammonium nitrate (AN), an ~95:5 mixture of AN and fuel oil (ANFO), urea nitrate (UN), nitrate due to environmental pollution, and samples that did not contain any explosive (blanks). The preliminary results clearly show that the incorporation of machine learning methods can lead to a significant improvement in IMS selectivity. (Liu et al., 2019). The effort to enhance the selectivity and reliability several work have been done such as (López et al., 2017) that used Principal component Analysis (PCA) on metal oxide sensor (MOX) array and that was able to identify explosive samples and discriminated between them and other substances like Ethanol and Vinegar, a k-Nearest Neighborhood algorithm was used with k equal to 3. A Leave-one-out cross-validation strategy was established to estimate the classification rate of the final model which they recorded as 86%. (Wang et al., 2005) had previously used a novel intelligent technique based on support vector machine (SVM) classification for electronic nasal signal detection. SVM functions under the tenet of minimizing structural risk, which ensures improved generalization capacity. After demonstrating the SVM's fundamental idea, the gas classifications were recognized using the SVM as a classifier. The method can overcome the drawbacks of artificial neural networks by classifying complex patterns, achieving a higher recognition rate at a reasonably small size of training sample set. There has been a presentation and discussion of the tests conducted to identify three distinct gases: acetone, gasoline, and ethanol. The findings show that the SVM classifier performs well in generalization and raises the tested samples' average recognition rate to 88.33%. This indicates that the suggested approach for electronic nose signal recognition is successful. One of the area of electronic nose sensor to improve is the area of selectivity and this to to enhance the accuracy of detection of the analytes.

In further development, the application of a convolutional neural network (CNN) to facilitate IED detection was proposed by Colreavy-donnelly et al.,(2020). An autonomous sensor array was utilized in a related research to find the devices in areas that were too dangerous for a person to survey. CNN and its training approach are appropriate for using the sensor system in this work. In real time, this convolutional neural network can detect and discriminate between natural features of the surrounding undergrowth and a potential IED. In well-lit environments, the CNN was able to identify the IEDs with 98.7% accuracy because to the training process.

The suggested CNN performs better than its rivals, including the deterministic approach, when the results are compared to those of other convolutional neural networks and a deterministic algorithm. The limitation of his work is that the environment must be well illuminated before high accuracy could be recorded, what happen if the attack is to take place in a dark environment.

According Fisher *et al.,* (2020), the preferred technique for finding traces of explosives in most airport and border crossing environments is ion mobility spectrometry (IMS). The IMS detection limits are low enough to meet security standards for the majority of explosives. Nonetheless, the selectivity is insufficient for certain explosive families. One such category of explosives is nitrate-based explosives, where it can be difficult to distinguish between different nitrate hazards and ambient nitrates. Machine learning techniques were applied to investigate the degree of enhancement in IMS selectivity for nitrate-based explosives detection, using a limited database. This exploratory investigation looked at five kinds of nitrate: urea nitrate (UN), nitrate from environmental contamination, ammonium nitrate (AN), a ˆ95:5 mixture of AN and fuel oil (ANFO), and samples free of explosives (blanks). The initial findings unequivocally demonstrate that applying machine learning techniques can significantly increase IMS selectivity. Zapata & García-Ruiz, (2021) conducted thorough analyses of a few basic ideas regarding explosives and the two widely used categories of them according to either their application or their velocity of detonation. They claim that while the current classifications are very helpful in the legal and military spheres, they are of no use in figuring out the chemical makeup of explosives. The classification of explosives according to their chemical makeup was the main topic of their review. This classification succeeded in creating a distinct general classification by combining the chemical classifications of explosives present in literature. Explosive was classified into single explosive and mixture explosive; the single explosive was further classified into organic and inorganic explosive. The work provides adequate knowledge of the chemical composition of explosives but did not indicate the appropriate sensor to indicate the presence of these chemical composition.

Wongwattanaporn, (2021) proposed a way of finding a suitable classification technique to be implemented in an electronic nose so as to imitate the sniffer dogs in detecting the explosive chemical substances. In the work, eight different classification techniques, which are Logistic Regression, Support Vector Machine (SVM), Decision Tree, Random Forest (RF), Adaptive Boosting, K-Nearest Neighbors, Gaussian Naive Bayes, and Multilayer Perceptron in both binary and multi-class gas sensor array open-source datasets where compare in terms of accuracy of detection. The experimental results show that RF and SVM models perform better with average score of 99.66 and 98.93, respectively. Much data where needed to carry out the training, in real life scenarios adequate data may not be available for training of the model which may reduce the accuracy of the model, he did not equally focus of detecting the explosive trace within an area.

Djedidi et al., (2021) suggested an innovative method for detecting the presence of one of the three harmful gases—CO, NO2, or O3—either alone or in mixes, relying on a single physical sensor and data-driven algorithms. In the hardware portion of the project, a single Metal Oxide (MOX) sensor was connected to two heaters. A supervised machine learning model was implemented in the software portion. The sensor changes its electric signals in response to the various gases and their mixtures that it is subjected to. The core dataset for the discrimination consists of these raw signals and the heater readings. The raw dataset is enhanced by computing multiple time-domain characteristics for every measurement in order to improve the classification results even more. Following a ranking of the characteristics, the features that best address the categorization problem are chosen. Following data preprocessing, a multi-Support Vector Machine model is trained and validated using the features that were chosen. The system was able to detect and classify the various gases with high accuracy, but with the use of multi-Support Vector model computation time will be high and when you don't have much data, it will affect the accuracy of the system.

2.7 Summary of Literature and Research Gap

The review of similar works on Explosive Trace Detection (ETD) can be classified under the categories and the gap as identified from literature summarized as followed:

The use of Animal in Explosive Trace Detection: It was established that animal such as dogs, rats and bees is one of the best method for detecting explosive trace and they are currently still been used **(**Chuen *et al.,* 2020**)**. They could detect multiple analytes the same time and Bees particularly can be used to monitor large area against explosive trace. Generally the use of animals has drawback due to the tendency of the animal like dogs and rats getting distracted and tired and can only be used effectively for a few hours a day. Sometimes they get confused in case they smell explosive from several sources simultaneously. The use of animals can be restricted in areas where human beings are present. It is equally very expensive to train animals for explosive trace detection and to train them for such it require long period of time (Kishore *et al.*, 2019). There is therefore need to develop a system that can monitor an environment of interest irrespective of the terrine of the environment and such system can work independently without constant human intervention. Since the system will be setup once it will reduce cost compare with the use of animal to detect explosive traces.

Explosive Trace Detection based on analytical instruments: in this approach a method called chromatography is used, gas chromatography (GC), high pressure liquid chromatography (LC), and ion chromatography (Wasilewski *et al.*, 2021). Pronounced method involves spectroscopic or spectrometric methods such as infrared, ion mobility spectrometry (IMS), mass spectrometry (MS), and Colorimetric and Raman technology. This approach uses two sets of anionic and cationic analytical methods after conversion of the chemicals to respective ions to allow identification and confirmation of the presence of inorganic explosive residue. One of the major drawback of this method is that these devices are bulky and highly expensive to deploy to tackle the challenges of increasing terrorism. Inability of the technologies to monitor large area is also a limitation. Since sensor can be so tinny, the sensor network base approach can be hidden and thereby become invisible to people carry explosives, into the secure areas. This make the proposed method viable to be deployed in an area without terrorists knowing that such detector system is present in the environment.

Electronics Nose in Explosive trace detection: Electronic nose which is a technological device designed to mimics animal in sensing explosive substance explores the biological olfactory function. Its ability to distinguish complex volatiles substances, makes it unique to the principle of olfactory system. The Electronics nose has the sensing part and the artificial neural network that makes the system achieve better results (Liu *et al.,* 2019). The limitation is that they may not be able to detect multiple analytes the same time and if they are to achieve that there must be in array. The array of sensor can comprise several sensors types and thereby be able to detect multiple types of explosive trace. This make the system highly reliable.

The Sensor Network: For the Electronics nose to have wider applications and coverage the sensor array network and wireless sensor networks are been introduced. Sensor array were built for detection of multiple constituents, while WSN where used for wide area cover but one major challenge here is the problem of latency and sensitivity of the sensors (Al-mousawi & Al-mousawi, 2019). Solving the challenge of sensitity has made machine learning model a better approach in designing a sensity system that could detect explosive traces with high accuracy.

Machine Learning in Explosive Trace Detection: For accuracy of detection and high sensitivity of Sensor network that detect explosive trace, different machine Learning Algorithm are been developed in Explosive Trace Detection. Convectional Machine Learning model such as Support Vector Machine, KNN and CNN where used and to achieve high sensitivity and accuracy the Deep Learning Model such as Convolutional Neural Network was proposed and achieve better results compare to other methods (Wongwattanaporn, 2021). Deep learning was also introduced to improve selectivity, it achieved that with large dataset that could not solve the problem of latency. The limitation of the traditional machine learning model is that the system was more accurate on what it has been trained for and much data were also need

The proposed method is Deep Transfer Learning for Explosive Trace Detection (DTLETD) is effective in solving the problem of explosive trace detection from limited data. Explosive trace data are very limited because of the nature of restrictions in acquiring the data and also the cost. There is need to develop a system based on DTLETD that can work on edge device that will be light in size with high accuracy of detection of explosive trace in the presence of other chemicals. The development of lighter weighted model that could be used on edge device while solving accuracy problem is one of the main problem DTLETD tries to solve.

CHAPTER THREE
METHODOLOGY

3.1 Problem Formulation

The security of a localize place against the high rise of explosive attack has become inevitable and the electronics sensor network play a significant role in being used to detect traces of explosive within an area to be secured. For accurate, precise and timely explosive trace detection system, machine leaning approach has been used for sensor base detection system but using the existing machine learning approach could only detect traces that the models are familiar with. The issue of lack of explosive data and longer time of training using deep learning is also a problem desiring solution. To solve the problems, there is need to develop Deep Transfer Learning for Explosive Trace (DTLET) model based on CNN model. The proposed method will be developed based on the CNN model and is expected to be accurate and light weight for deployment on edge devices. The system is expected to be fast in detection with little dataset.

3.2 Proposed Framework for Explosive Trace Detection

The proposed framework for area based explosive trace detection system consist of a CNN based model known as GasNet that will be fine-tuned then reconstructed into a new model, this model was used to train explosive trace data from scratch as indicated in Figure 3.1. The knowledge gained was used to test and validated explosive trace data from the sensors array. The sensors are placed within the environment of interest to form array of sensor network which can be in a form of Wireless Sensor Network. These sensors respond to explosive trace and their response are converted to electrical signal that will be converted to digital signal that form the new input to the Deep Learning transfer model for explosive trace detection. Figure 3.1 shows the complete framework for area based explosive trace detection consisting of sensor network, signal conditioning, signal conversion process and the proposed model of DTLETD. The adopted base model is GasNet (Pai *et al.*,2018) which will be fine-tuned with appropriate layer adjustment and then the learned knowledge will be transferred to predict explosive trace. The validation data was generation from the sensor in the implementation model of the area-based explosive trace detection system. This set up is meant to generate data for the developed model for validation. The result of the prediction will be used to notify the appropriate authority for corresponding actions.

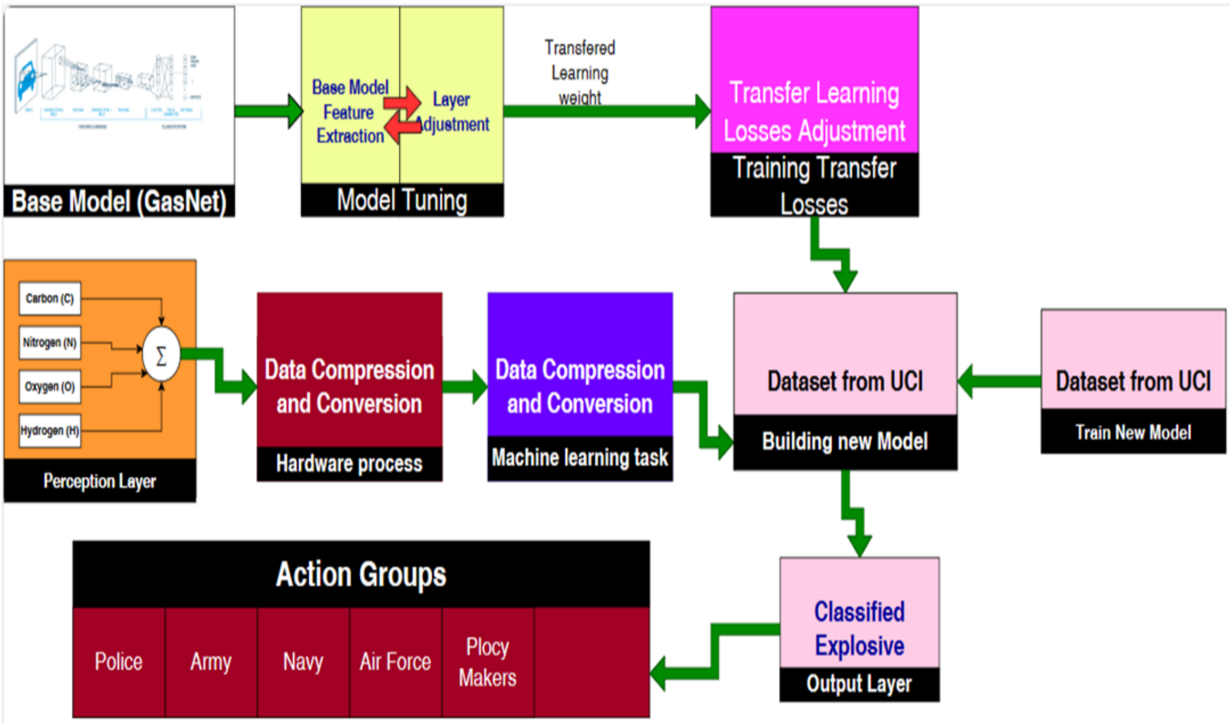

Figure 3.1: Conceptual Framework of DTLETD

3.3 Research Process and activities

The explosive trace Detection system shall involve development of an accurate classifier for the detection of substances containing explosive is achieve through series of operational activities. Figure 3.2 shows the training model activity program which involve receiving a Deep convolution neural neatwork (GasNet) model that is used to train explosive trace dataset, the model is adjusted and fine-tuned to form a new base model. The training and testing performance results was obtained for both training dataset and testing dataset and will be presented in Chapter four. Figure 3.2 shows the Activity diagram for training the model of how input data is received to the model, layers freeze and reconstructed to obtain the new model.

