UNIVERSITY of RWANDA

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College of Science and Technology

AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS

Research Thesis Title: A Wearable Device for Respiratory Diseases Monitoring in Crowded Spaces. Case study of COVID-19

A dissertation submitted in partial fulfillment of the requirements for the award of masters of science degree in internet of things: Embedded computing system

Submitted By:

Name: Rosette Lukonge Savanna (**Ref. No: 221000581)**

December,2022

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Supervised by:

- Prof Damien HANYURWIMFURA
- Dr. James RWIGEMA

December, 2022

Student Declaration

I declare that this Dissertation contains my work except when specifically acknowledged.

Student Name: Rosette Lukonge Savanna

Student Reference Number: 221000581

Student Signature: ____________________________

Date: ______________________________

Bonafide Certificate

This is to certify that the project entitled "A Wearable Device for Respiratory Diseases Monitoring in Crowded Spaces" is a record of original work done by Rosette Lukonge Savanna with registration number 221000581 in partial fulfillment of the requirement for the award of Masters of Science in Internet of Things in College of Science and Technology, University of Rwanda, the Academic year 2021/2022

This work has been submitted under the guidance of Prof. Damien HANYURWIMFURA and Dr. James RWIGEMA

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The Head of Masters and Training

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ABSTRACT

The Sustainable Development Goal (SGD) number 3 is focused on Good health and hygiene. Necessary measures need to be put in place to contribute toward the fulfilment of this goal. According to the World Health Organization (WHO), there have been rising cases of chronic respiratory disease especially in developing countries resulting to over four million death annually across the globe. In addition to the, COVID-19 pandemic some other highly contagious respiratory diseases include tuberculosis, chronic obstructive pulmonary disease (COPD), lung cancer, influenza among others. Most of the time it may be difficult to tell if around an infected person leading to avoidable transmissions. Therefore, this research project was proposed as a measure to control and minimize the spread of such diseases. This study aimed at developing an AI (Artificial Intelligence) powered system that can be able to monitor the risk of spread of respiratory diseases through a wearable device to contain such disease and reduce their effects. In this study, we are proposing a contactless system that is able to detect an environment with a high risk of respiratory disease contamination. The device applies Internet of Things (IoT) sensing technologies for data collection from the user's immediate surrounding environment, mainly proximity to others, cough sound and body temperature. The collected data is then processed on the embedded device and Machine Learning (ML) algorithms applied for analysis of data to predict a possible exposure to respiratory diseases. The user will then get alerts to take appropriate actions to avoid possible infections. The collected data is also sent to the things speak platform from time to time via cellular network for further analytics and future research. This is an improvement to existing solutions in which data analytics and machine learning are applied on the cloud. This was necessitated due to connectivity constraints in Africa, energy constraints, and the need for real-time response. We move AI capabilities from cloud to data source (edge devices) using TinyML.

Keywords: IoT, Machine Learning, TinyML, Respiratory diseases, Wearable device

LIST OF ACRONYMS

AI- Artificial Intelligence

ANN- Artificial Neural Network

BLE- Bluetooth Low Energy

CNN- Convolutional Neural Network

COPD-Chronic Obstructive Pulmonary Disease

CSV-Comma Separated Values

DL- Deep Learning

GND- Ground (human immunodeficiency virus

HIV- Human Immunodeficiency Virus

AIDS-Acquired Immune Deficiency Syndrome

IoT – Internet of Things

ISR-Interrupt Service Routine

LCD- Liquid Crystal Display

LED- Light Emitting Diode

ML- Machine Learning

NN- Neural Network

OLED- Organic Light-Emitting Diode

RAM- Random Access Memory

RBC- Rwanda Biomedical Center

ROM- Read-Only Memory

WHO- World Health Organization

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CHAPTER 1

INTRODUCTION

1.0. Introduction

Respiratory diseases affect passages of the air, including the lungs, bronchi, bronchioles, and nasal passages. Conditions considered respiratory-related include not only acute respiratory infections, such as common cold, sinusitis, pharyngitis, epiglottitis, and tracheobronchitis but also chronic respiratory diseases, such as lung cancer, asthma, and chronic obstructive pulmonary disease.

One of the most frequent acute and chronic diseases in the world is respiratory disease. They are widespread across all age groups and sections of society, regardless of the degree of development they have[1] This is due to a fast increase in risk factors such as: population growth and urbanization (more frequent close interpersonal contact favors transmission of respiratory infections); economic growth and industrialization in some regions, which raise levels of atmospheric air pollution; deterioration of the socioeconomic situation in many developing countries with a concomitant reduction in funding for health services; Large populations in rural and peri-urban areas of the world are affected by high levels of indoor air pollution, tobacco use is becoming more common in developing nations, and the HIV/AIDS epidemic is accompanied by respiratory diseases that are the most common symptoms of AIDS [1]

With a population of over 11 million, the prevalence of common communicable diseases in Rwanda is a serious concern [2]. Lower respiratory infections are among the top 10 causes of death in Rwanda, although unanticipated, it is a severe health concern in Rwanda. After a lifetime of exposure to variables that cause lower respiratory infections, the elderly, especially those over 80, are particularly susceptible to them [2].

According to the World Health Organization (WHO), Nearly 90% of COPD fatalities in people under the age of 70 take place in low- and middle-income nations [3]. COPD is thought to be the cause of about 3 million deaths annually, or around 6% of all deaths worldwide [3]

For example, Coronavirus disease (COVID-19) reported by the WHO as an infectious disease caused by the SARS-CoV-2 virus [4] which can spread from an infected person’s mouth or nose in small liquid particles when they cough, sneeze, speak, sing or breathe [5] has already claimed the lives of 6,266,324 people since the first outbreak [6].

That’s why to lower infection rates and limit the burden on medical resources, detection technologies are required to keep people safe because no cure has ever been identified so far, and people must take precautions to protect themselves from this pandemic.

Since the beginning of time, human has always tried to enhance their living conditions, always wanted to make daily duties easier in order to live a better life. Thanks to new technologies, they help us to achieve that. IoT is a network of things that are wirelessly connected and can interact without human intervention [7]. In the healthcare industry, IoT enables highly effective real-time remote monitoring. Nowadays, Early detection and prediction of chronic disorders is a critical aspect that many researchers are focusing on. With the spread of COVID-19 around the world, digital health technology has been adopted in response to maintain healthcare delivery during lockdowns [8].

IoT has been used in healthcare for data collection and monitoring data, while AI is in charge of analyzing the growing amounts of data and taking actions based on what it learns from data [9]. AI has been used to improve healthcare outcomes, it has been a powerful weapon to fight the COVID-19 storm. Data-driven decision-making (also known as DDDM) allows us to make smarter and smarter solutions, DDDM enables observers to spot patterns and opportunities, confirm hypotheses, predict future trends, optimize operational efforts, and produce actionable insights [5]. AI has opened up the possibility of using aggregated healthcare data to create strong models that can automate diagnosis and enable a more precise approach to medicine by personalizing treatments and directing resources with maximum efficiency in a timely and dynamic manner [10].

In existing related AI-based solutions for example [11], data has to be sent to the cloud when AI intelligence is applied. Such cloud-based solutions are faced with challenges, especially in the African context namely; poor connectivity, high costs of connectivity, high latencies, and energy constraints [12] This call for edge-based solutions the data is gathered from the environment by tiny electronic devices which are very limited in energy, computing, and memory resources [13]. These constraints bring up a new approach “tiny machine learning” (TinyML), which calls for implementing the ML algorithm within the IoT device. The aim of the TinyML framework in IoT is to provide low latency, effective bandwidth utilization, strengthen data safety, enhance privacy, and reduce cost. TinyML enables IoT devices to work consistently without constant connection to cloud services while providing accurate machine learning services, this makes it a viable alternative for IoT applications looking for cost-effective solutions [14].

This study was aimed at prototyping a wearable device that can be able to assess the environment for possible COVID 19 risks and give appropriate real-time alerts to users. In the proposed solution, sound and contactless temperature sensors are used to collect data from the environment with TinyML being used to perform analytics at the edge. This project fits in the context of applying IoT and AI for detecting communicable diseases from fusion of cough sounds, sneezing sounds, and body temperature data. The implementation and realization of IoT for detection and monitoring of communicable diseases is needed in Rwanda given the risk of contracting respiratory diseases as people interact in public spaces. The proposed system will also go a long way in helping the health authorities collect data that can be used for further research and for planning.

1.0. Problem statement

Different infectious diseases are usually transmitted from one person to another by direct transmission of bacteria, viruses, or other organisms. When a person infected with the bacterium or virus touches, kisses, coughs or sneezes on someone who isn't affected, this can happen [15]. However, the impact of COVID-19 has been particularly severe for those suffering from chronic illnesses like heart disease, diabetes, cancer, chronic obstructive pulmonary disease, chronic renal disease, and obesity [16] [17] [18]. While communicable diseases continue to be the leading cause of morbidity and mortality in Rwanda, non-communicable disorders such as hypertension are on the rise [19] which can be dangerous with COVID-19. So far around the world, COVID-19 has no effective treatment, we have to live with it like other diseases like malaria and so on. As declared by the UK government, the coronavirus is here to stay, and the time has come to learn to live with it [20]. Detection of COVID-19 task is performed through different tests, the "reverse transcription-polymerase chain reaction (RT-PCR)" test and the Rapid test. PCR test is time-consuming, costly and results are delivered with delay [21] and rapid tests have low sensitivity and low accuracy (false negatives are more common) [22]. A real-time protection mechanism could be a good approach to contain this disease.