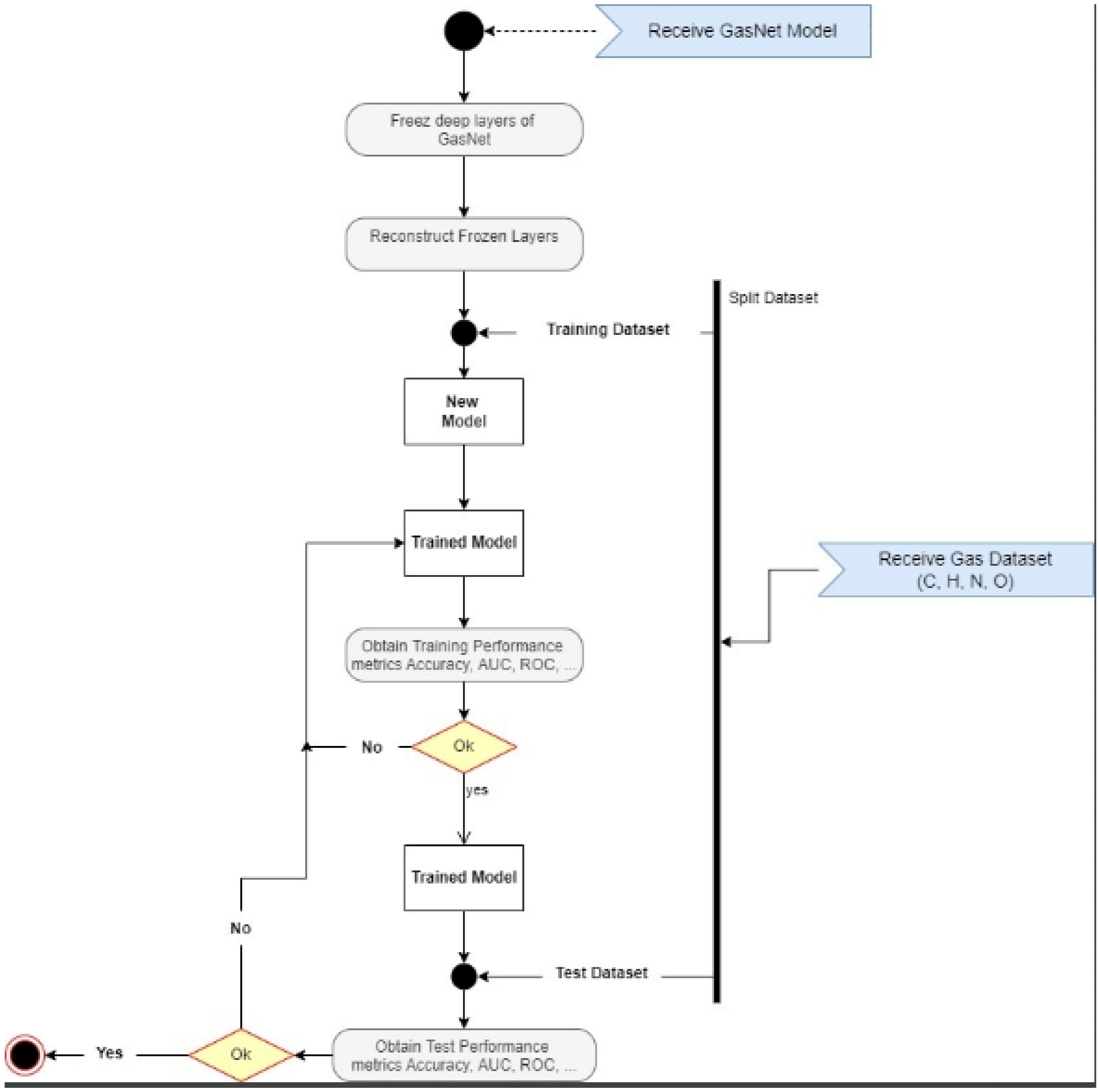

Figure 3.2: Activity Diagram for Training the model

The development activity diagram for the transfer learning model is shown in Figure 3.3 where the input data is from the sensor array network. The sensor data is Preprocessed and used on the developed model based on knowledge gained from Figure 3.2 to classify explosive trace. The performance of the system is evaluated for corresponding results.

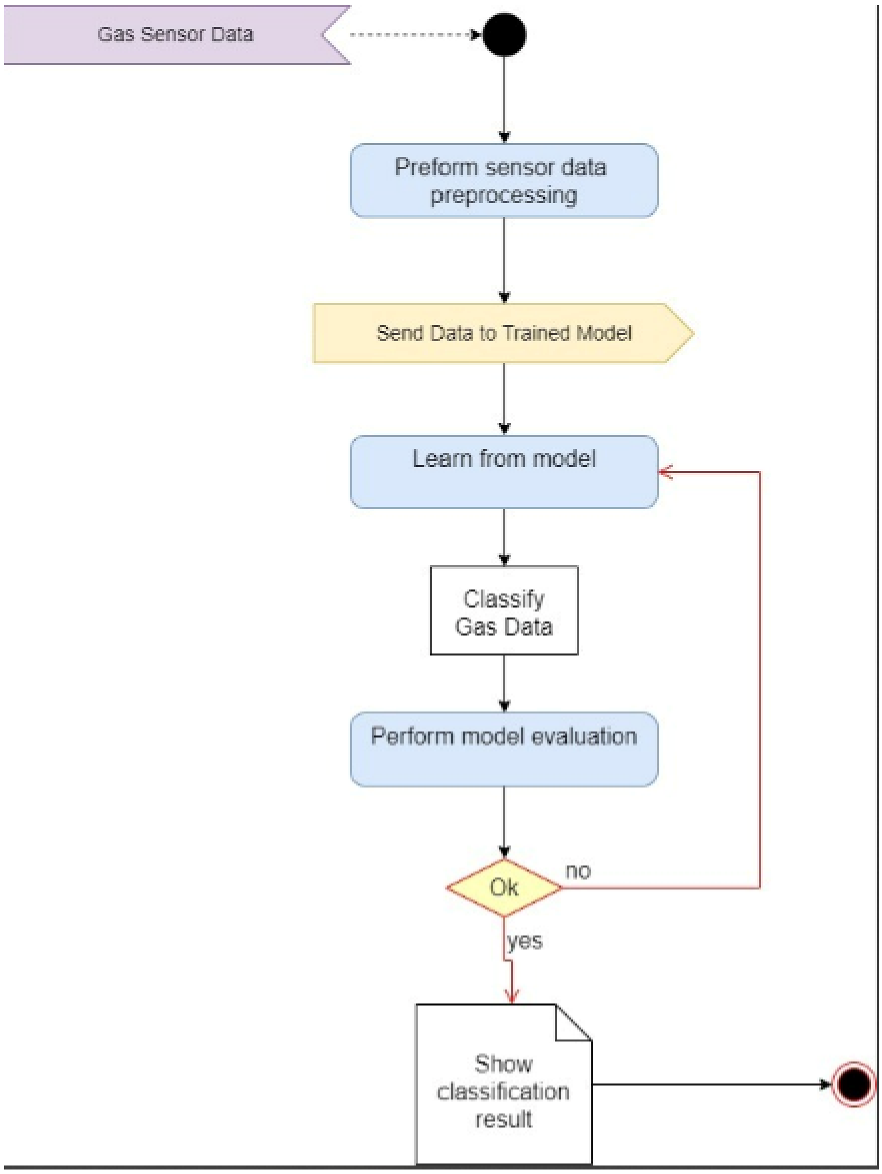

Figure 3.3: Development Activity Diagram for deep transfer learning

3.4 Deep Transfer Learning for Explosive Trace Detection Model

In this work, we utilized the possibility of Deep Learning (DL) model to accurately detect explosive traces results with limited explosive trace data set collection which is important for future experiment design that could detect explosive trace with limited explosive trace data on edge devices. The system is to detect the explosive trace very fast with high accuracy. The Deep transfer learning model is developed to be accurate, fast and light-weight classification that can be deployed in sensor network in order to identify explosive substances within an environment. Since the deep learning model requires considerable large volume of explosive data for better performance. Explosive trace data is very scarce because of the restriction in the manufacturing of explosive and the precursors of same. It will be very necessary to use readily available data with similar characteristic to first train the model before implementing it on explosive trace data. The conceptual model of Deep transfer learning is shown in Figure 3.4. Available online dataset from gaseous pollutant will be used as source data, while target data will be the explosive trace dataset collected from Sensor Network.

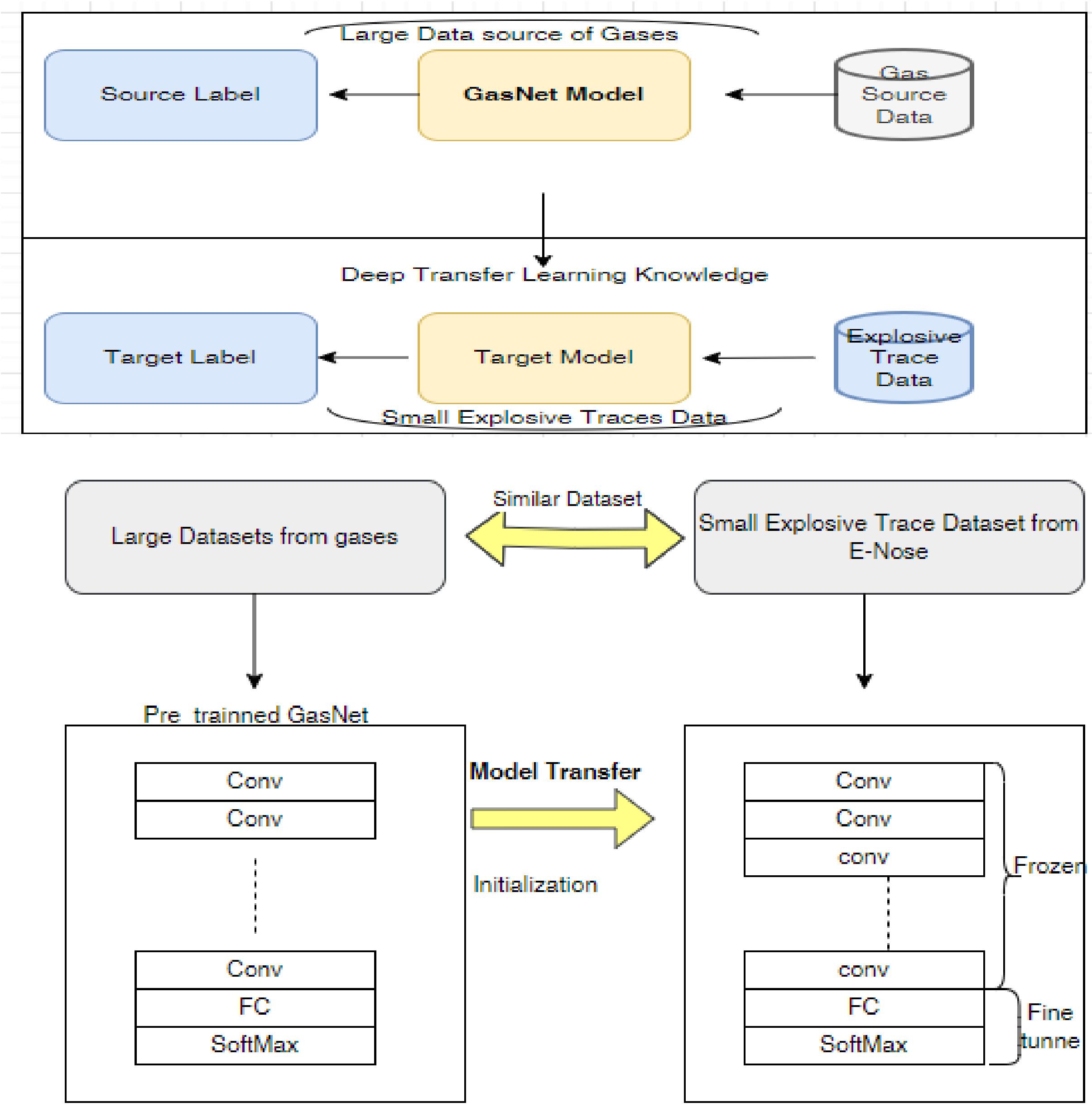

Figure 3.4: DTL Technique conceptual diagram

The source data are input into Deep Transfer Learning (DTCNN) for training based on GasNet DTCNN model. The model will be transfer to the target data to achieve the ETDTL model. Fine tuning will be done to achieve the best result in case of any variation between the source data and target data.

3.5 Data Collection

The dataset (Hossny *el tal.*, 2020) used in this research is the numerical data representing the concentration of gas traces. It is a vector of one-dimensional (non-spatial) data consisting of 1 X 5 features for a total of 69, 514 samples, with input features being C, N, O, H, and output feature being the target. The output state is either 1 or 0, where 1 represent a case when the combined concentrations of the input features suggest explosive trace, and 0 represent a case of non-explosive trace. However, since this dataset is on-spatial in nature, whereas deep learning and CNN in particular performs well on spatial or image data, it is appropriate to convert the source data to spatial or 2-dimensional data, a procedure which will map the vector samples into corresponding pixel equivalents as shown in Figure. 3.3, where the feature vector x is mapped or transposed to feature vector for each target sample.

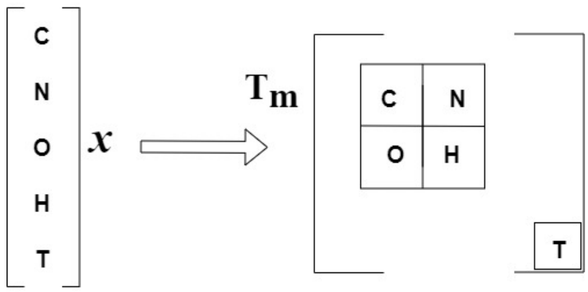

Figure 3.2: Data to Image Conversion

The conversion process follows a process that defined in the block diagram represented in Figure. 3.4, which shows that the process begins with obtaining the dataset, next is cleaning the dataset by scaling and normalizing the sample data. Feature engineering and visualization is performed to analyze the characteristics of the data. The fourth stage is to convert the vector data to spatial data before using it to tune the GasNet and eventually training a new model.

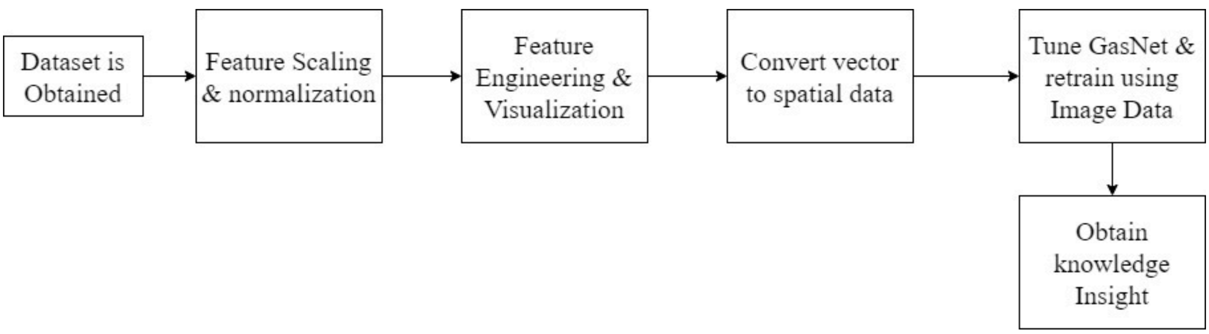

Figure 3.3: Block Diagram for Data Conversion

3.5.1 Data Normalization

The preprocessing approach starts with data normalization which involves the process of ensuring that all the feature data are within same range of 0 and 1. This process is important for ensuring that dataset does not overfit or underfit the model during training.