Existing real-time solutions for example [8], AI capabilities are implemented in the cloud which is a barrier to the African context where internet infrastructures and energy are limited. Also, it's a contact sensing solution, it can be used for self-monitoring only. That's this study proposed a contactless and TinyML driven solution to monitor the environment against a possible covid-19 exposure.

1.2 Aims and Objectives

1.2.1 Aims

The aim of this study was to design and prototype a real-time environmental monitoring system capable of detecting a possible respiratory disease contamination risk.

1.2.2 Objectives

The general objective of this study was to develop a smart wearable device for risk monitoring against respiratory diseases. To achieve the general objective of this research, the study was guided by the following specific objectives:

I. To investigate the state of the art of respiratory disease risk monitoring and alert systems and solutions.

II. To find out the latest open source IoT and ML technologies that are used for wearable devices.

III. To investigate and clean available open datasets for respiratory diseases relating to cough sounds and body temperature

IV. To Build, train, and evaluate the machine learning model and optimize for implementation on an Edge device.

V. To design and prototype a TinyML-driven wearable device that can detect potential respiratory disease risks.

1.3 Hypothesis

Our hypotheses were as follows; 1) There are existing open data sets that can be used to train an AI model to predict respiratory diseases potential exposure risks 2) Open source technologies can be exploited to train an Artificial Intelligence Model and optimize it for the monitoring of respiratory diseases on an embedded device.

1.4 Research Questions

The study was guided by the following questions:

1. What existing solutions can be used to monitor respiratory disease risks?
2. Which open source IoT and ML technologies can be used in wearable devices for health monitoring?
3. How can AI models be trained to be deployed on embedded devices for inference?
4. What is the best user notification and cloud storage platforms for IoT massive data?

1.5 Study Scope

The study was focused on latest technologies of AI and IoT to develop a wearable device that can scan the environment for potential exposure risk to respiratory diseases. Our prototype will however not focus on two common symptoms of respiratory disease i.e. Cough sounds and body temperature. In addition, due to limited resources and time constraints open source data sets will be explored in training the ML model.

1.6 Significance of the Study

The system will be of benefit to the population at large by helping them to be aware of any possible exposure to respiratory diseases and thus avoid infections from time to time. Such actions will lead to healthier and more productive citizens leading to economic growth. Hospitalization cases resulting from respiratory diseases will also be greatly reduced leading to fewer strains in the health sector.

Health care professionals will spend their time on complex issues, therefore improving the care of the most in need.

The solution will be of great value in the process of mass collection of health data, complementing the health data that are collected in healthcare facilities. This will enable the training of efficient AI models for respiratory diseases monitoring and detection.

1.7 Organization of the Document

The rest of this document is organized as follows: The next chapter gives a review of related literature; Chapter 3 describes the methodology used in the study, the research process is outlined, the ML process and the system design methodology and materials also presented; Chapter 4 presents the system design and analysis, the system architecture, the system-level design, the simulation model, and embedded system layout are presented; Chapter 5 System Results, analysis, and discussion shows an evaluation of the model training, the results obtained from both the cloud, the embedded simulated and real system, and the analysis of trade-offs in different embedded system parameters and also presents a comparison of different models; A conclusion the document by presenting the recommendations drawn from this study.

CHAPTER 2

LITERATURE REVIEW

2.0. Overview

In this section a review of related literature is presented showing the basis for the Integration of Internet of Things and TinyML in the monitoring and diagnosis of Respiratory Diseases. The application of IoT in the prevention of respiratory diseases is first presented, this is followed by the use of IoT in monitoring and diagnosis of respiratory diseases. The use of machines in respiratory disease medicine is explored including the efforts and opportunity the tinyML presents for more intelligent smart health solutions. Lastly identified gaps that this thesis intends to address are presented.

2.1. IoT in prevention of respiratory diseases

Currently, in clinical scenarios, little research or practice focuses on disease prevention or avoidance of disease risk factors. It is only physical examinations and various screening programs for high-risk populations such as low-dose CT screening for lung cancer [23].

However, both health economics research and governor policy still maintain a wait-and-see attitude toward large-scale population-wide screening programs because of the burdens, costs, and benefits of the population as a whole [24].

However, some pilot trials use mobile phone-based apps, such as the Apple Research app, to enroll specific populations with various potential disease developments and apply lifestyle change intervention to prevent future disease worsening [25].

Additionally, as part of studies supported by the Bill & Melinda Gates Foundation and The United Nations Children's Fund (UNICEF), Zindagi et al. applied big data analysis tools to improve the vaccine delivery system in Pakistan [26]. Instead of manually recording each individual’s data, they applied near-field communication (NFC) chip embedded immunization cards to the local population and deployed a classification algorithm to clean incoming vaccine records and avoid potentially falsified records in real-time. This significantly reduced the cost and workload of vaccination centers and increased the efficiency of their services. Because vaccines for some respiratory diseases are in short supply, methods to improve early detection are needed.

2.2. IoT in monitoring and diagnosis of respiratory diseases

In 2016, researchers in [27] designed a brand-new portable spirometry which is combined with a set of medical Internet of Things systems to automatically follow-up patients with COPD. The system uploaded pulmonary test data to the cloud and doctors could receive it on their mobile phones and iPads instantly. Meanwhile, the system platform allowed onsite physicians to easily obtain input from top hospital health teams, including the latest guidelines and instructions for quality control and comments on test results. This system solved both the problem of lack of resources and equipment and the gap in professional training and clinical experience among hospitals and doctors at different levels. It is also very efficient to collect piecemeal information from a patient, atomically combine and analyze the raw data, and then queue it for review by the appropriate team of clinicians.

Air pollution and other environmental indicators that trigger diseases such as asthma are difficult for individuals to access. However, when combined with handheld devices that patients use on a daily basis, such as cell phones and GPS devices, physicians can easily track environmental parameters that may be triggering patient symptoms for early warning and detection and send warning signals. Chan et al. designed a similar concept study by Apple ResearchKit based on a prospective collection of longitudinal, multidimensional data (e.g., surveys, devices, geolocation, and air quality) in a subset of users over the 6-month study period in 7,593 participants from across the United States [28] In the study they found the enrollment based on cell phone, especially iPhone will limit the recruitment of the higher education level of patients due to the characteristics of the certain type of cellphone users.

In a study [29], an IoT system is built based on the integration of several independent applications. Furthermore, the scheme consists of four main components such as an environmental sensor box, patient monitoring tool, Android app and web graphical user interface (GUI). The Web GUI helps healthcare professionals, such as doctors and nurses, monitor patient status obtained from patient monitoring tools. In addition, patients and physicians can assess weather and environmental conditions to determine whether they are safe or harmful for their patients. Finally, patients need an Android-based app to connect all systems and monitor all conditions, including health and environmental conditions.

It is noted in [30] that people who have suffered from chronic diseases need to constantly monitor their vital signs. The vital signs of our body are heart rate, temperature, blood pressure, respiratory rate, oxygen saturation and blood glucose level. The respiratory rate monitor is one of the important vital signs which is useful for patients who are admitted in Intensive Care Unit (ICU). The respiratory rate is calculated by using LM35 temperature sensor and monitors the patient's respiration continuously based on voltage value of inhaled and exhaled air. NRF24l01 is used to transmit the sensor data from home to medical center. Then the data is published in a webserver using Ethernet to know the patient's status which is useful for doctors. And also, the data is displayed in a Liquid Crystal Display (LCD). When the threshold is reached, an alert is generated and a message is also generated on the web page. This allows doctors and healthcare workers to know the patient's status without delay. Using data mining techniques, people can know their condition without the help of medical professionals.

An IoT architecture for monitoring COVID 19 is recommended in [31]. Infrared sensors can be used in public restrooms to automatically operate doors and water supplies. Infrared thermometers can be used to check body temperature and identify infected people in crowds, and optical cameras can be used to recognize faces at the entrances of airports, train stations, bus stops, shopping malls, etc. Similarly, the sensors proposed in the architecture can be installed to monitor body temperature, automatic door operation, water control in public places and restrooms, online meetings to avoid direct contact and human interaction. For small applications or personal use, a configuration of a temperature sensor, a NodeMCU, or an Arduino board with sensors and internet can be used. Mobile apps can be developed using App Inventor, an open source platform provided by MIT. ThingSpeak is MATLAB's open-source web service API for storing and retrieving data from Things/ sensors using HTTP and MQTT protocols over the Internet or local networks.

2.3 Use of ML in predicting possible respiratory diseases

Patient monitoring systems for stroke patients have been proposed to minimize future recurrences by alerting physicians and caregivers to fluctuations in stroke risk factors. Data analysis and decision-making based on a patient's real-time health parameters help physicians make systematic diagnoses, followed by customized and restorative treatments for the disease. The proposed model uses classification algorithms for diagnosis and prediction [32].The ensemble method of tree-based classification-Random Forest give an accuracy of 93% .

The review in [33] aims to identify and describe published research on the use of AI and ML in the field of respiratory diseases. The search strategy used in PubMed was '(((pulmonary) OR respiratory)) AND ((artificial intelligence) OR machine learning)". The majority of identified studies were in the chronic obstructive pulmonary disease (COPD) area, specifically COPD and chest computed tomography scans, pulmonary function test interpretation, exacerbations and treatment. Another area of interest is the application of AI and ML to the diagnosis of interstitial lung disease, with several other studies in the areas of mechanical ventilation, interpretation of chest radiographs, and diagnosis of bronchial asthma .