The method used to achieve this was Min – Max scaling technique, shown in equation 3.1 below.

$$X' = \frac{x - x_{min}}{x^{max} - x_{min}} \qquad 3.1$$

Where x_{max} = the largest value of the feature

x_{min} = the smallest value of the feature

if x is minimum, $x - x_{min} = 0$ hence $x' = 0$

if x is maximum, $x - x_{min} = x_{max} - x_{min}$ hence $x' = 1$

if x is between max and min value, x' is between 0 and 1

3.5.2 Data Visualization and Balancing

The dataset used consists of 10, 000 data points or samples. The data were in two categories, namely explosive and non-explosive categories. Figure 3.4 shows the distribution of the dataset based on these categories.

The dataset was pre-processed after checking to determine if there were any missing value and dataset balanced between the two classes were done.

Figure 3.4 show the distribution of data categorize into explosive and non-explosive image that is as a result of numeric data conversion to create the image. During this process, the numerical values were read row by row, and using the row matrix to form a new 2x2 matrix. Each value in the matrix was used as a pixel value representing a shade of images.

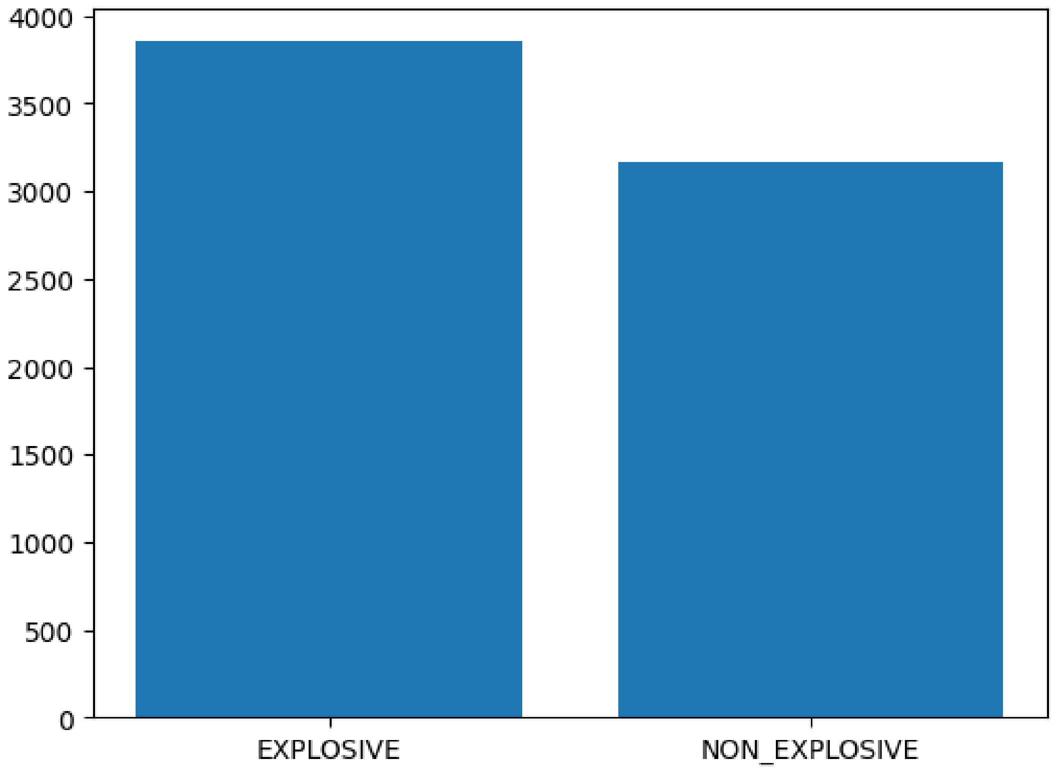

Figure 3.4: Distribution of the dataset categories

The distribution shows that the explosive category has a total of 5, 347 samples (53%), while the non-explosive category has 4,653 (47%) data samples. This distribution was a case of slight imbalance in the dataset, since there is the existence of majority and minority classes in the dataset. Such situation could lead to biased predictions and misleading accuracy. Therefore, this data must be balanced.

To create a balance in the dataset, the Synthetic Minority Oversampling Technique (SMOT) was used. This approach uses linear interpolation to create synthetic values of the minority class. Algorithm 1 below was used to implement the SMOT.

Algorithm 1:

Let the minority class set = A, such that $x \in A$

Loop*:*

Determine the k-nearest neighbor by computing the Euclidean distance between each x in set A

Set new x' between each nearest neighbor such $x' \in A$ *that where* $x' = x + rand\,(0,1) * |x - x_k|$*. Fix new point as x' along the lines segments of the neighbors*

Set N = N – 1

If N ≤ 0

Goto 5

Else Goto Loop

Stop

3.5.3 Data Conversion to 2D

During this process, the numerical values were read row by row, and using the row matrix to form a new 2x2 matrix. Each value in the matrix was used as a pixel value representing a shade of image as shown in figure 3.6 information. In this way, images were formed from numerical data. The output images were separated and stored as JPEG files into folders based on their respective classes. The two main folders created for this purpose were "Explosive" and "Non-Explosive". The code for the implementation is shown in appendix A in the appendices section. Moreover, the data were divided into training, testing and validation subsets. The training subset was 70% of the whole dataset, test subset was 20% and validation subset 10%.

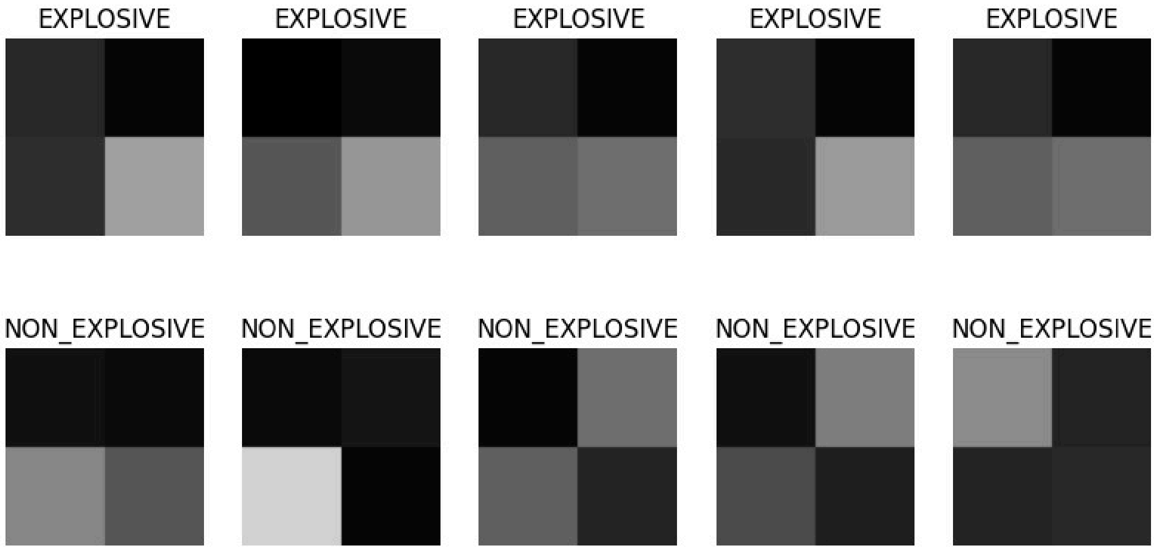

Figure 3.5: Explosive Trace Images and non-Explosive Images

This stage involves loading and preprocessing image data from the subsets. This was done by first defining variables for holding the image path where the images were stored. The code for achieving this is shown in Figure 3.7 below.

```
path='/content/drive/MyDrive/Dataset/'
print("Dataset path:  ")
print(os.listdir(path))

train_dir=path+'Train'
test_dir=path+'Test'
val_dir=path+'Val'
print("Sample path:  ")
print(val_dir)
```

Figure 3.6: Code for Data to Image Conversion

When the images were loaded into the variables, the dimensions were further reshaped to ensure that they all maintain the same size. This was achieved using the following code in python.

```
input_shape = (24, 24, 1)  # Adjust dimensions based on your dataset
```

This means that all the images will maintain height and width pixel dimensions of 24 x 24, 1 channel since the images are already in gray scale.

3.5.4. Image Data Augmentation

Data augmentation is process that ensured that our model generalized well. The **ImageDataGenerator** class in keras was used for this purpose. The process includes a series of random transformation of images such as rotation, flipping, zooming, cropping and brightness/contrast adjustment. This stage was achieved using the code snippet shown in figure 3.8 below, while the full code for the augmentation was shown in appendix E

```
# Data augmentation for the training set (optional but recommended)
train_datagen = ImageDataGenerator(
    rescale=1./255,      # Normalize pixel values to [0, 1]
    rotation_range=40,  # Randomly rotate images
    width_shift_range=0.2,  # Randomly shift images horizontally
    height_shift_range=0.2,  # Randomly shift images vertically
    shear_range=0.2,  # Shear transformations
    zoom_range=0.2,  # Randomly zoom images
    horizontal_flip=True,  # Randomly flip images horizontally
    fill_mode='nearest'  # Fill mode for pixel values outside the image
)
```

Figure 3.7: Image Data Augmentation code

The code show that our images were randomly rotated by 40 degrees, scaled by a factor of 1/255, horizontally and vertically skewed to 0.2, and zoomed by a factor of 0.2.

3.5.5. Convolution Neural Network Development

In this stage, the CNN model was developed with the development phase following the general structure of the CNN architecture. The stages involved the following layer development:

1. Convolution layer design
2. Fully connected layer design
3. Design of the Output Layer

3.5.5.1. Design of the Convolution Layer

The convolution layer consists of the following:

1. Image feature map or image matrix, X, which is a 2x2, which was scaled by padding to 3x3 matrix (2D)
2. A filter, f, a 2x2 matrix.

The operation performed at this layer therefore is the convolution, Z(2x2) of X and f, which is the sum of the element-wise product of X and f, and this can be expressed as:

$$Z(2,2) = \Sigma X(3,3) * f(2,2) \qquad 3.2$$

Our convolution layer with 3 D-sub layers was developed using keras in the code snippet presented in Figure 3.9

```
layers.Conv2D(32, (2, 2), activation='relu', input_shape=input_shape),
layers.MaxPooling2D((2, 2)),
layers.Conv2D(64, (2, 2), activation='relu'),
layers.MaxPooling2D((2, 2)),
layers.Conv2D(128, (2, 2), activation='relu'),
layers.MaxPooling2D((2, 2)),
```

Figure 3.8: Code for Convolution Layer Development

The first 2D convolution layer was a designed with 32 filters, each being a 2x2 matrix filter, which uses the Rectified Linear Unit (ReLU) activation function. The output of the first convolution (Conv) layer was passed through 2x2 Max Pooling operation, before being fed to the next Conv layer. The second Conv layer had 64 2x2 filters, with ReLU activation function. The third Conv layer had 128 2x2 filters also with ReLU activation function.

3.5.5.2. Design of the Fully Connected Layer

This is a neural network layer and can only work with 1D data. This implies that the output of the last Conv layer, which is a 2D must be converted into a 1D image by flattening as shown in Figure 3.10, and was now to be fed into the fully connected layer. In the fully connected (FC) layer, linear and non-linear transformation operations were performed on the 1D data fed into it.

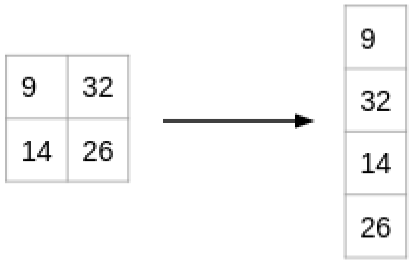

Figure 3.9: Conversion of 2D to 1D

The linear transformation operation is represented by equation 3.3 below.

$$Z = w^T \cdot X + b \qquad 2.3$$

Were

X is a vector of the image feature extracted from Conv layers
w is a 4x2 the matrix of weight (a matrix of randomly assigned values)
b is a vector of biases (a constant value)

The FC had 2 neuron to linearly transform 4 data points in the X image vector. Therefore, Z was given as

$$Z = \begin{bmatrix} w_{11} & w_{21} & w_{31} & w_{41} \\ w_{12} & w_{22} & w_{32} & w_{42} \end{bmatrix} \begin{bmatrix} D_1 \\ D_2 \\ D_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \qquad 3.4$$

During the non-linear transformation, an activation function was chosen for the output of the FC. Sigmoid function in equation 3.5 was the best choice at this stage because we are dealing with binary classification.

$$f(x) = \frac{1}{1 + e^{-x}} \qquad 3.$$

The final task during the model development was to determine the method of optimization, a process that was used to update the learning rate of the model to ensure that all computations converge correctly. Adam gradient decent defined in equation 3.6 was used.

$$\theta_2 = \theta_1 - (\alpha \times \text{gradient parameter}) \tag{2.6}$$

Where

θ_1 is the New parameter

θ_2 is the old parameter

α is the learning rate (a constant that determines the amount of change to be made to old parameter)

Gradient is the change in classification error with respect to parameter

The code snippet that was used for the implementation is illustrated in Figure 3.11

```
layers.Flatten(),
layers.Dense(128, activation='relu'),
layers.Dense(2, activation='sigmoid')  # num_classes is the number of output classes
```

Figure 3.10: Model Optimization Code

3.6. Approach and Technique(s) for Explosive Trace Detection Using Deep Transfer Learning

The approach and technique used in this research is experimental approach, in which experimental model of machine learning algorithm based on Deep Transfer Learning was developed for the purpose of detecting explosive traces by means of classification. Transfer Learning (TL) is a machine learning method that transfers the skill used in learning a task to another scenario of learning a different task. Deep Transfer Learning (DTL) is a TL that is based on the deep neural network architecture.

In this research, explosive traces were detected using Artificial Intelligence (AI) model. Deep Transfer Learning model was developed from a base model known as GasNet from (Barrera et al., 2020) which was developed from Deep Convolution Neural Network with 38 layers. Out of these number of layers, 6 inner (deep) layers were frozen, reconstructed (tuned) and trained using Explosive Gas concentration dataset from UCI website. To classify explosive gas within an area, sensor are deployed to detect the concentration of Carbon (C), Hydrogen (H), Oxygen (O), and Nitrogen (N) gasses, which are combined and sent to the newly trained model. The model then uses the learned knowledge to classify the gas combinations as either explosive or not.

3.6.1 Transfer Learning Model Formulation for Explosive Trace Detection

Transfer learning is based on the theory of Identical Element (IE), which state that transfer of learning will take place if the two tasks to learn from have identical features (Campbell et al., 2006). This suggests that in the case of this research work, that GasNet and the proposed model of this research should have some sort of identical features in their input dataset. This implies that the output of output function may be different from each other.