Artificial intelligence (AI) and machine learning are increasingly being used in medicine. AI is characterized by well-defined tasks such as image recognition which include classification of skin biopsy lesions, determination of diabetic retinopathy severity, and detection of brain tumors. The study gives an overview of the use of AI in medicine, especially in respiratory medicine to assess images of lung cancer, diagnose fibrotic lung disease, and most recently aid in the interpretation of pulmonary function tests and diagnosis of multiple obstructive and restrictive pulmonary diseases. To develop and validate AI algorithms requires large amounts of well-structured data, and algorithms must work with varying levels of data quality. Clinicians need to understand how AI works in the context of heterogeneous conditions such as asthma and chronic obstructive pulmonary disease where diagnostic criteria overlap. They also need to know how AI use fits into routine clinical practice and how issues of patients' safety are addressed. AI has a clear role to play in assisting physicians in the clinical setting, but being recent adoption means that confidence in its use has not yet been fully built [34].

A study was done whose main objective was to establish and evaluate an alternative LUR model that could estimate the prevalence of chronic respiratory diseases, as opposed to the traditional LUR model that typically assesses air pollutants. In addition, the study also evaluated various analytical techniques that often form the basis of spatial models. The results demonstrated that machine learning techniques such as Support Vector Machines are the most efficient and have the lowest Root Mean Square (RMSE) for computing such models. Furthermore, this study shows that the most important remote sensing predictors are the blue and infrared bands. The proposed model is a spatial modeling approach that can determine the prevalence of chronic respiratory diseases in the city of Quito and may serve as a useful tool for health authorities in policy and decision-making [35].

IeBRI 2017 Challenge used a database of 920 records from 126 subjects to predict whether breathing cycles contained random sounds such as crackles, gasps, or both. The best-performing team achieved an accuracy rate of about 50%. Using a machine learning approach with an improved decision tree model and more audio features yielded the same results. A new approach proposed in [36] focuses on creating a new patient-level model that can determine whether a patient is feeling unwell by taking the predicted results of the first classification model as input. The new model was able to achieve a good prediction of 85% and could potentially be used as a tool for physicians to make better diagnoses.

Study done by [37]. noted that lung sound auscultation using various portable devices is one of the most widely used, inexpensive and simple methods for early detection of respiratory disease but due to the lack of medical professionals to correctly interpret and diagnose based on respiratory sounds led to the implementation of machine learning and deep learning algorithms for respiratory disease classification and prediction. Therefore, the study presented some relevant work done in this area and a proposed method for classifying the Breath Sound Database of the International Conference on Biomedical and Health Informatics (ICBHI' 17) scientific challenge respiratory sound database. The method used Mel-frequency cepstral coefficients (MFCC) to extract features and compute a convolutional neural network (CNN) to classify the database. The results showed that the proposed method provides 90.21% accuracy which is a suitable method for faster classification of breath sounds collected by various devices.

The risk of respiratory diseases has increased significantly due to their ease of spread, and many researchers in different fields have taken responsibility for addressing the prevalence of these diseases [38]. The best known of these diseases and the current challenge is Covid-19. The researchers in this study provided a comprehensive review of research on respiratory disease detection and classification using machine learning. The research includes the top 50 papers published from 2018 to the end of 2021. The results of the study provided an analysis of research trends in this area in relation to the techniques and data used. These results will enable future researchers to plan their research and choose the best ways to make a good contribution before entering this research field.

A paper [39] emphasizes the importance of machine learning in computer-assisted lung sound analysis. By searching electronic resources such as IEEE, Springer, Elsevier, PubMed, and ACM digital library databases, articles were identified on computational lung noise analysis using machine learning techniques. A brief description of the types of lung sounds and their characteristics is provided. In this review, focus is on specific lung sounds/disorders, number of subjects, signal processing and classification methods, and the results of analysis of lung sounds using machine learning methods performed by previous researchers.

2.4 TinyML and its application in respiratory health

The integration of Internet of Things (IoT) and machine learning (ML) is driving the emergence of TinyML, a subset of ML where models are constrained to be executed on low-resource embedded devices. Currently, most IoT applications in Africa are based on cloud-centric architectures, and connectivity, power, and cost challenges make it difficult to leverage ML-driven intelligence, making TinyML an ideal solution for such challenges. A study in [40] presents an introduction to TinyML, its general applications, solutions to concerns about the impact of artificial intelligence (AI) in achieving the Sustainable Development Goals (SDGs), and a strategy for development. Information Technology (ICT4D) TinyML technical requirements. A taxonomy of TinyML applications is highlighted with a concrete example from Africa. Various challenges for adopting TinyML in Africa were also presented and the opportunities arising from such challenges were highlighted. This shows TinyML has great potential in Africa, where the use of embedded systems and AI is still inadequate.

It is noted in [41] that healthcare is an area that can benefit from the large amount of raw data generated by wearables and wearable devices. This data must be sent to the cloud for processing due to the computationally intensive nature of current state-of-the-art neural network implementations. The emerging TinyML technology is an alternative approach proposed by the scientific community to create autonomous and secure devices that can collect, process, and alert on data without transmitting it to external entities. The study reviewed the contribution of TinyML's new technology in healthcare applications at the edge that require the integration of machine learning algorithms and its solutions specifically in wearable devices. Additionally, TinyML's neural network optimization capabilities are well suited to bring intelligence and autonomy to devices used in areas such as healthcare.

Furthermore, it is emphasized that machine learning has become an integral part of existing technological domains. Combining edge computing with the Internet of Things (IoT) offers new ways to enable implicit machine learning techniques on resource-constrained embedded devices at the edge of the network. Traditional machine learning requires tremendous power to predict scenarios. Embedded Machine Learning – The TinyML paradigm aims to move such plethora from traditional high-end systems to low-end clients. Several challenges must be overcome during such transition. These include maintaining the accuracy of learning models, providing capabilities from training to deployment on resource-efficient frugal tiny edge devices, optimizing processing power, and improving reliability. An intuitive overview of such possibilities in TinyML was presented in [42].

Additionally, [43] observes that the Internet of Things (IoT) has received a lot of attention recently as IoT devices are being deployed in various fields. Many of these devices are based on machine learning (ML) models so they can make intelligent decisions. IoT devices typically have limited resources, which limits their ability to run complex ML models such as deep learning (DL). Additionally, connecting IoT devices to the cloud to transmit raw data and perform processing slows system response, exposes private data, and increases communication costs. Therefore, to address these issues, there is a new technology called Tiny Machine Learning (TinyML) that has paved the way for overcoming the challenges of IoT devices. This technology allows data to be processed locally on the device without sending it to the cloud. Also, TinyML permits the inference of ML models.

In the respiratory disease domain, a study aimed to investigate the possibility of detecting respiratory diseases using edge AI is presented in [44]. Thanks to recent advances in open source edge AI frameworks, the study presents a prototyping design of an offline STM32 based portable kit locally embedding a tiny Machine Learning (TinyML) trained model to predict respiratory disease. Results also show that the accuracy and peak memory for the model are affected by preprocessing, type of sensors and the number of sensors. In addition to the early detection of respiratory diseases, the proposed solution will be of great value in the process of mass collection of exhaled breath data to enable the training of efficient AI models for respiratory diseases..

Another health application is the cough detection system proposed in [43] using Edge Impulse Studio and Arduino 33 BLE Sense. It can distinguish between genuine coughs and generic unwanted signals in the background. In the study, Edge Impulse Studio was used to train a large dataset of different samples on coughs and unwanted sounds. A highly efficient machine learning-based TinyML model was designed to instantly determine cough responses. The proposed system was found to achieve nearly 97% detection accuracy.

2.6 Identified study gaps

From the reviewed studies. The capabilities of the emerging technologies of IoT and ML have been highlighted. With applications in the healthcare sectors focusing on monitoring and diagnosis of diseases. Existing applications with respiratory disease focus mainly involve the use of chest image and sound classifications with the ML being done in cloud-based architectures. The use of cloud-based architecture has been noted to be a challenge in Africa and for health applications due to privacy, latency and connectivity challenges. Our proposed study tends to fill the identified gaps by not only introducing the concept of data fusion to monitor two or more parameters in diagnosing respiratory diseases but also applying TinyML to enable ML at the edge to overcome the challenges highlighted in the previous studies.

CHAPTER 3

RESEARCH METHODOLOGY

In this chapter the methodology, tools and process used to conduct the study are outlined. First presented are the steps undertaken to complete the study, this is followed by the AI model creation and last but not least the methods used in the prototype design and development presented.

3.1 Research Process

The research process began with an idea that prompted further interrogation by undertaking of a comprehensive literature review. This led to the topic of the study that was formulated based on the identified gaps from literature and existing solutions. The research proposal was then prepared and presented for approval. On approval the steps that followed included;

1. Research problem identification: identifying a research problem which is the heart of the research.
2. Literature review: review of works related to our case study and presentation of their limitations and weaknesses.

3. Research proposal: to propose our research project to the academic staff
4. System level design: here it is all about the design of the proposed solution. Selection of appropriate components is done here.
5. Data acquisition and data preprocessing: collect data from existing data sources and perform data cleaning and preparation.
6. ML model development, deployment and optimization: this concern the development of the ML model, its deployment on the tiny embedded device as well as the improvement of its performances.
7. Prototype development: here we will develop a prototype of the proposed wearable device solution.
8. Final thesis redaction and presentation

The table below shows the timeline of activities

Table 1: Timeline

Activities	**Timeline**										
	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**July**	**Aug**	**Sep**	**Oct**	**Nov**
Research problem identification											
Literature review											
Research proposal											
System level design											
Data acquisition and data preprocessing											
Prototype development											
CNN model development, deployment and optimization											

Final thesis redaction and presentation											

3.2 System Development

The Software prototyping approach was selected as the software development method for the development of the wearable device for respiratory disease risk monitoring. The selection of this model was guided by the need to understand the need of the users and come up with system requirements at an early stage. In addition, it was possible to get user feedbacks enabling the researcher to understand what is expected from the solution.

Advantages of software prototyping;

- The prototype is a representation of the projected solution with reduced functionalities
- The users are able to evaluate the performance of the system and make recommendations for improvement before implementation
- The system developer gets the opportunity to understand the requirements that may have been considered in the initial stages
- Makes the system development process to be faster
- Clear and detailed understanding of requirements possible

The prototyping process consists of four main processes; functional selection, system construction, system evaluation and use of the system. The first step involves the selection of functions to be prototyped this is the followed be the construction of the prototype. After construction the system is evaluated and the prototype is further used as a part of the new system or for outlining future system specifications. Prototyping is an iterative process that involves a four step involving users and developers:

i. Initial requirement specification.

ii. Prototype development.

iii. The prototype is implemented, tested and used.

iv. Revision and enhancement of the prototype.

During the process several iterations are undertaken with the third and fourth steps being repeated until the system is accepted by the user as shown in figure 1.

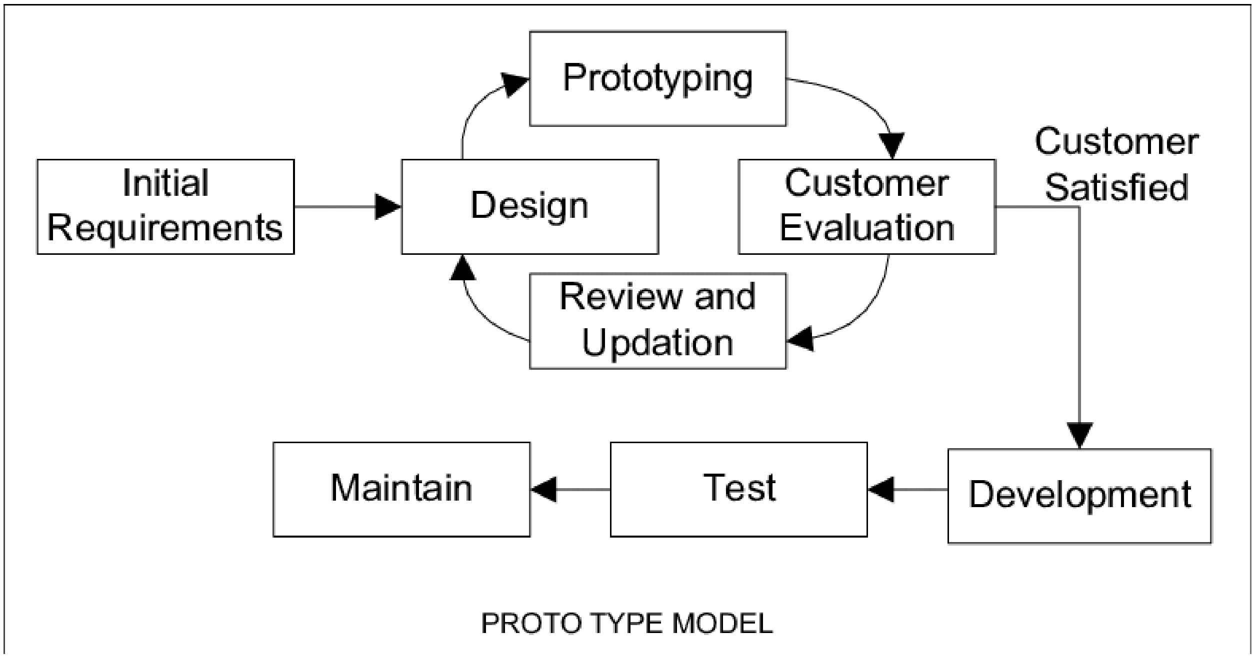

Figure 1: Prototype Model

3.3 Machine Learning Steps

The machine learning steps followed the normal steps undertaken in any machine learning algorithm. Figure 3.2 shows the steps

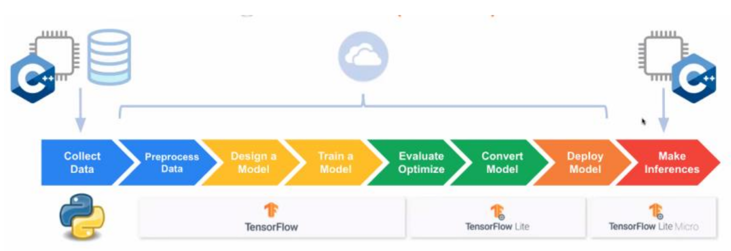

Figure 2: Machine learning steps

A. Data Collection

The machine learning steps began with data collection. The quality and quantity of data determined how accurate the model would be. Open source data sets were the sources of data that were used as inputs for the training.

B. Data Pre-processing

The collected data was cleaned in preparation for training. Fields that were not needed were deleted, dealt with missing values, corrected errors and removed duplicates. The data was the converted into JSON format and uploaded into the cloud-based machine learning platform. The data was also separated into validation set and training sets. The data was the pre-processed so as to generate features for training.

C. Model Design

After pre-processing the machine learning mode was designed, the inputs to the model training were the soil moisture level and soil temperature raw features of the data were selected and a Keras Neural Network selected for training the model with the expected output being a classification as to whether the is a respiratory disease risk or not.

D. Model Training

The model was then trained. At this stage different number of epochs, dense layers and learning rates were experimented till the optimum training parameters were reached. The on-device resources needed by the model were also tested. This step also included hyperparameter tuning, used to tune model parameters for improved performance.

E. Evaluation and Optimization

The test data was used to evaluate the performance of the model on unseen data. This unseen data is meant to be somewhat representative of model performance in the real world, but still helps tune the model (as opposed to test data, which does not). The model was also optimized for performance in an embedded device

F. Model Conversion

After evaluation the model was converted into a tiny machine learning model that can run on an embedded device in readiness for deployment.

G. Make Inferences

Using further (test set) data which had, until this point, been withheld from the model (and for which class labels are known), were used to test the model in both the cloud environment and on the embedded device; a better approximation of how the model will perform in the real world.

3.4 Software Tools

The following software tools and platforms were used in the study

A. Arduino IDE

The open-source Arduino Software (IDE) makes it easy to write code and upload it to the board. This software can be used with any Arduino board.

B. Tensor Flow Lite

Tensor Flow Lite is an open-source, product ready, cross-platform deep learning framework that converts a pre-trained model in Tensor Flow to a special format that can be optimized for speed or storage [45]. This will be used in training and deployment of the prediction model for irrigation. Figure 3.4 give the steps in the working of tensor flow light.

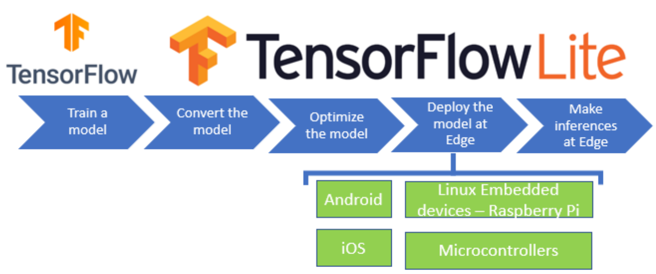

Figure 3: Tensor Flow Lite

C. ThingSpeak

ThingSpeak is an IoT analytics platform service that allows you to aggregate, visualize, and analyze live data streams[46].

CHAPTER 4

SYSTEM ANALYSIS AND DESIGN

In this chapter, the material and methods used in the study are given. The first section gives the system requirements and the high-level system architecture. This is followed by a detailed embedded System-level design showing the system block diagram, Original Equipment Manufacturer (OEM) components, system Program Description Language (PDLs), use case diagrams, and system flow charts. Lastly, the modelling and layout of the embedded system are given.

4.1 System requirements

The functional requirements include the product features that must be included to enable the system meet its objectives while the non-functional requirements included quality attributes that affect the behavior of the system. Table 2 gives the functional and non-functional requirements for the system.

Table 2: System requirements

Functional requirements	Non-functional requirements
The system must be able to: • Capture cough sound events from the environment • Perform Contactless temperature measurements of people • Measure the proximity of a person to others • Process the collected data on the embedded devices	• Availability: the system's functionality and services should be available for use with all operations 99.99% of the time • Usability: the system should be easy to use. • Reliability: The system should work without failure for at least 5 years • Scalability: The system must grow without negative influence on its performance.

• Apply machine learning algorithms to predict possible respiratory disease risks • Display the prediction results and risk status in real-time • Alert the user to take precaution in case a possible contamination risk is detected • Send the collected data to a cloud platform for storage	• Power consumption: It should be in a position to consume as low power as possible to conserve energy and the environment. • Data Integrity: the system should be in a position to secure access to confidential data for the users. • Performance: the system should ensure optimal responsiveness to various user interactions with it at all times • Recoverability: In case of failure, the system should have a self-recovery backup procedure • Flexibility: Flexible service-based architecture will be highly desirable for future extension • Security: ensure that the software is protected from unauthorized access to the system and its stored data. • Size: the system should be designed using miniaturized devices for portability (small size) • Regulatory requirements: the system should confirm the traffic regulatory requirements

5.3. System Architecture

The system will be made up of sensing units, a processing unit, and a notification unit. As the user wearing the devices moves and interacts with others, the sensing unit will be able to measure temperatures and cough sound from the environment. The collected data will be processed in real-time and TinyML used to perform analytics to predict any risk of exposure to respiratory diseases. In case of risks, the user will be alerted with notifications being given on a screen, LEDs, and buzzer alerts. an IR temperature sensor will be used for contactless temperature measurement with the sound data collected via sound sensor embedded on the microcontroller. As user output, a micro OLED (displayer for wearable devices), RGB LEDs, a 5-way navigation button, and a buzzer will be used. A proximity sensor will be used to detect closeness to other people. The collected data will also be sent to the things speak cloud platform.