The notation representing TL in its general context is that if a domain, D is given by

$$D = \{X, P(X)\} \tag{3.7}$$

Where X = Feature Space

P(X) = Marginal Probability Distribution

X = $\{x_1, x_2, x_3 \ldots, x_n\} \in X$

In the context of this research, x_1, x_2, x_3, x_4 will represent C, H, N, and O, and hence will be represented as $x_C\ x_H, x_N, x_O$

This therefore implies that, given an explosive classification label, Y, can be determined by the predictive function, $f(.)$, which can be learned from the training dataset $(x_i, y_i) | i \in X$, where $x_i \in X$, and $y_i \in Y$. This implies that $f(x_i) \equiv P(y_i | x_i)$ is the conditional probability of detecting an explosive gas from a given set of $x_C\ x_H, x_N, x_O$

The conceptual framework is presented in figure. 3.2. The framework shows the various layers involved in the development of the model, which achieves the first objective of this research.

The base model is a DCNN model that have been previously trained with very large dataset, for the detection of gases in an e-nose application. The model was tuned by reconstructing the inner or deep layers by freezing 6 layers and replacing them with new ones for the application of the task at hand. This process is also known as feature extraction. The final stage is the training of the new model by adjusting and testing on new data.

In this framework, the base model is first tuned by freezing 6 inner layers and reconstructing them by introducing new layers since $P(Y t / X t)_{Explosive} \neq P(Y s / X s)_{GasNet})$.

3.6.2 Transfer Learning Model Development

The developed CNN model in section 3.5.5 was modified at the output layers so that data generated by a simulation model were fed into it for further training and to demonstrate a virtual deployment environment (see section 3.x1) for areal-based explosive testing. This setup was necessary to be able to test the model with real-time data for the sake of validating the results of the model's performance metrics.

The procedure in developing the DTLETD model is represented in the activity diagram shown in figure 3.12 that shows the data generation stage, development of new model and new model validation. This process the following stages:

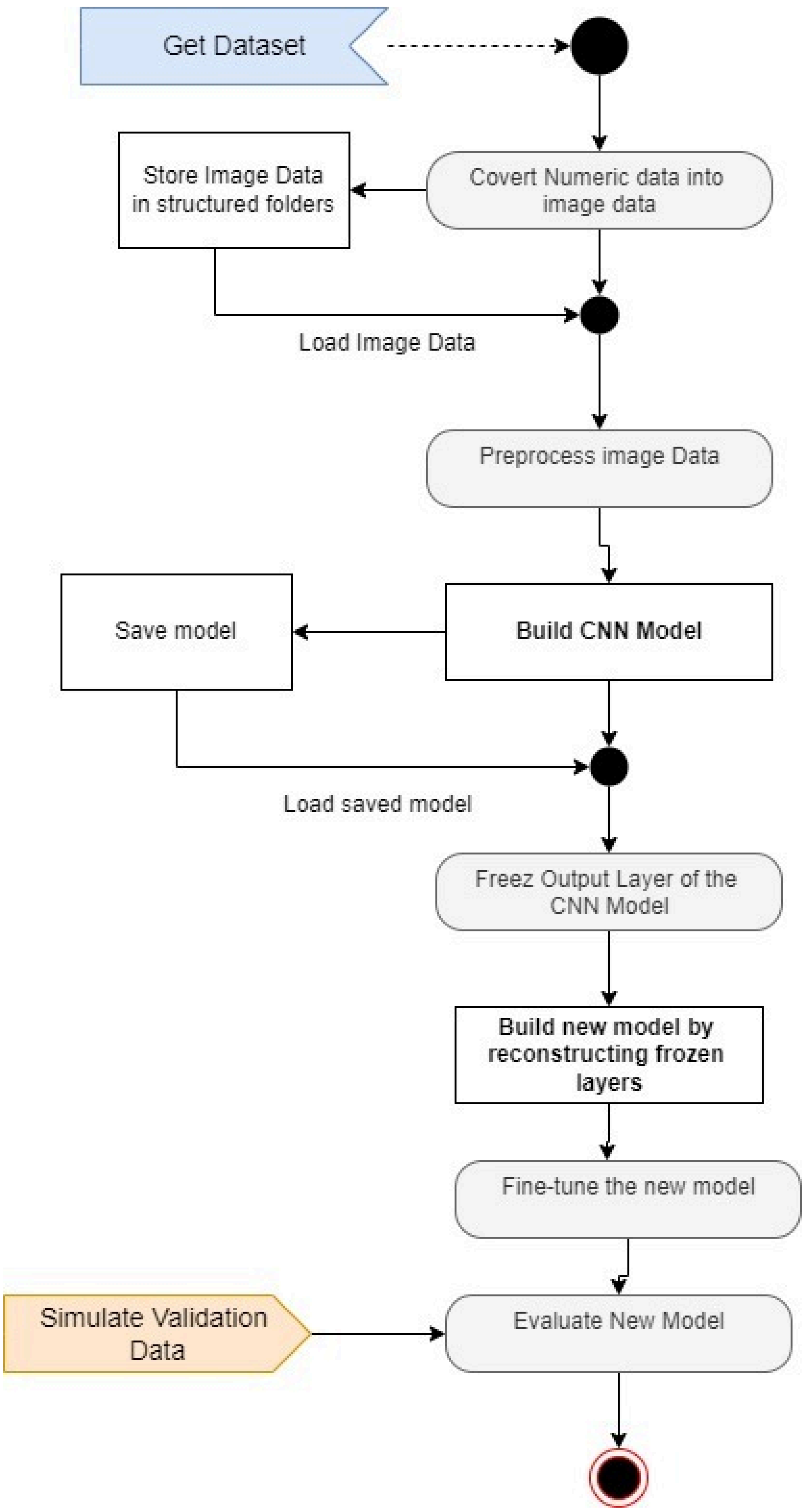

Figure 3.12: Transfer Learning Activity Diagram for Explosive Trace Detection

As it can be seen in figure 3.12, a set of simulated data were generated using the simulation model in section 3.7. The generated data were in the range and format of the dataset used in training the base model. That is data were generated each for C, N, O and H features respectively. A set of 20 samples of simulated data were generated as shown in table 4.1.

After storing the simulated data in a table, the pre-trained CNN model was loaded the Convolution Layer of the CNN model was frozen to prevent that layer from being affected by the modification during the development of the transfer learning model. The code section responsible for this is given in figure 3.13

```
for layer in base_model.layers[:-5]:
    layer.trainable = False
```

Figure 3.13: Code for Freezing the Convolution Layer

This stage was for the development of the remaining layers of the CNN model in order to develop a new model, while retaining the components of the frozen layer. This was achieved using the code snippet in figure 3.14. The code has the first line for initializing a model variable, followed by the line that called the base-model, which is the pre-built CNN model. After that was then added, a new output layer (flatten layer). A new dense layer with 128 units was added, and each fully connected to the flattened layer through ReLU activation function. This was followed by a dropout layer with a dropout rate of 0.5. Finally, an output layer was added with a single unit of sigmoid activation function.

```
model = models.Sequential()
model.add(base_model)
model.add(layers.Flatten())
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dropout(0.5))
model.add(layers.Dense(1, activation='sigmoid'))
```

Figure 3.4: Code for creating new model

During this stage, the newly developed model was trained using the validation data samples, which was about 10% of the base dataset. The code snippet is presented in figure 3.15 and the full code is shown in appendix C. The code typically represents steps for the model to learn from new data samples while retaining its knowledge of the previous experience. The code also specified the hypermeters, such as learning rate, batch size, and epochs.

```
history = model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // batch_size,
    epochs=epochs,
    validation_data=val_generator,
    validation_steps=val_generator.samples // batch_size,
    callbacks=[lr_scheduler]
)
```

Figure 3.11: Code for fine-tuning the new model

The next stage was the evaluation of the newly built model. The fine-tuning accuracy score and the AUC were determined and recorded. The system was further tested using the simulation gas data, and the test accuracy score and AUC were recorded as well. Graphs of the system training validation losses against the epochs as well as losses against learning rate were also plotted and presented in figure 4.8 and 4.9 respectively.

3.7 System Deployment and Testing

The block diagram of figure 3.16 represents the implementation model of the area-based explosive trace detection system. This set up is meant to generate data for the developed model for validation as shown in the design framework in figure 3.1. The diagram has four major sections, which include the Input Unit, Edge Interface Unit (EIU), Cloud Intelligent Unit (CIU), and the Output Unit.

3.7.1 Description of the Input Unit

The input unit consists of an array of three sensors from the MQ series. The sensors are responsible for the sensing of the explosive traces by detecting certain characteristics of the various trace components in the deployed environment. Our input trace elements are the C, N, O, and H gases as shown in figure 3.1. Therefore, the categories of MQ series sensors used were such that could detect the presence of these trace elements. For instance, MQ-7 was used for detecting CO from which C was detected, MQ- was used for the detection of Hydrogen gas, while MQ-135 was used for the detection of the Oxygen and Nitrogen gases.

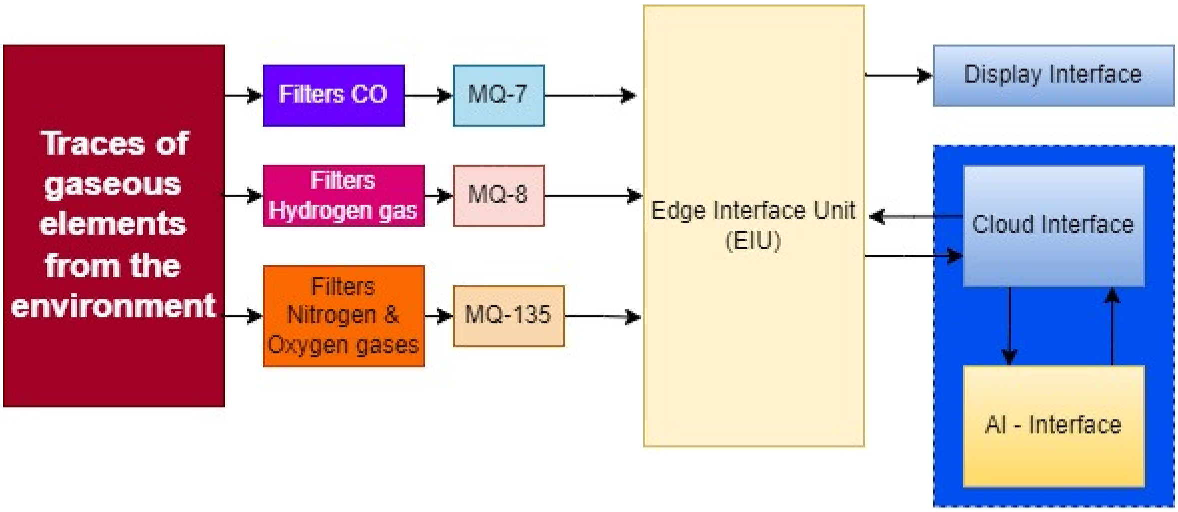

Figure 3.12: Block Diagram of the Implementation model

The characteristics features of these sensors are presented in table 3.1. The sensors simply converts any gas trace within its range of detection into an equivalent analogue signal, which is measurable as a voltage range at the output pin of the sensors. The output analogue voltage was fed into the EIU for further processing tasks.

Table 3.1: Characteristics of the Sensor used

Characteristics	**Sensors**		
	MQ-7	**MQ-8**	**MQ-135**
Operating voltage	+5V	+5V	+5V
Sensitive to	CO	Hydrogen	NOH, NH3
Analogue output range	0 – 5V	0 – 5V	0 – 5V

3.7.2 Description of the Edge Interface Unit (EIU)

The EIU represents the processing unit, which receives the input signals from the sensor array. Firstly, the EIU performs the analogue to digital conversion on all the input signals. Secondly, the EIU separate the input signals into various components before compressing the signals using 50th term averaging methods to reduce signal noise due to false trigger. Thirdly, the compressed digital signal was packaged transmitted to the cloud using HTTP protocol and Thingspeak cloud. The result of the out was collected. It should be noted that the out graph generated on thinkspeak has a 10^{-1} multiplier, this is to accommodate thingspeak value range.

3.7.3 Cloud Intelligent Unit (CIU)

At the CIU, each signal component was collated for storage, visualization and further classification processing using the already built Transfer Learning Model.

Communication between this unit and the EIU is full duplex mode to allow for feedback to the EIU and for effective communication of the result of classification to the output unit. The output unit is an LCD module, which was used primarily for the display of the classification result at any selected instance.

3.7.4 System Circuit Development and Testing

For a real deployment and testing for the detection of explosive traces, circuit in figure 3.17 was developed following the block diagram in figure 3.16 as described in section 3.7.1 above, the input interface was realized using the MQ series gas sensors. The EIC was realized using Arduino Uno with in-built ESP wifi module. The wifi module enabled seamless transmission of data to the cloud. The output of the MQ-8 was connected to the analogue input of the Arduino board (A0), MQ-7 was like-wise connected to the A1 pin and MQ-135 was connected to the A2 of the Arduino board. During the simulation testing, the potentiometers, RV1, RV2, and RV3 were varied to allow the MQ sensors to generate random output values. Each set of generated output values were processed accordingly and transmitted to the cloud server using the HTTP protocol. The Arduino code for proteus simulation is shown in appendix F.