Figure 4: System diagram

4.1.2 IoT System Architecture

◊ **Perception Layer**

In charge of collecting information from the environment. Here we are collecting sound event, temperature, and distance.

◊ **Network Layer**

In charge of the system connectivity.

◊ **Middleware Layer**

In charge of processing the collected data. For this particular system, we developed a ML model capable of extracting insights from data.

◊ **Application Layer**

Interfaces the system to the user.

◊ **Business Layer**

Is all about the business and economic aspect of the project.

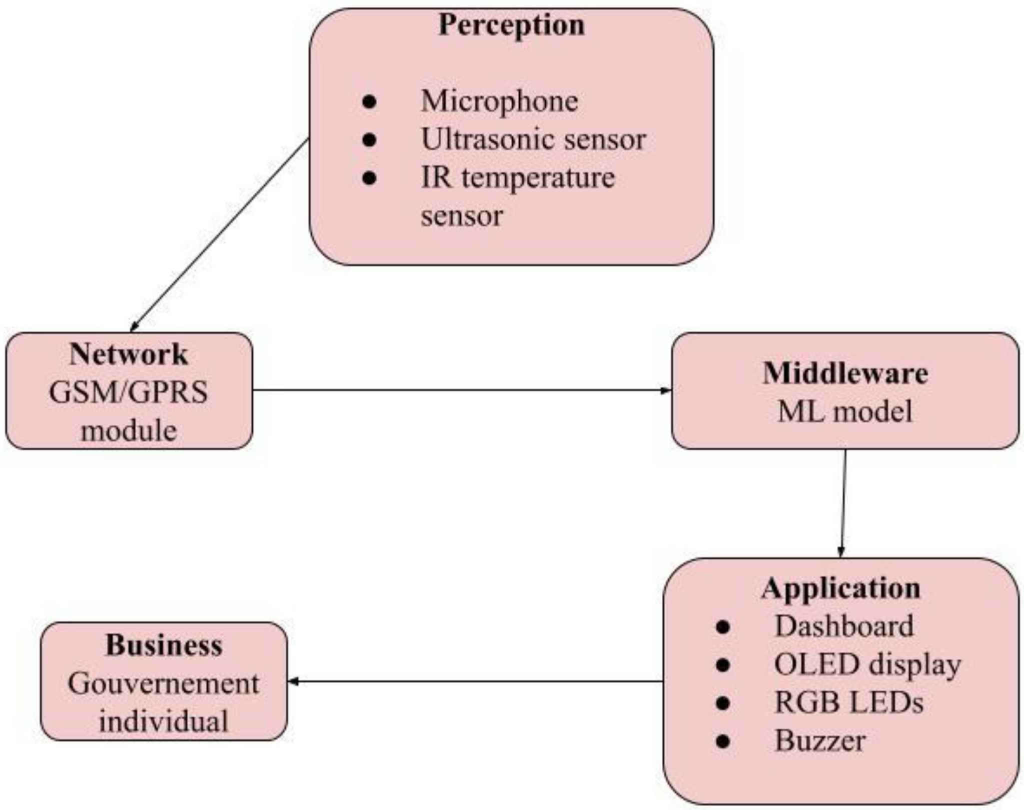

Figure 5: IoT system architecture

4.2 Embedded System-Level Design

4.2.1. System Block Diagram

Components used are:

- Microphone: to capture sound events from the environment
- PIR sensor: to delimit the sensing area
- IR temperature: for contact less body temperature measurement

- 5-way navigation button: to help the user to control the device
- Arduino nano BLE sense: AI enabled processing unit
- GSM/GPRS module: for communication to the cloud and for geolocation of a possible case of respiratory disease
- Buzzer: to alert the user if an exposure to respiratory disease is detected
- Micro OLED: for displaying different measurements
- RGB LEDs display
- Thermoelectric generator: to harvest power from body heat
- Lithium ion battery: for suppling power to the device

The system block diagram is shown on the figure below

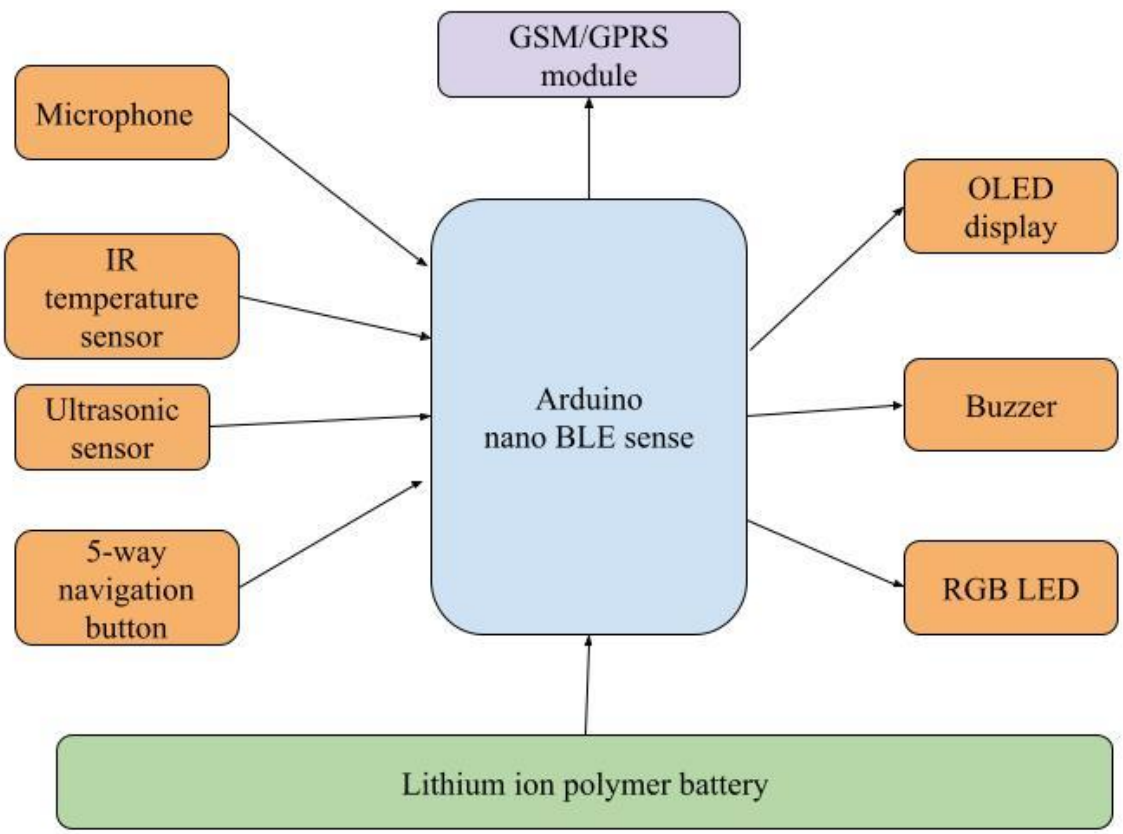

Figure 6: System block diagram

4.2.2. Hardware Components

The main hardware components for the prototype include the following;

- Arduino nano BLE sense which is the smallest Arduino board sustainable for wearable devices. This board has machine learning capabilities and embedded sensors (Microphone was our interest), that is why we chose it for this project. Arduino nano BLE sense is shown on the figure below

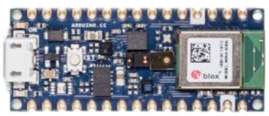

Figure 7: Arduino nano BLE sense

- IR temperature sensor (AMG8831) used to measure temperature. This sensor has been selected for this project because it provides contactless temperature measurement. The sensor is shown on the figure below

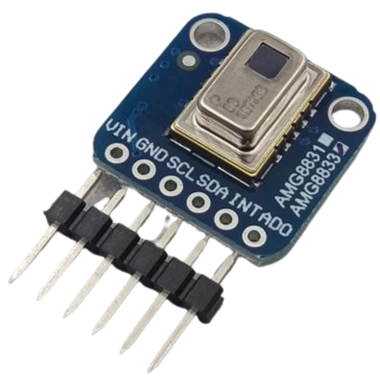

Figure 8: IR temperature sensor

- 5-way navigation button used to enable the user to navigate through the wearable device. It is shown on the figure below

Figure 9: 5-way navigation button

- GSM/GPRS module (SIM800) used for connectivity to send data to the cloud platform. This module was selected because of its size good for wearable devices. it is shown below

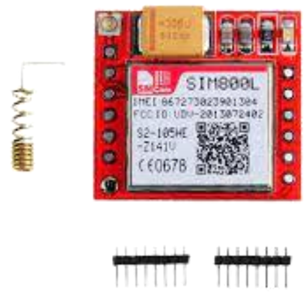

Figure 10: SIM800L GSM/GPRS module

- OLED display used to display measurements and notifications to the user, chosen because of its size because wearable devices require small size devices.