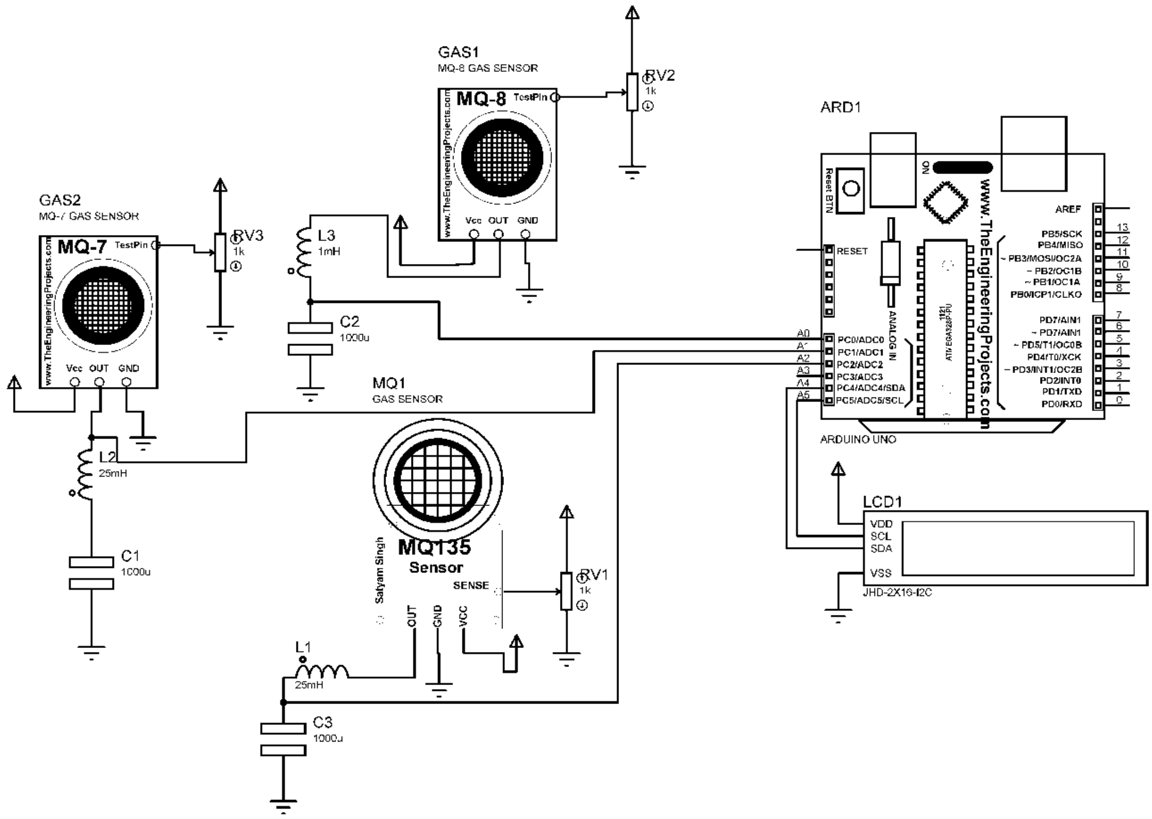

Figure 3.13: Circuit diagram of the Implemented system

3.8 Description of Performance evaluation parameters/metrics

The acquired dataset is split into a training dataset and a test dataset, with 70% of the data allocated for training and 20% for testing, while 10% for validation. This hold-out method is commonly used to train DNN(Nguyen et al., 2021). The training dataset used to train the model utilizing a three-fold cross-validation approach. This approach helps to prevent the model from becoming biased by analyzing the evaluation metrics on different folds of the data. The test dataset will be employed to assess the accuracy of the trained model on sensor dataset for the trained model to make predictions and comparing those predictions to the actual values.

The trained model accuracy is obtained using Equation 3.7 and Equation 3.8, with the test dataset. Where TP is the True Positive, FP is the False Positive, FN is the False Negative, and TN is the True Negative. TP refers to an accurate prediction of a positive explosive trace, while TN refers to an accurate prediction of a negative explosive trace. FP occurs when a negative explosive trace is predicted as a positive one, and FN occurs when a positive explosive trace is predicted as a negative one. The F1-score was computed using Precision (Equation 3.9) and Recall (Equation 3.10).

Confusion matrices are an effective tool for evaluating the accuracy of a classification model as they provide a more detailed breakdown of the model's performance than a simple accuracy score. Specifically, a confusion matrix tallies the number of true positives, true negatives, false positives, and false negatives for each class or category. By examining these values, we can calculate a range of performance metrics such as precision, recall, and F1 score, which provide a more balance and informative picture of the model's accuracy. Additionally, by evaluating a model's accuracy using a confusion matrix, we can identify which categories or classes are being misclassified most frequently and adjust our model accordingly. This can help us optimize our model's accuracy for specific applications and ensure that it is performing effectively in real-world scenarios.

We will also use Area under Curve (AUC) to check whether the performance score is a true representation of the accuracy. The higher the AUC the better the system performance and that is a better way to check the system robustness.

The validation of the model, the model was tested on Explosive trace dataset from other sensor network but in this virtual simulated network generated a live explosive data to determine its performance. The performance is compared with other traditional machine learning methods and other DL model in terms of accuracy and AUC. This proposed method is achieved using Python software, Keras with Tensorflow as the backend. The trained GasNet model will then be imported from keras to be ran on core i5, 8GHz Laptop, using NVIDIA GTX960 GPU.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100 \qquad 3.7$$

$$F1-score = \frac{2 \times precision \times Recall}{Precision + Recall} \qquad 3.8$$

$$Precision = \frac{TP}{TP + FP} \quad 3.9$$

$$Recall = \frac{TP}{TP + FN} \quad 3.10$$

Apart from these metrics the Receiver Operating Characteristic Area under Curve (ROC-AUC) was also used to test the level of accuracy of the model

AUC = Area under the ROC curve

The ROC curve is a plot of the True Positive Rate (TPR) on the vertical axis, given as

$$TPR = \frac{TP}{TP + FN} \quad 3.11$$

Against the False Positive Rate (FPR) on the horizontal axis, given as

$$FPR = \frac{FP}{TN + FP} \quad 3.12$$

3.9 Tools used in Implementation

The tools that was utilized to realize this research include the following:

a. Core i5, 8ghz personal Computer (PC) that was used to carry out all the software operations
b. Draw.io software was used to design the framework, flowchart and diagrams.
c. Google Collab was used to deploy the machine learning models, it was able to handle the computational load of classification.
d. Python software was used to write the codes
e. Keras with Tensorflow as the backend was used to train the model before it was exported to be ran on the PC with.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Preamble

The results for the various experiments are presented in this chapter, firstly with the system evaluation, the result for the proposed base model of CNN and the DTLETD. The result was discussed after its presentation and was finally compared with other known models all in accordance with the research questions to be addressed.

4.2 System Evaluation

In this study, the results are presented both Deep Learning model and Deep Transfer Learning Model. The Deep Learning model validation accuracy serves as a measure of how well the model perform on the explosive trace data. The performance of the model will be evaluate when transfer has not occur. The second evaluation will be on the Deep Transfer Learning model, where the model training loss will be evaluated together with the performance rate on limited data. The rate at which the developed model learn will also be evaluated. By presenting the results in this way, we can demonstrate the effectiveness and generalization capability of DTL model and provide insight into how it can be further improved in the future. Overall, emphasis is placed on learning rate and thorough evaluation to ensure that the model is performing at a high accuracy and is ready for deployment in real-world scenarios on edge devices.

Deep learning models have become increasingly popular and powerful in recent years, providing accurate predictions, and helping to enable many innovative applications.

4.3 Results presentation and Analysis for Explosive trace Detection using CNN

The results obtained from data preprocessing to the point of model deployment is presented in this session with the corresponding analysis of the results.

4.3.1 Explosive Data Preparation Results

This results in this section shows explosive and non-explosive data set and the data conversion. Figure 4.1 is the explosive trace and non-explosive trace data distribution used in this work while figure 4.2 shows the data conversion result of the same.

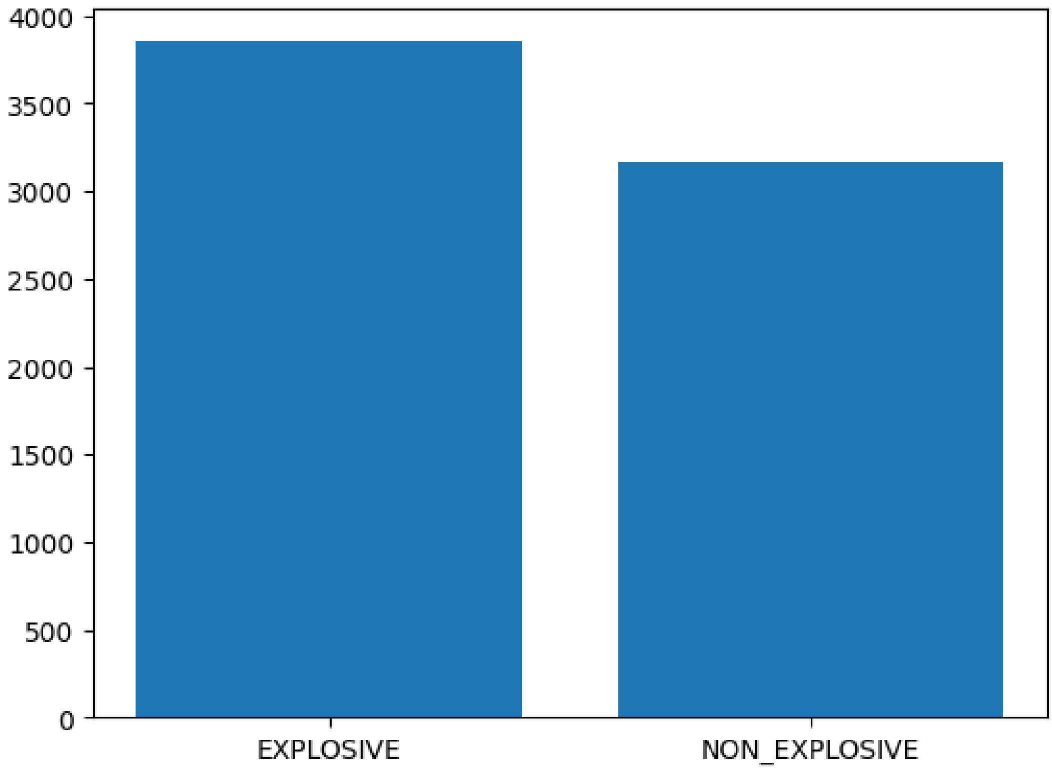

Figure 4.1: Explosive and Non-Explosive Dataset Distribution result

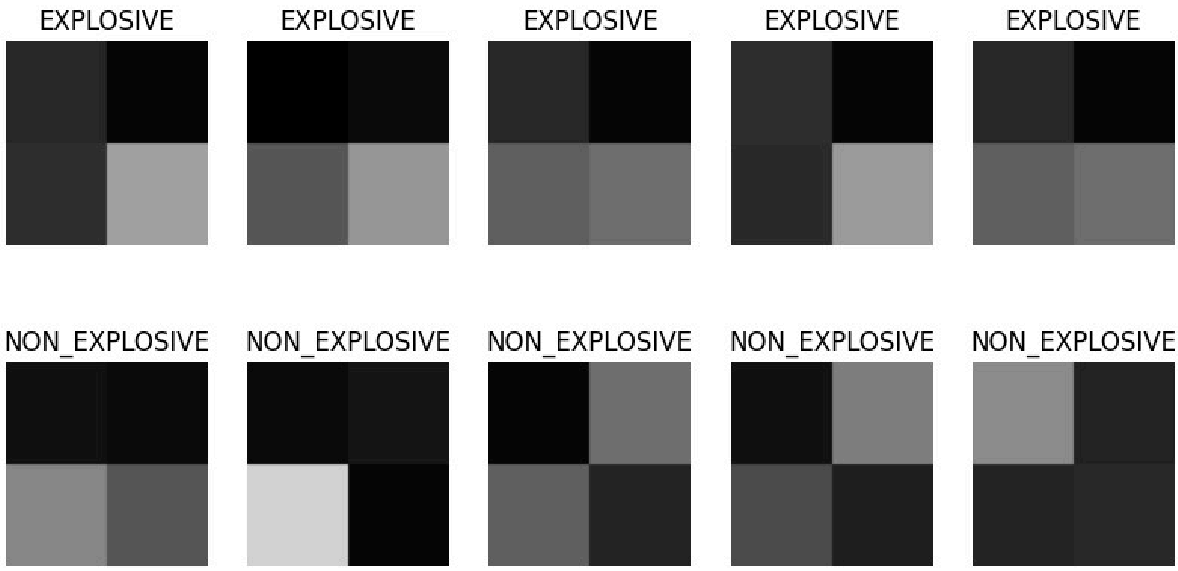

Figure 4.2: Result of Explosive and Non-Explosive 2D Data

4.3.2 The result and Analysis of CNN on Explosive Trace Detection

The result of the model deployed using python 3.10 is shown in Figure 4.3, it shows the graph of loss against the epochs. The result show that during each epoch, the losses in the developed model was inversely proportional to the epochs. Meaning that error that would produce misleading production was reduced sufficiently. This confirms that the model performed well with the dataset. The validation was done using validation dataset.

The result of the training performance evaluation is shown in Figure 4.4, it presents how the model performed during training. Accuracy was used as the metric of evaluation. From that graph, we see that during each iteration, the accuracy of the model was increasing and achieved 98.2% accuracy score.

The confusion matrix was used to evaluate the system performance during testing. This plot is shown in Figure 4.5. The result shows that all the 32 samples used for the test were correctly classified. Out of that number, 18 samples were correctly classified as explosive, while the remaining 14 samples were also correctly classified as non-explosives. Also the ROC curve in Figure 4.6 also confirms that the model performed very well. For both classes, the model archived an area under curve (AUC) value as 1. This is the highest any model can achieve. These result and those of other metrics are presented in table 4.1 and appendix G shows the calculation.

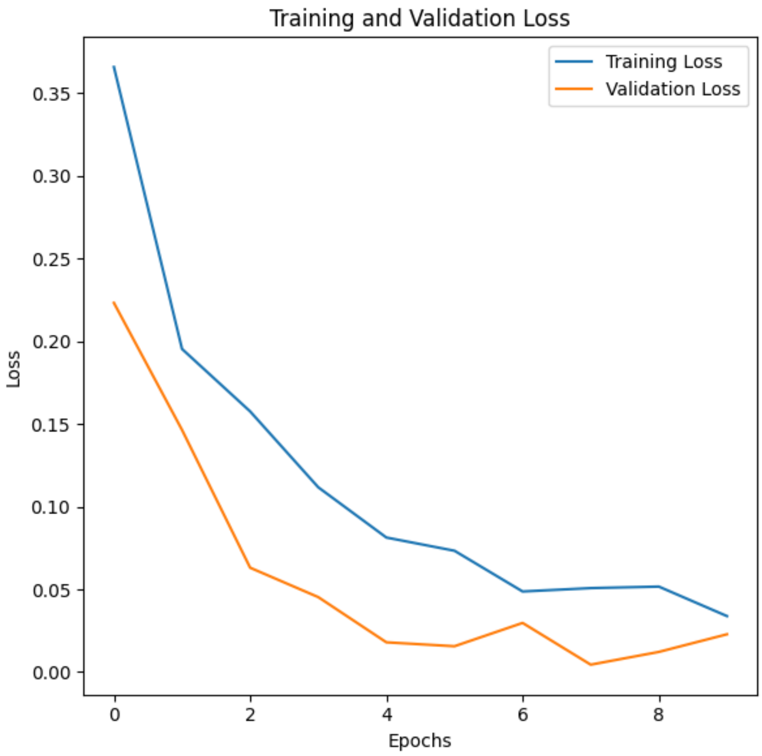

Figure 4.3: Training and Validation Losses Result

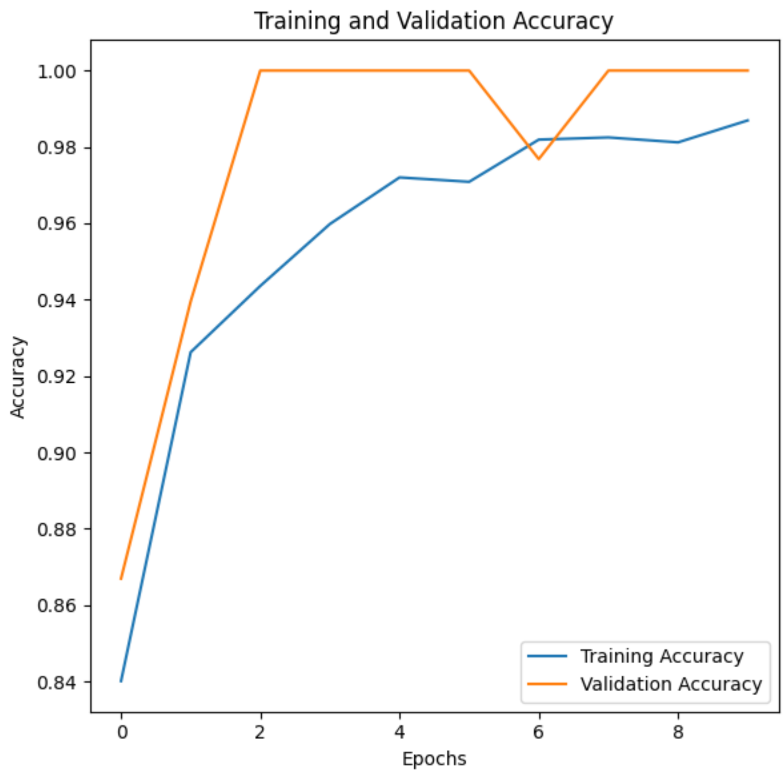

Figure 4.4: Graph of Accuracy against Epochs Result

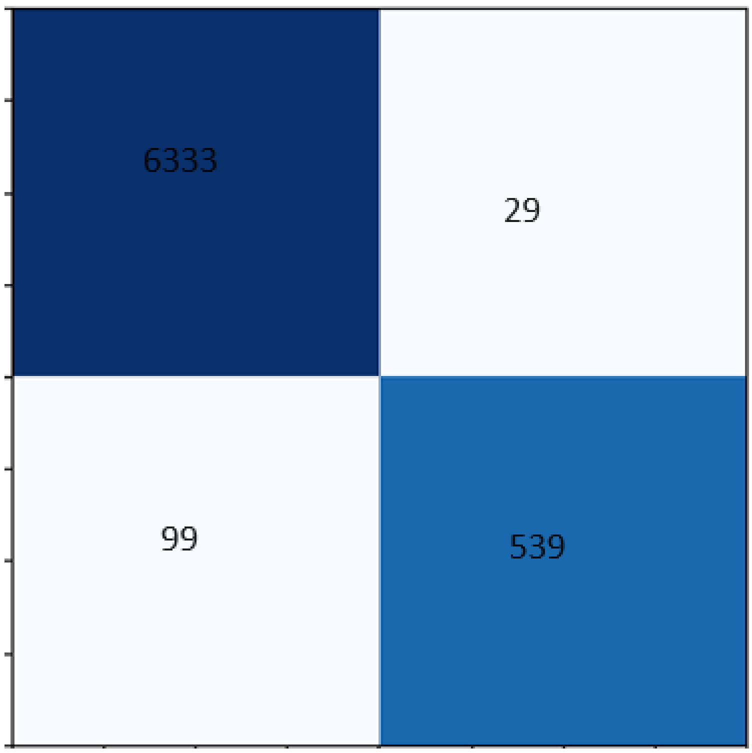

Figure 4.5: Confusion Metrix of the CNN after Training with 7000 data points

Table 4.1 Other performance Metrics of the CNN Model

ACC	PRECISION	RECALL	F-1 SCORE	SPECIFICITY	FPR	TPR	AUC
0.982	0.985	0.985	0.985	0.949	0.051	0.985	1.00

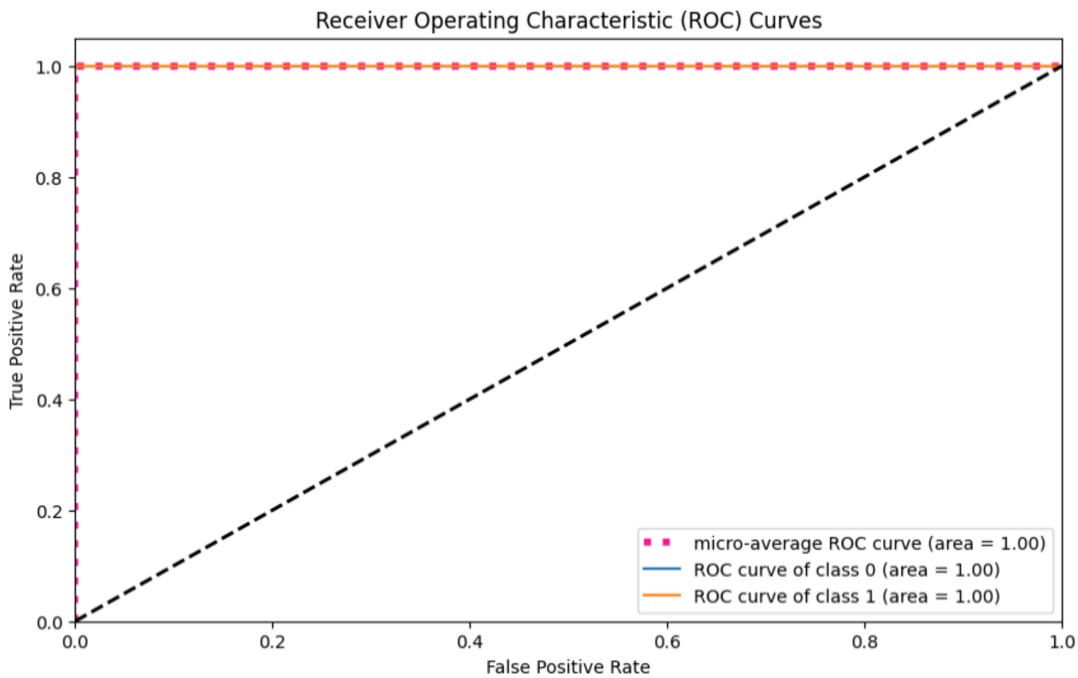

Figure 4.6: Receiver Operation Characteristic Curve (ROC)

4.3.3 Result of Deep Transfer Learning Model for Explosive trace detection

The simulation model described in section 3.6.1 was first used to generate some random new samples of data resembling those of the original dataset. The generated samples were stored in table 4.1. These set of data was used for the validation testing of the model, by being used as input to the transfer learning model. The prediction yielded the target values in each case.

The developed transfer learning model was trained with only 3 epochs and the graph in Figure 4.8 was generated. The graph is a plot of training losses and validation losses against the epochs. The result show that the training losses dropped sharply from 0.15 to 0.08 during the iteration of the first epoch and converged before the second epoch. The validation losses also dropped from less than 0.05 to 0 within the first epoch and it remained 0 during the second epoch.

The result reveals the following significant achievements:

1. The transfer learning model took less time (about 92 seconds) to train against a training time of about 1287 seconds used to train the CNN model.
2. The transfer learning model converged faster than the with nearly zero losses for both training and validation

The Convergence of learning rate of the Transfer Learning Model is shown in appendix D while Figure 4.9 is a graph of the training and validation accuracy against the epochs is presented. During the iteration of the first epoch, it can be seen that the training accuracy already reach 99.7%, while the validation accuracy remained at 100% from the iteration of the first epoch. Confusion matric presented in Figure 4.7 is also the performance report obtained during this time. Other results were the reports of other performance matrices shown in table 4.2.

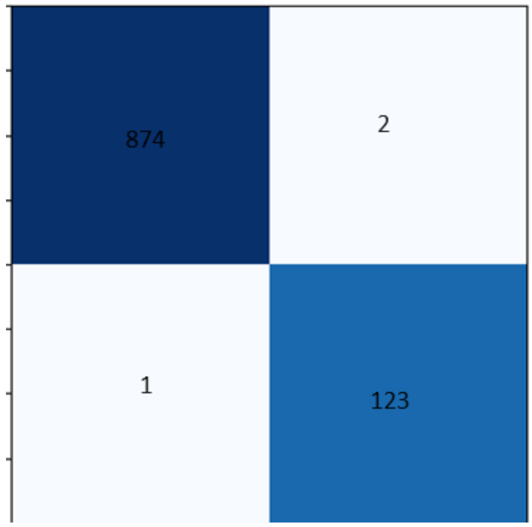

Figure 4.7: Confusion matrix of the DTLETD after Training with 1000 data points

Table 4.2: DTLETD Performance Metrics

ACC	PRECISION	RECALL	F-1 SCORE	SPECIFICITY	False Positive Rate	True Positive Rate	AUC
0.997	0.999	0.999	0.999	0.984	0.016	0.999	0.89

This result confirms that the transfer learning model adjusted very quickly with the dataset to achieve very high and stable performance with the few data samples and small epoch size.

The graph in Figure 4.10 represents the effect of the tuning of the learning rate (lr) hyperparameter on the training losses. The lr was kept as small as 10^{-3} at the start of the training. It was gradually increased as the training progresses. The effect of increasing this hyperparameters was that the losses got smaller until it converged at lr = 1.25×10^{-3}.