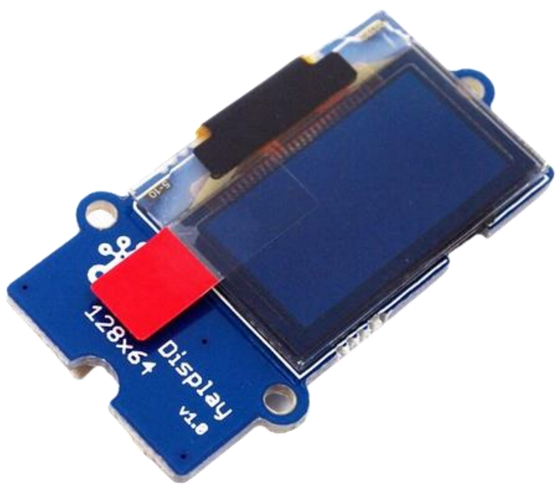

Figure 11: OLED Display

- Buzzer and RGB LEDs used for quick alert to the user in case an exposure risk is detected.

4.2.3 System PDL

Program description language (PDL) is free format English like text and was used to describe the flow of control and data in the system [47].

```
BEGIN/Welcome
        Display "COVID Exposure Alert System"
        Wait 5 sec
        Clear Display
        CALL Distance
END/ Welcome
BEGIN/Distance
        Calculate distance D
      IF D<=2m THEN
                CALL Send data
                CALL Temp
      ENDIF
END/ Distance
BEGIN/Temp
        Measure temperature T
        Display T
        Wait 1 sec
        Clear Display
        CALL Send data
        CALL Inference
END/ Temp
BEGIN/Inference
        Record sound
        Display predictions
        Wait 3 sec
        Clear Display
```

```
        IF label==" COVID-19" THEN
                Display "covid Exposure risk"
                 Turn-on buzzer
                Turn-on red LED
                Wait 3 secs
                Clear Display
                Turn-off buzzer
                Turn-off red LED
                 CALL Send data
        ELSEIF label==" Cough" THEN
                Display "Normal Cough detected"
                Turn-on yellow LED
                Wait 3 secs
                Clear Display
                Turn-off yellow LED
                CALL Send data
        ELSEIF label==" Noise" THEN
                Display "Safe environment"
                Turn-on green LED
                Wait 3 secs
                Clear Display
                Turn-off green LED
                CALL Send data
        ENDIF

    CALL Send data
END/ Inference
BEGIN/Send data
    Initialize GPRS module
    Start connection
```

```
        Begin sending
        Display "Data sent"
        Wait 3 secs
        Clear Display
        Wait 5 sec
END/ Send data


BEGIN/MAIN
        Initialization
        DO Forever
            CALL Welcome
        ENDDO
END/MAIN
```

4.2.4 System Flow Charts

Below are the system Flow charts

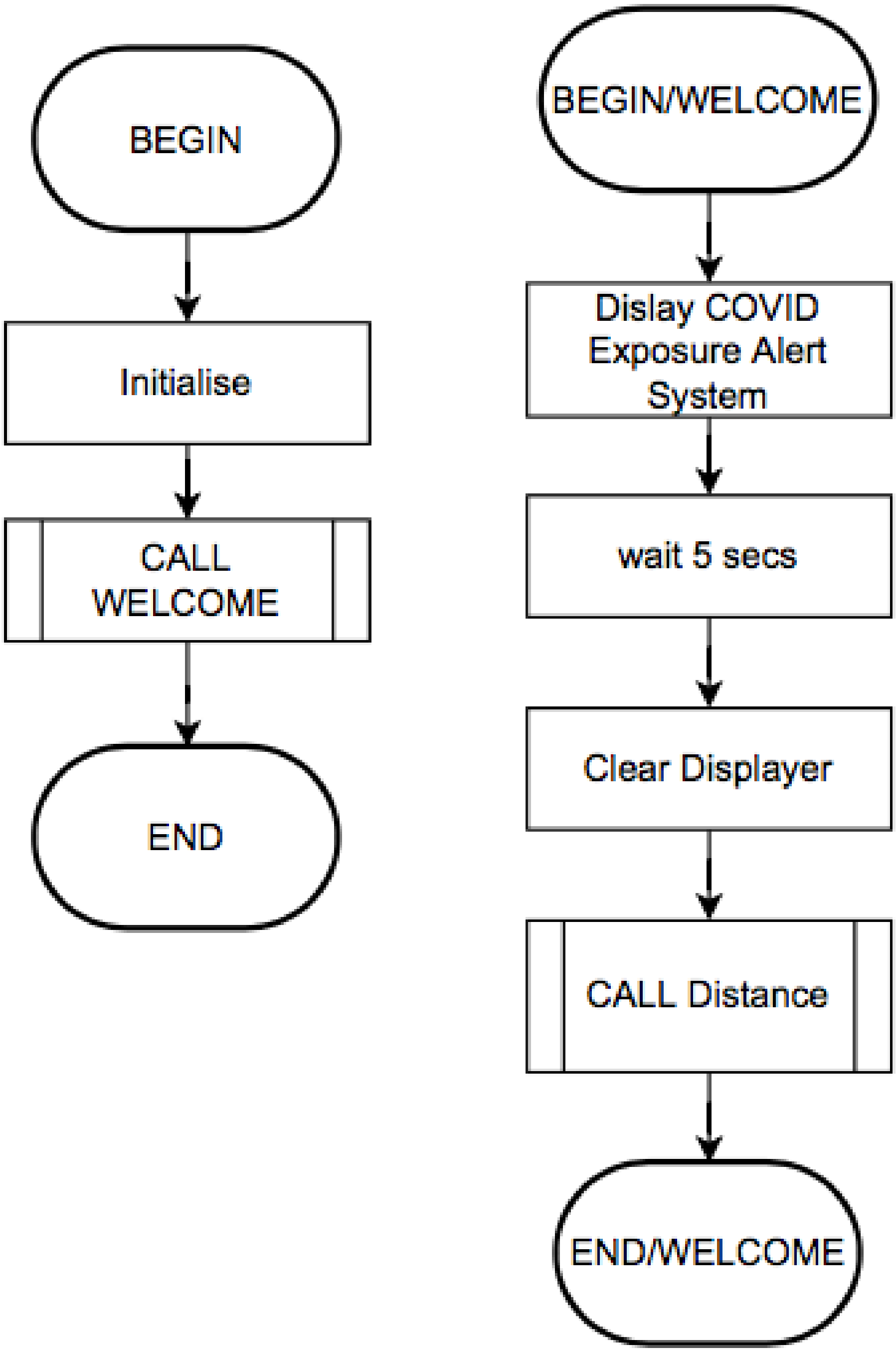

Figure 12: Flow chart (1)

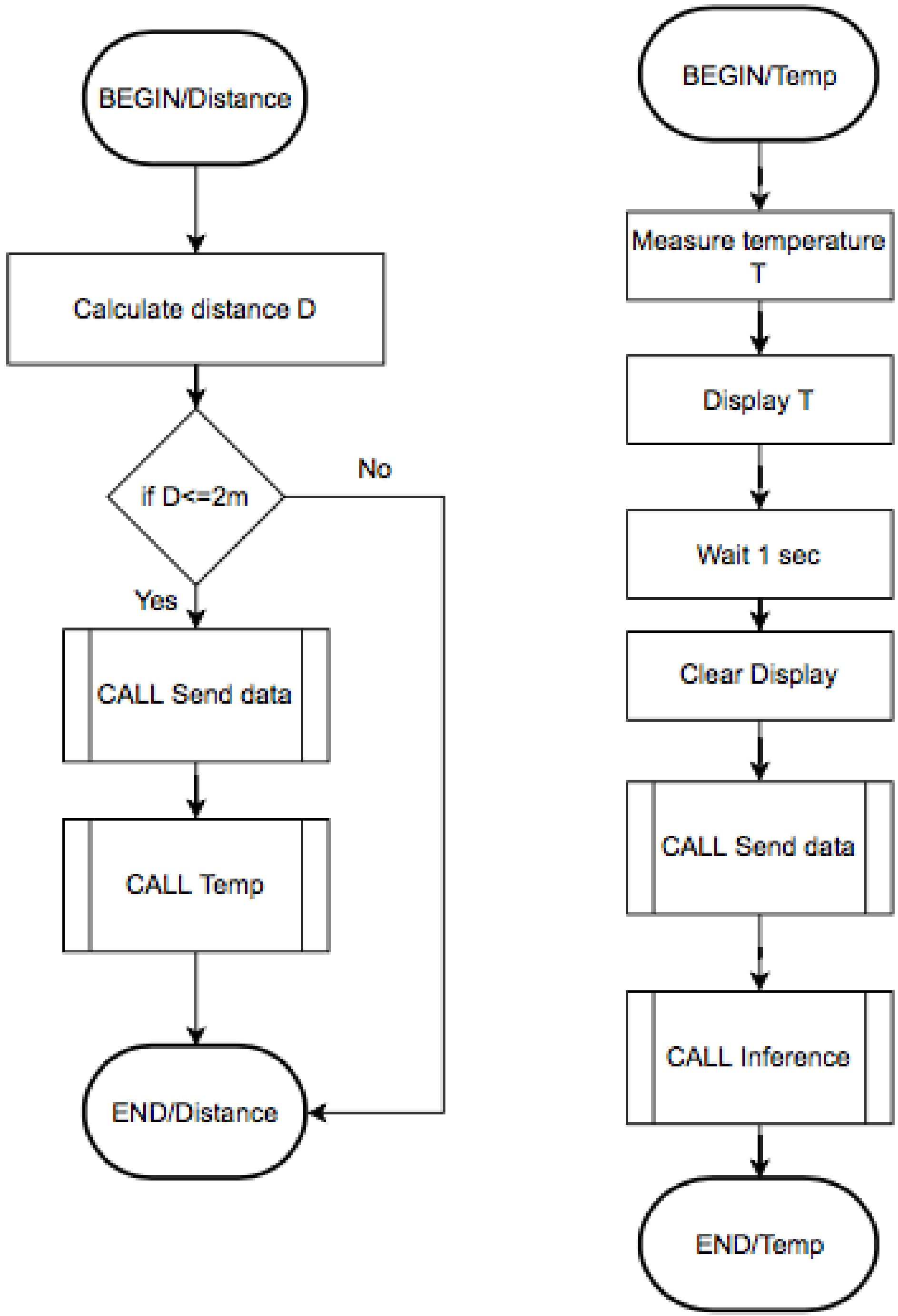

Figure 13: Flow chart (2)

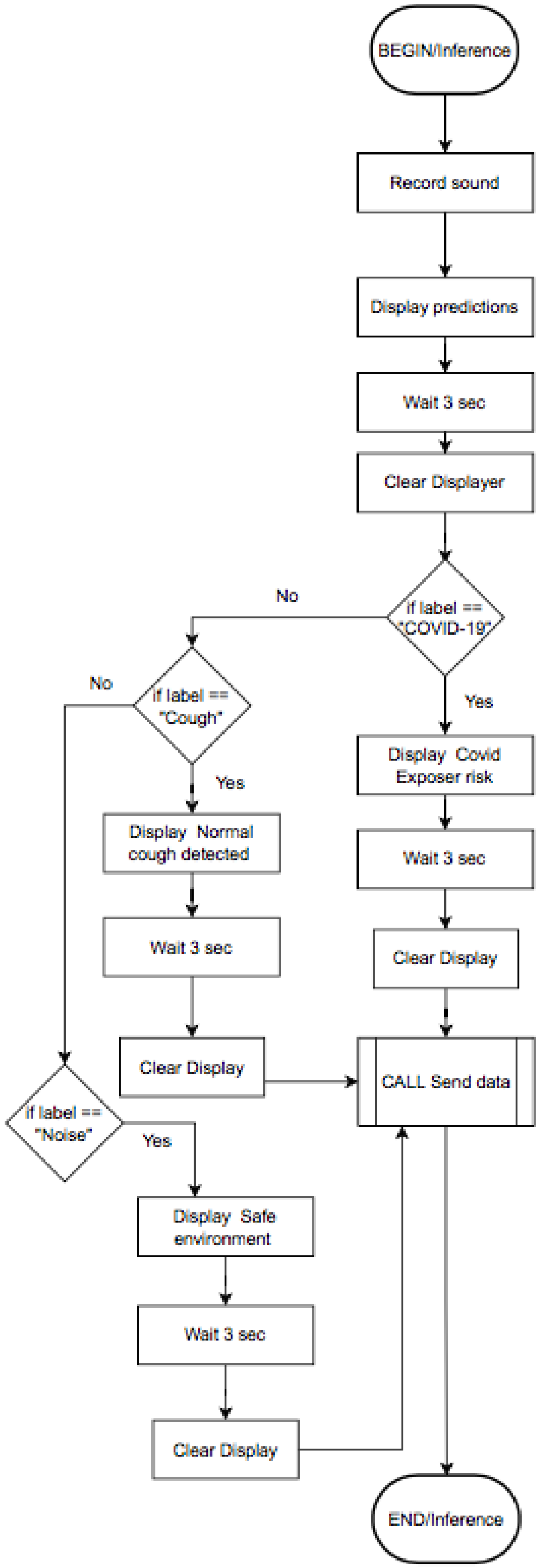

Figure 14: Flow chart (3)

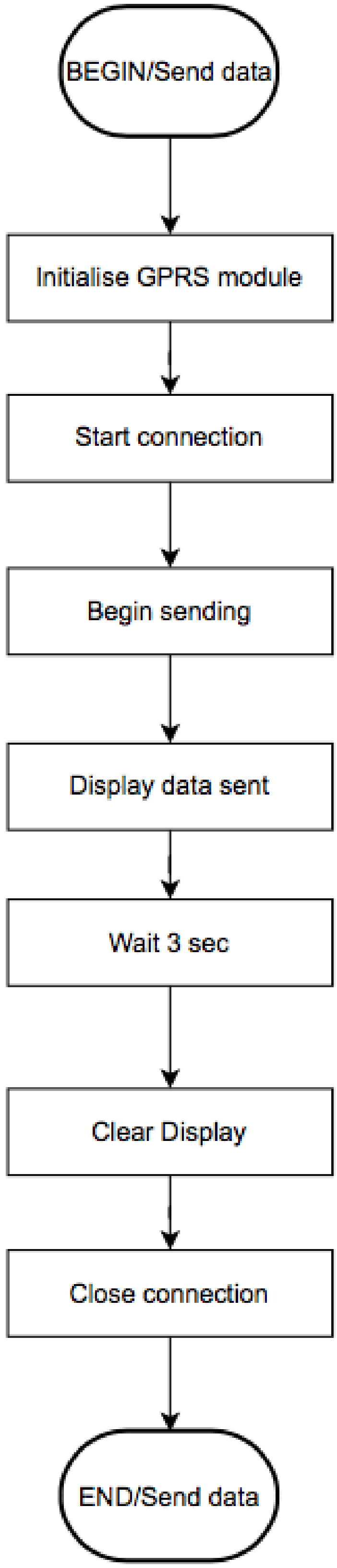

Figure 15: Flow chart (4)

4.2.6 Use Case Diagram

Use cases represent the system from the perspective of the actor. The figure below shows the use case diagram of the developed system.

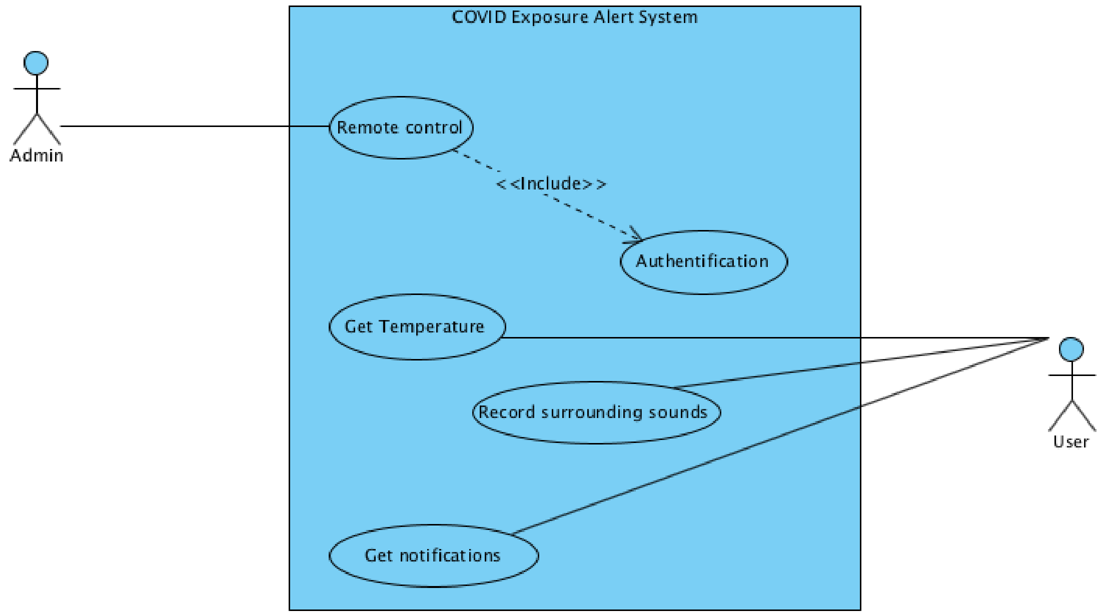

Figure 16: Use case diagram

4.5 ML Model design

This section outlines the respiratory disease ML model. The first section describes the dataset used for training of the model followed by a description of the training process and thereafter a validation and testing of the model.

A. Datasets

Two sets of open data sets were used, in the first set, the dataset used consists of 135 cough files and 52 non-cough files from Google's AudioSet, 40 cough files and 1,960 non-cough files from the ESC-50 dataset, and 256 cough files and 10,801 non-cough files from the FSDKaggle2018 dataset. The second was data collected in an edge impulse project to classify covid and non covid coughs.

B. Data formatting

First, the dataset was divided into three categories labeled COVID-19 Coughs, Normal Coughs, and Noise. 600 observations in total were made for each class. Each class's data was split into 20% test data at random. The embedded ML training platform edge impulse, powered by edge impulse, was then used to upload data into the digital signal processing pipeline. Additionally, 20% of the data is divided into a validation set and 60% is left as the training set.

C. Model Training

A Neural Network classifier based on Keras and tensor flow light was used to train the model. A learning rate of 0.02 with 300 training cycles was applied with a 1D Convolutional architecture with 8 layers including input, reshape, pool, flatten and output layers. Figure 17 shows the model architecture.