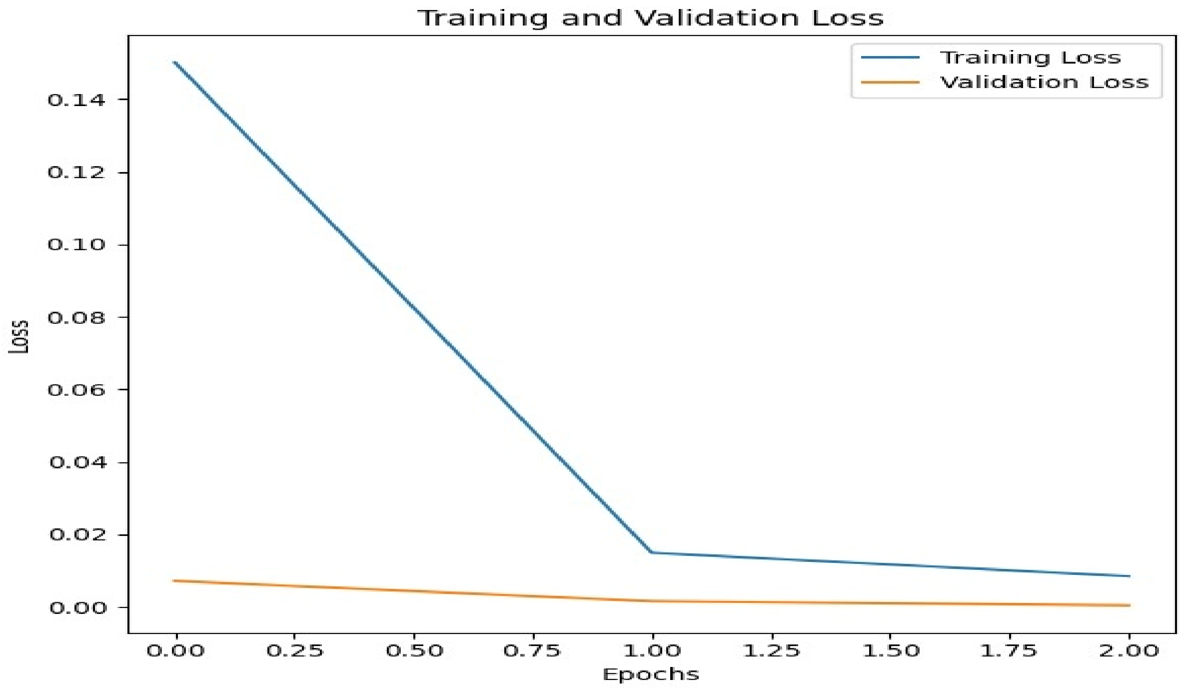

Figure 4.8: Transfer Learning Training and Validation Losses against Epochs

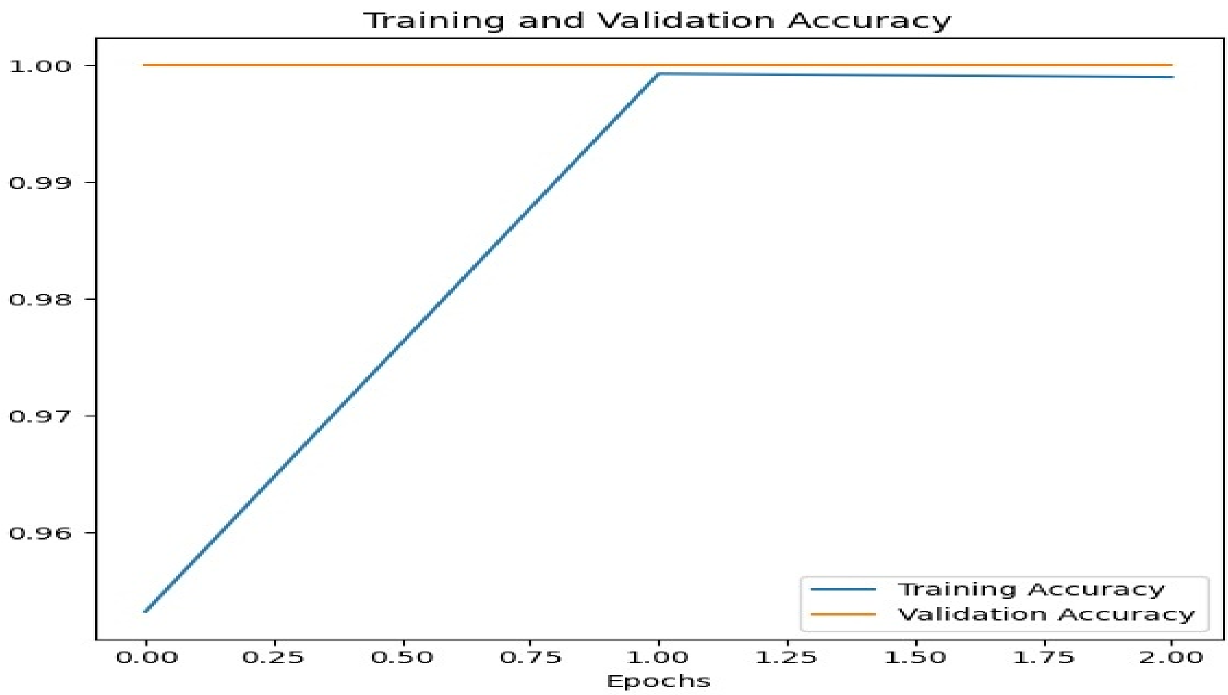

Figure 4.9: Transfer Learning training accuracy and validation against Epochs

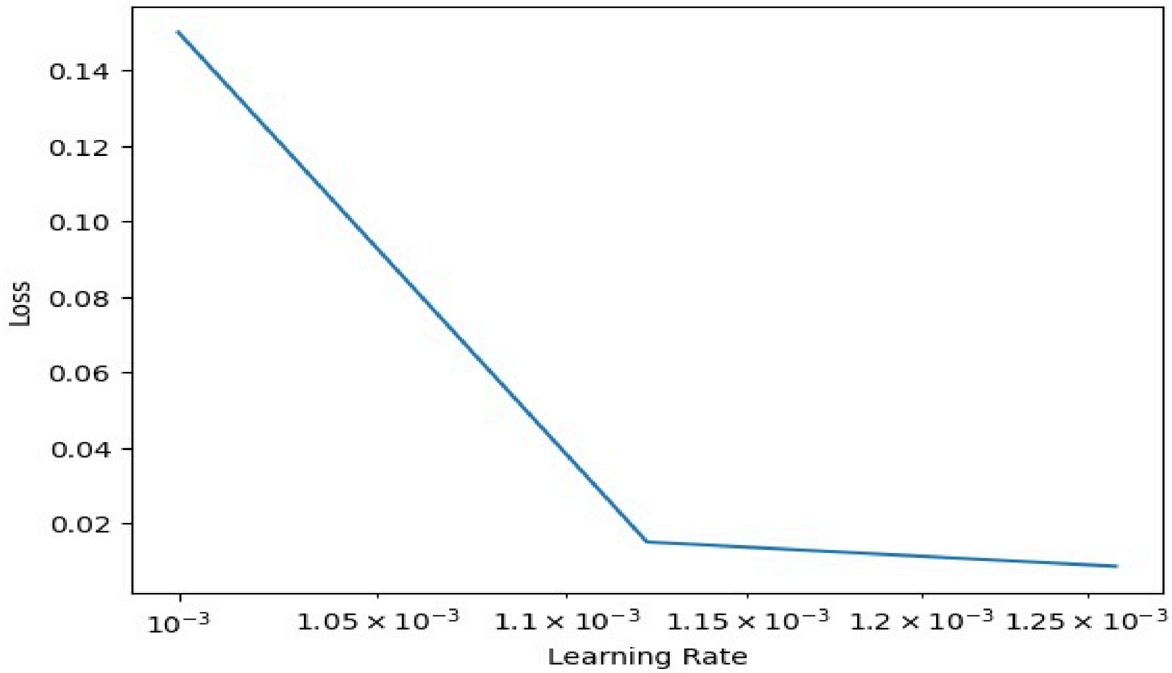

Figure 4.10: Effect of Tunning on the learning rate

4.3.4 Results of the Simulation Model

The simulation model of the system deployment was completed using Proteus and Thingspeak cloud. The circuit was setup as shown in Figure 3.15. During simulation, the system communicated with the Thingspeak cloud via a Wi-Fi connection interface and show the data transmission progress illustrated in Figure 4.11.

Other results of data transmission to the cloud are shown in Figure 4.12 (a) through 4.12(d). This shows the various values of the explosive traced detected by simulation model over a period of about 30 minutes with 10^{-1} multiplier. The range of values were between 0 and 1 as used in the original dataset. These simulated data were used also to further validate the transfer learning model, which yielded the results shown in table 4.1, showing that the model achieved an average prediction accuracy of 99.7%, with an average AUC value of about 0.89. The system also yielded a precession of 96%. This result shows that the developed transfer learning model could still produce high performance metrics values after deploying different data on it.

Table 4.3: Simulated Sample Data of Explosive Trace

C	N	O	H	Target
0.677983	0.164722	0.516603	0.589594	1
0.528973	0.694318	0.860471	0.136377	1
0.053052	0.356432	0.106087	0.519277	1
0.748067	0.553447	0.365401	0.520955	0
0.032338	0.981841	0.780361	0.325508	0
0.96217	0.301966	0.399381	0.468742	1
0.432215	0.988033	0.067858	0.074884	0
0.096146	0.264949	0.124858	0.552386	0
0.69259	0.382476	0.323922	0.740827	1
0.24087	0.505574	0.499285	0.229094	1
0.830683	0.717169	0.967844	0.50378	0

```
Carbon: 0.40 mil
Nitrogen: 0.70 mil
Oxygen: 0.40 mil
Hydrogen: 0.60 mil
Data pushed successfull
```

Figure 4.11: Data Transmission between thing speak and Wi-Fi

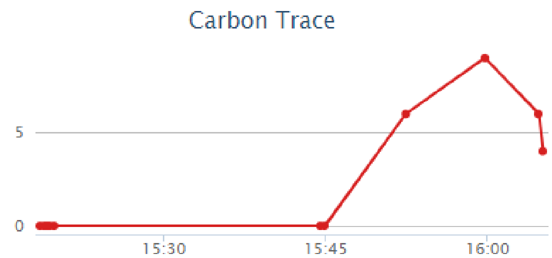

Figure 4.12 (a)

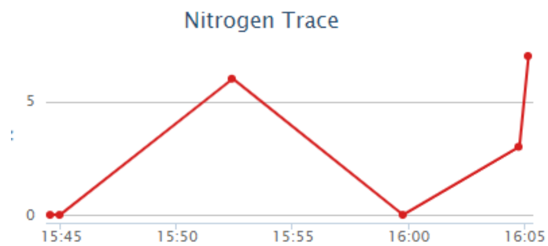

Figure 4.12 (b)

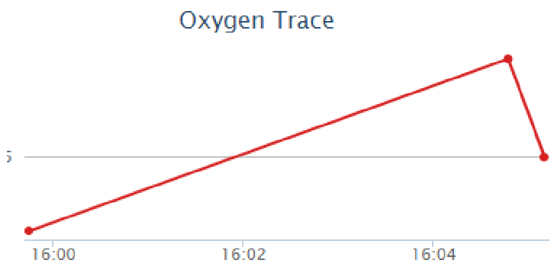

Figure 4.12 (c)

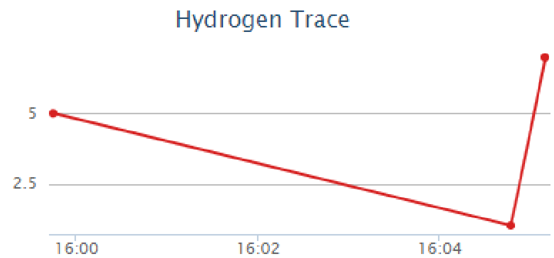

Figure 4.12 (d)

Figure 4.12: Graphic value for Explosive Traces Transmission

4.4 Discussion of the Results

This studies tend to develop an AI base system that can detect explosive trace automatically within an environment of interest using transfer learning model. The framework for the system was developed as shown in figure 3.1 base on deep transfer learning that can detect explosive trace with few explosive trace data with minimal time of training required. The designed framework is in such a way for the system to operate within a smart city by communicating with appropriate authority the presence of explosive trace to be able to take prompt action.

The explosive dataset obtained is a time serial dataset and was converted to a 2D dataset after normalization as presented in Figure 4.2 through serial data to image data generator as presented in section 3.3, this results is to generate an improved results for the CNN model.

The Gas-Net base model was development and with 70% of the data used for training the model, 20% for testing and 10% for validation for the 1,000 data points used, the system perform with high accuracy of 98.2% with an AUC of 1. Since the performance of the system high and acceptable as confirm by the AUC test, the knowledge of the model can be transferred for live test using fewer dataset based on deep transfer learning.

From the result of the experiment shown for the transfer learning model in Figure 4.8 through 4.10, it was discovered that less time is required to train transfer learning model against the CNN base model. The transfer learning model converged faster with nearly zero losses for both training and validation experiment. Since the iteration of the first epoch has training accuracy of 99.7% and validation accuracy at 100%, this result confirms that the transfer learning model adjusted very quickly with the dataset to achieve very high and stable performance with the few data samples and small epoch size.

The result in figure 4.11 and 4.12 validate that deep transfer learning model will produce high performance metrics values after deploying different data on it with the ability to maintain such performance with reduced data. Deep transfer learning is appropriate for area base explosive trace detection where the system is expected to perform with high accuracy with less data and fast adaptation.

4.5 Benchmark of the results

The performance of the model is compared with other model such as Support Vector Machine, ImageNet, Random Forest and K-Near Neighbor, The Deep Transfer Learning for Explosive Trace Detection (DTLETD) outperformed all with an improve training accuracy of 99.7 and AUC of 0.89 as shown in Table 4.4. The detail performance is shown in table 4.5 and the graphical representation of accuracy and AUC shown in figure 4.13. The parameter setting use for the SVN, ImageNet, RNN, AlexNet shown in appendix H.

Table 4.4: Comparing the proposed model and other Machine Learning Models

MODEL	Validation Accuracy	Validation AUC	Training Time(s)
SVM	76	0.50	31.2
ImageNet	77	0.64	26.3
RNN	62%	0.63	28.8
AlexNet	67%	0.71	26.3
CNN	98.2	1.00	29.4
DTLETD	99.7	0.89	25.4

Table 4.5: Metrics of the Benchmarking Results

	ACC	PRECISION	RECALL	F-1 SCORE	SPECIFICITY	FPR	TPR
CNN	0.982	0.985	0.985	0.985	0.949	0.051	0.985
DTLETD	0.997	0.999	0.999	0.999	0.984	0.016	0.999
SVM	0.762	0.773	0.773	0.773	0.748	0.252	0.773
ImageNet	0.773	0.798	0.798	0.798	0.742	0.258	0.798
RNN	0.626	0.715	0.715	0.715	0.561	0.439	0.715
AlexNet	0.671	0.699	0.699	0.699	0.640	0.360	0.699

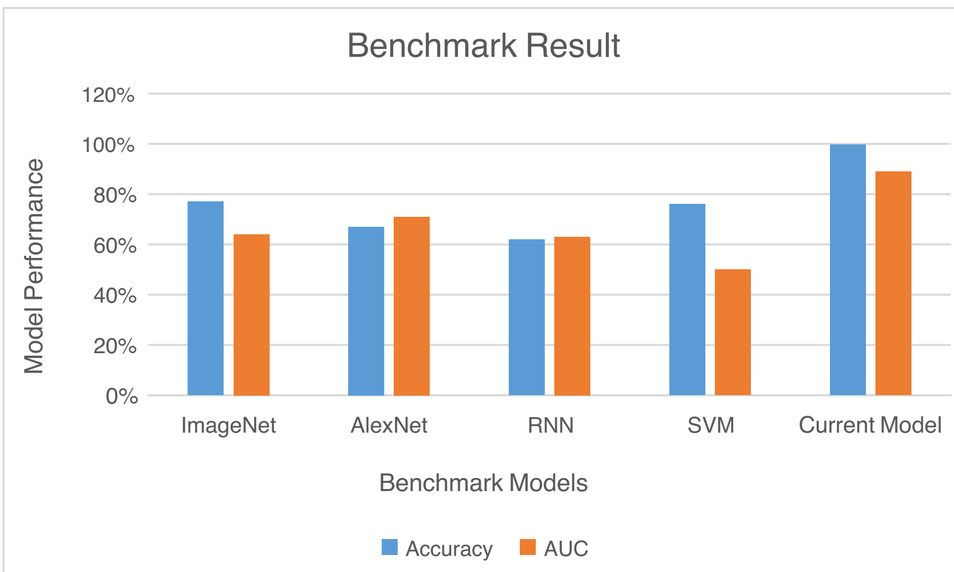

Figure 4.13: Comparing accuracy and AUC of Current Model with other models

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

Attacks on people and several public organization has made explosive trace detection a concern on how best to secure sensitive environment of interest against potential attracts. The limitation of human apparatus with the introduction of AI models have led to the development of smart systems that can detect explosive trace within an environment automatically leveraging of machine leaning approach. Several attempts have been made in developing machine model that can accurately detect explosive trace leveraging on WSN technology.

In this work, a framework for area based explosive detection was designed to accurately utilize deep transfer learning model to detect explosive trace. The deep transfer learning model was developed to solve the problem need for quick adaptation of model and also to be able to accurately function with little available data. The system was validated using 10% of the available data and was found to have high accuracy. This result shows that deep transfer learning model can work well in detecting explosive trace very fast with little information available and that can be done even on edge devices.

5.2 Conclusion

Since terrorist attacks has become a global challenge in public places an AI system that utilizes WSN technology and deep transfer learning model is proposed. The system was able to detect explosive trace that compose of carbon, hydrogen, oxygen and Nitrogen component within an area.

The system recorded an accuracy of 98.2% with an AUC of 1 when the deep learning base model (CNN) was used. However, upon simulation, data were used to validate the transfer learning model, the model achieved an average prediction accuracy of 99.7%, with an average AUC value of about 0.89. The system also yielded a precession of 96% and recorded the least training time compare with existing models. This result shows that the developed transfer learning model could still produce high performance metrics values after deploying different data on it. It shows that deep transfer learning model can adapt faster in detecting explosive trace and will work well on edge devices because of its ability to predict explosive traces well in the presence of few dataset.

5.3 Recommendations

This research focuses on detection of explosive trace that is only a particular type of explosive. The bulk type explosive is not considered, the two types of explosives can be detected by integrating different both chemical sensors and vision sensor through enhanced AI integrated model. This can bring about an enhance security of the area of interest against terrorist attack in the form of bombs.

5.4 Contributions to Knowledge

At the course of this research, we have provided the following contributions to knowledge:

i. A 2D gas data visualization for Deep learning model developed. The model generate explosive image data from explosive trace serial data. This is shown in section 3.5.2 it transform explosive trace serial data and produce image data that is suitable for the deep convolutional network. The accuracy of the model was increased when the image was generated. It also made the operation more robust.

ii. An explosive trace detection Framework was designed to show the stages of development in explosive trace detection. This design begins with the deep learning base model, to how layers of the models are been frozen to develop a new model. The framework is discussed in section 3.2 and figure 3.1 is the designed framework. The framework also show how real-time explosive data will be generated from sensor network to validate the model and anytime explosive trace is being detected, appropriated authority will be notified for prompt action. This has achieved the second objective of this research.

iii. An improved Explosive Trace Detection model (IETD) based on Deep transfer learning. A model for explosive trace detection was developed called DTLETD as stated in objective three. Section 3.6.2 explained the procedure for the model, while development while figure 3.12 shows the model developmental diagram. The model was tested and recorded a better performance compare to existing model

iv. A light weighted model for explosive trace detection that can be run on edge computers. The DTLETD model developed is scalable and have a fast training rate that was able to perform optimally using limited data as recorded in the validation test in section 4.3.4 and proved with the graph in figure 4.9. This system is lighter than the normal deep learning model. This fulfilled objective three. The live deployment on edge device is beyond the scope of this work as discussed in the scope.

5.5 Future Research Directions

- One main recommendation for future direction is the development of ML model that can detect both explosive traces and bulk explosive the same time. The model should be able to detect explosive substance in different state.
- Considering WSN design and mapping that will comprehensibly cover the area of interest, this involves how the sensors should communicate effectively with one another and the base server.
- Deploying the proposed deep transfer learning model for real-time implementation on edge devices can be used by security agents to monitor sensitive areas of interest against explosive
- Another area to be considered is developing IOT base system that can communicate with security agent and with exact location of the explosive trace in an area, this will make the system part of smart city development.
- Another area that can be considered is sensor design that could lead in-cooperating ML algorithm that can improve the sensitivity of explosive trace detection.

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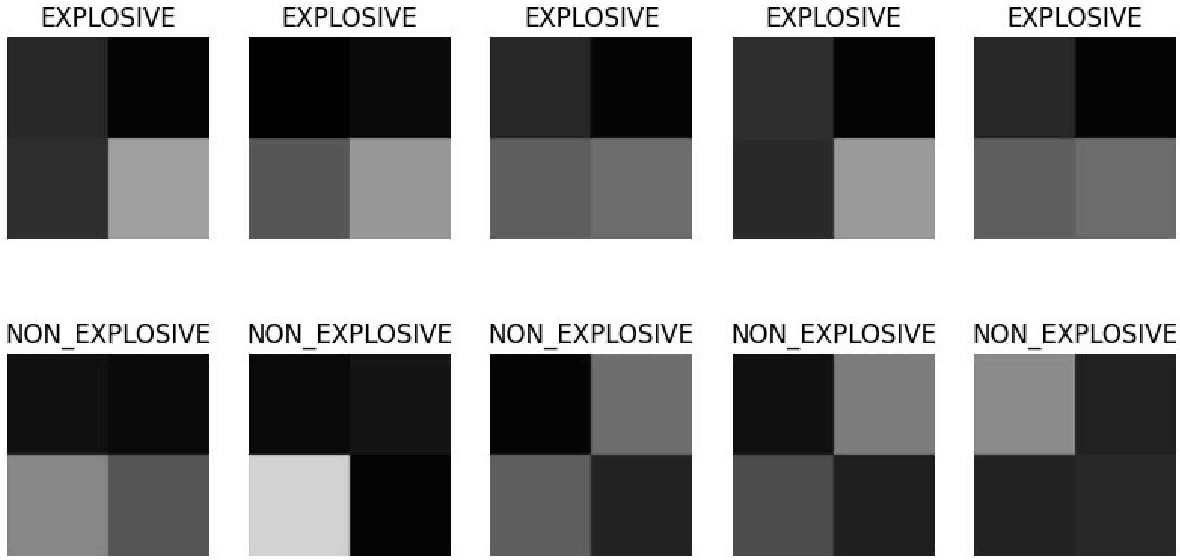
APPENDICES

APPENDIX A: Program code for converting numerical data into 2D images

```
numeric_dataset = pd.read_csv('samples.csv')
image_width = 2
image_height = 2
min_val = numeric_dataset.min().min()
max_val = numeric_dataset.max().max()
numeric_dataset = (numeric_dataset - min_val) / (max_val - min_val)
class1_data = numeric_dataset[numeric_dataset['Target'] == 1]
class0_data = numeric_dataset[numeric_dataset['Target'] == 0]
class1_data = class1_data.drop('Target', axis=1)
class0_data = class0_data.drop('Target', axis=1)
output_dir = 'explosive_dataset'
os.makedirs(output_dir, exist_ok=True)
for i, row in class1_data.iterrows():
    # Convert the row data to a NumPy array and reshape it into an image
    image_data = row.to_numpy().reshape(image_height, image_width)
    # Create a grayscale image
    plt.figure(figsize=(2, 2))  # Adjust the figure size as needed
    plt.axis('off')  # Turn off axis labels
    plt.imshow(image_data, cmap='gray', vmin=0, vmax=1)  # Set cmap to 'gray' for grayscale
images
    # Save the image with a unique filename
    image_filename = os.path.join(output_dir, f'image_{i}.png')
    plt.savefig(image_filename, bbox_inches='tight', pad_inches=0, dpi=100)
    plt.close()
# Create a directory to save the generated images
output_dir = 'non_explosive_dataset'
os.makedirs(output_dir, exist_ok=True)
# Loop through each row in the numeric dataset and create an image for each
for i, row in class0_data.iterrows():
    # Convert the row data to a NumPy array and reshape it into an image
    image_data = row.to_numpy().reshape(image_height, image_width)

    # Create a grayscale image
    plt.figure(figsize=(2, 2))  # Adjust the figure size as needed
    plt.axis('off')  # Turn off axis labels
    plt.imshow(image_data, cmap='gray', vmin=0, vmax=1)  # Set cmap to 'gray' for grayscale
images
    # Save the image with a unique filename
    image_filename = os.path.join(output_dir, f'image_{i}.png')
    plt.savefig(image_filename, bbox_inches='tight', pad_inches=0, dpi=100)
    plt.close()
print("Image dataset created successfully.")
```

APPENDIX B: Sample 2D image of dataset



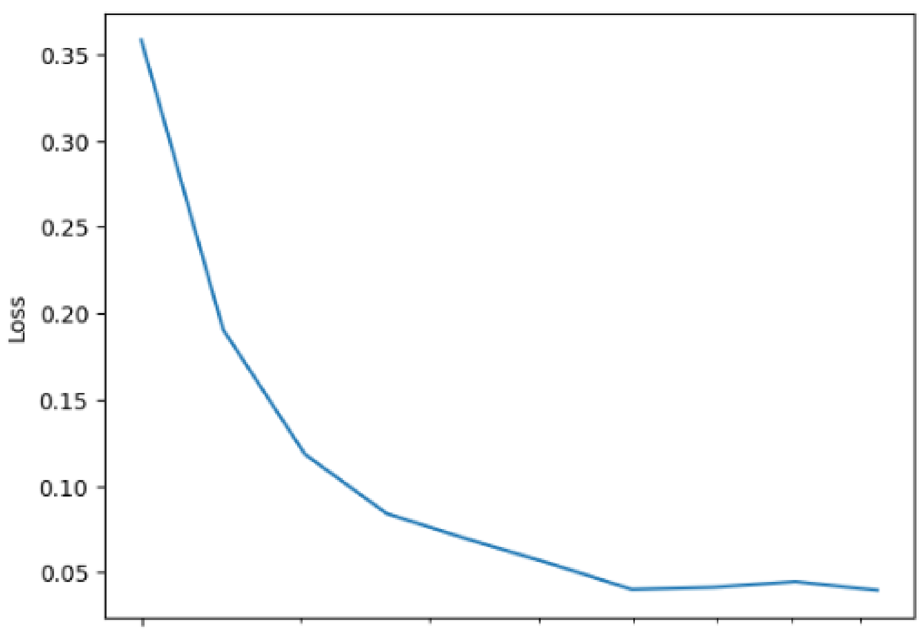
APPENDIX C; Transfer Learning Model Training for 10 Epochs

```
[ ] # Train the model
    history = model.fit(
        train_generator,
        steps_per_epoch=train_generator.samples // batch_size,
        epochs=epochs,
        validation_data=validation_generator,
        validation_steps=validation_generator.samples // batch_size,
        callbacks=[lr_scheduler]
    )
```

```
Epoch 1/10
218/218 [==============================] - 1014s 5s/step - loss: 0.3580 - accuracy: 0.8417 - val_loss: 0.1296 - val_accuracy: 0.9224 - lr: 0.0010
Epoch 2/10
218/218 [==============================] - 28s 126ms/step - loss: 0.1906 - accuracy: 0.9256 - val_loss: 0.1648 - val_accuracy: 0.9052 - lr: 0.0011
Epoch 3/10
218/218 [==============================] - 29s 131ms/step - loss: 0.1184 - accuracy: 0.9558 - val_loss: 0.0424 - val_accuracy: 0.9607 - lr: 0.0013
Epoch 4/10
218/218 [==============================] - 28s 128ms/step - loss: 0.0841 - accuracy: 0.9671 - val_loss: 0.0197 - val_accuracy: 0.9829 - lr: 0.0014
Epoch 5/10
218/218 [==============================] - 28s 127ms/step - loss: 0.0692 - accuracy: 0.9756 - val_loss: 0.1166 - val_accuracy: 0.9607 - lr: 0.0016
Epoch 6/10
218/218 [==============================] - 27s 124ms/step - loss: 0.0552 - accuracy: 0.9811 - val_loss: 0.0140 - val_accuracy: 1.0000 - lr: 0.0018
Epoch 7/10
218/218 [==============================] - 27s 125ms/step - loss: 0.0402 - accuracy: 0.9845 - val_loss: 0.0046 - val_accuracy: 1.0000 - lr: 0.0020
```

APPENDIX D: Convergence of learning rate of the Transfer Learning Model

```
#import numpy as np
lrs = 0.001 * (10 ** (np.arange(10) / 20))
plt.semilogx(lrs, history.history["loss"])
plt.xlabel('Learning Rate')
plt.ylabel('Loss')
plt.show()
```



APPENDIX E: Initializing the Libraries and the colab directories

```python
import os
import glob
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import LearningRateScheduler
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, classification_report
import numpy as np
```

[ ]
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

[ ]
```python
path='/content/drive/MyDrive/Dataset/'
print("Dataset path:  ")
print(os.listdir(path))

train_dir=path+'Train'
test_dir=path+'Test'
val_dir=path+'Val'
print("Sample path:  ")
print(val_dir)
```

DATA AUGMENTATION SECTION

```python
# Data augmentation for the training set (optional but recommended)
train_datagen = ImageDataGenerator(
    rescale=1./255,      # Normalize pixel values to [0, 1]
    rotation_range=40,  # Randomly rotate images
    width_shift_range=0.2,  # Randomly shift images horizontally
    height_shift_range=0.2,  # Randomly shift images vertically
    shear_range=0.2,  # Shear transformations
    zoom_range=0.2,  # Randomly zoom images
    horizontal_flip=True,  # Randomly flip images horizontally
    fill_mode='nearest'  # Fill mode for pixel values outside the image
)
```

[ ]
```python
# Validation and test sets should not be augmented
validation_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)
```

APPENDIX F: Arduino code for proteus simulation

```
#include <ArduinoJson.h>

//Gas Sensor Pins
#define MQ4 A1
#define MQ135 A2
#define MQ7 A3

void setup()
{
Serial.begin(9600); // opens serial port, sets data rate 9600 bps
}

void loop()
{
root["C"] = ppm_N;
root["N"] = ppm_N;
root["O"] = ppm_O;
root["H"] = ppm_H;


root.prettyPrintTo(Serial);
Serial.println("");

//Minimum delay required for ThingSpeak to update is 16 seconds
delay(16000);
}
```

Code for Thingspeak channel:

```
#include <ESP8266WiFi.h>
#include <ESP8266HTTPClient.h>
#include <ArduinoJson.h>
#include <SoftwareSerial.h>
#include "ThingSpeak.h"

SoftwareSerial mySerial(5, 6);
WiFiClient client; // Creating WiFiClient Object

//ThingSpeak Channel's API Keys
unsigned long myChannelNumber = CHANNEL NUMBER;
const char * myWriteAPIKey = "API KEY";
```

```
//Add your WiFi credentials here
const char * WIFI_SSID = "SSID";
const char * WIFI_PASSWORD = "PASSWORD";

void setup() {
Serial.begin(9600);
mySerial.begin(9600);
WiFi.begin(WIFI_SSID, WIFI_PASSWORD);
Serial.print("connecting");
while (WiFi.status() != WL_CONNECTED) {
Serial.print(".");
delay(100);
}
Serial.println();
Serial.print("connected: ");
Serial.println(WiFi.localIP());
ThingSpeak.begin(client);
}

void loop() {
// Check WiFi Status
while (mySerial.available())
{
const size_t capacity = JSON_OBJECT_SIZE(7) + 100;
DynamicJsonBuffer jsonBuffer(capacity);
JsonObject& root = jsonBuffer.parseObject(mySerial);
if (!root.success()) {
Serial.println("parseObject() failed");
return;
}

float C = root["C"];
float N = root["N"];
float O = root["O"];
float H = root["H"];


Serial.print(C, 5);  Serial.print(",");
Serial.print(N, 5);  Serial.print(",");
Serial.print(O, 5);  Serial.print(",");
Serial.print(H, 5);

//Sending Gas Data to ThingSpeak
ThingSpeak.setField(1, C);
ThingSpeak.setField(2, N);
ThingSpeak.setField(3, O);
ThingSpeak.setField(5, H);
```

```
ThingSpeak.writeFields(myChannelNumber,myWriteAPIKey);
}
}
```

APPENDIX G

Total number of samples used = 1000

AUC = Area Under the ROC curve

The ROC curve is a plot of the True Positive Rate (TPR) on the vertical axis, given as

$$TPR = \frac{TP}{TP + FN}$$

Against the False Positive Rate (FPR) on the horizontal axis, given as

$$FPR = \frac{FP}{TN + FP}$$

TP = True Positive (Number of times the model predicted positive outcomes correctly)

FP = False Positive (Number of times the model predicted positive outcomes wrongly)

TN = True Negative (Number of times the model predicted negative outcomes correctly)

FN = False Negative (Number of times the model predicted negative outcomes wrongly)

$$ImageNet\ Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

$$= \frac{520 + 245}{520 + 0 + 245 + 235} = \frac{765}{1000} = 0.77 = 77\ \%$$

$$ImageNet\ AUC = 0.64$$

Confusion Matrix of AlexNet			
		Predicted Class	
		Non-Explosive	Explosive
Actual Class	Non-Explosive	**TP**	**FN**
		430	335
	Explosive	**FP**	**TN**
		0	235

$$ImageNet\ Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

$$= \frac{430 + 235}{430 + 335 + 235 + 0} = \frac{665}{1000} = 0.67 = 67\ \%$$

$$ImageNet\ AUC = 0.71$$

Confusion Matrix of RNN			
	Predicted Class		
		Explosive	Non-Explosive
Actual Class	Explosive	**TP**	**FN**
		332	345
	Non-Explosive	**FP**	**TN**
		35	288

$$ImageNet\ Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

$$= \frac{332 + 288}{332 + 345 + 228 + 35} = \frac{665}{1000} = 0.62 = 62\ \%$$

$$ImageNet\ AUC = 0.63$$

Confusion Matrix of SVM			
	Predicted Class		
		Explosive	Non-Explosive
Actual Class	Explosive	TP	FN
		521	**245**
	Non-Explosive	FP	TN
		0	**234**

$$ImageNet\ Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

$$= \frac{521 + 234}{521 + 245 + 234 + 0} = \frac{755}{1000} = 0.76 = 76\ \%$$

$$ImageNet\ AUC = \ 0.50$$

Summary

Model	ImageNet	AlexNet	RNN	SVM	Current Model
Accuracy	77%	67%	62%	76%	99.7%
AUC	0.64	0.71	0.63	0.50	0.89

APPENDIX H

RNN:

Dense Layers: 1

Activation function: sigmoid

droupout: 0.5

learning rate: 0.01

optimizer: rmsprop

SVM:

kernel type: sigmoid

c parameter: 0.5

ImageNet:

Dense Layers: 2

Dense layer = 4096 units, activation function ReLu

Dense layer = 4096 units, activation function ReLu

Dense layer = 1000 units, activation function sigmoid

Optimizer: SGD (0.9)

learning rate: 0.01

Batch size: 128

drupout:0.5

AlexNet:

Dense Layers: 2

Dense layer = 4096 units, activation function ReLu

Dense layer = 4096 units, activation function ReLu

Dense layer = 10 units, activation function sigmoid

Optimizer: SGD (0.9)

learning rate: 0.01

Batch size: 128

drupout:0.5