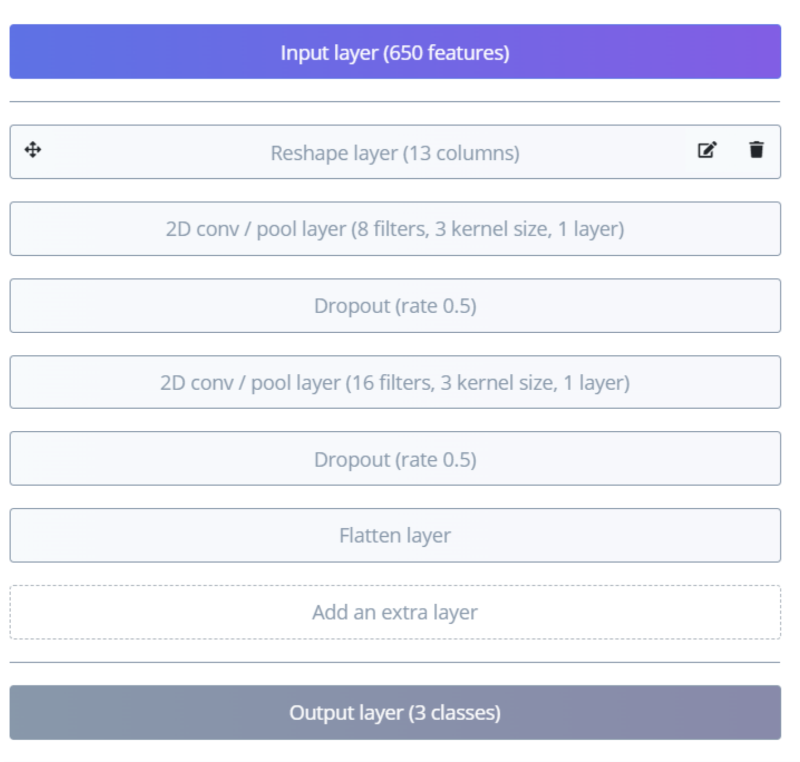

Figure 17: Model Architecture

D. Training Output

From the performance on the validation set, the accuracy was 68.2 % and a loss of 0.76. Better results would be achieved with more data and additional sets. Figure 5. show the confusion matrix for the model.

ACCURACY
68.2%

LOSS
0.71

Confusion matrix (validation set)

	COVID-19	COUGH	NOISE
COVID-19	54.0%	44.2%	1.8%
COUGH	15.6%	75.8%	8.6%
NOISE	3.4%	26.5%	70.1%
F1 SCORE	0.59	0.67	0.77

Figure 18: Model confusion matrix

4.4 Embedded Device Set-Up

We used Arduino nano BLE sense for data processing, on one hand. On the other hand, we used a microphone (embedded in Arduino BLE sense), an infrared temperature sensor, and an ultrasonic sensor for data collection. The output is communicated to the user through a micro OLED display. After data analysis, the results are sent to the cloud using a GSM/GPRS module.

The infrared temperature sensor and the OLED display use I2C communication and both were connected to Arduino SDA and SCL pins on hardware and on the software, they used different addresses to work together.

For the sim800l GSM/GPRS module, we used the Tx and Rx pins connected to digital pins 5 and 6. Due to the power requirement of the module (between 3.4V and 4.4V and 2A), it is powered by a step-down module and a power adapter. The ultrasonic sensor was connected to digital pins 2 and 3 respectively for trigger and echo pins. The prototype is shown on the figure below

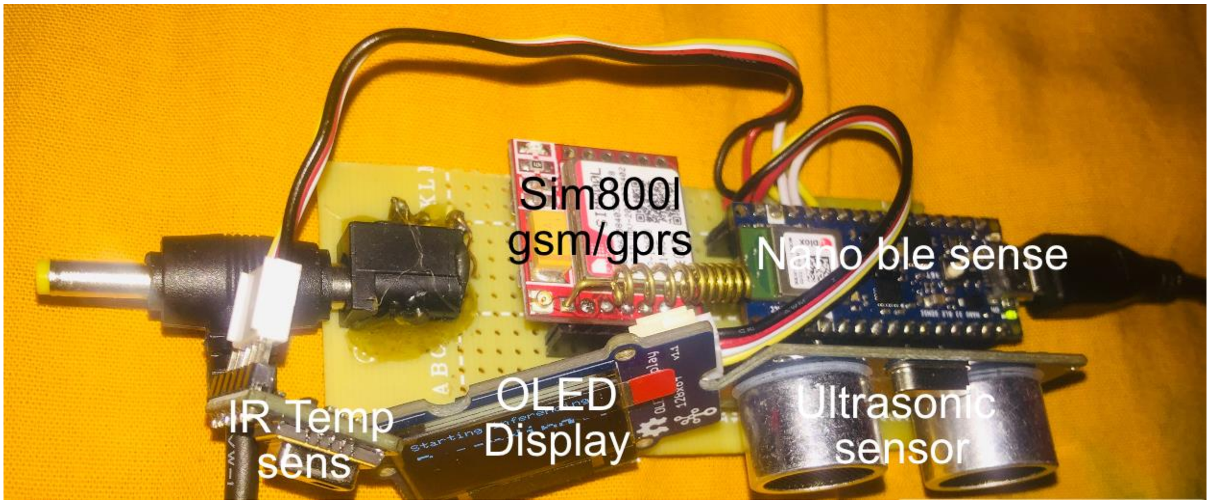

Figure 19: Prototype

According to the cloud Platform, we used ThingSpeak for data visualization on the cloud. We had a channel with 4 fields where field1 is for the device id, field2 for temperature measurements, field3 for distance measurements, and field4 for predictions.

CHAPTER 5

SYSTEM RESULTS, ANALYSIS AND DISCUSSIONS

In this section we present and analyze the results from our prototype as well as short discussion on obtained results.

5.1 ML Models Training Results

1. ML Validation classification

From the performance on the validation set, the accuracy was 68.2 % and a loss of 0.76. Better results would be achieved with more data and additional sets. Figure 5. and y show the confusion matrix and the data explorer for the validation set for the model respectively.

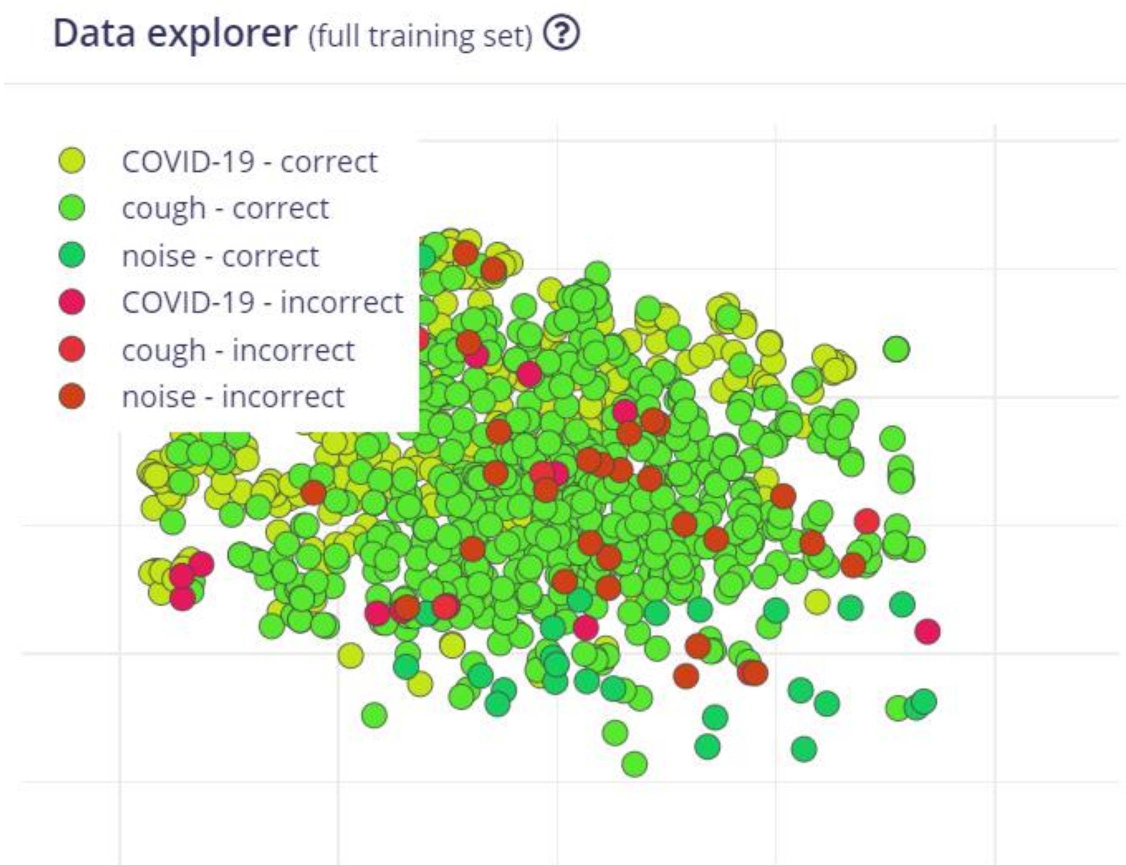

Figure 20:Training output

2. Test classification

So as to validate the model, test data from the open datasets was used to test. When the test data was applied on both the cloud and embedded device, the model predicted the cough sound with 77.08% accuracy. This shows that the model is effective in predicting the exposure to COVID-19 depending on the recorded cough sounds.

ACCURACY

77.08%

	COVID-19	COUGH	NOISE	UNCERTAIN
COVID-19	48.6%	2.9%	0%	48.6%
COUGH	0%	88.9%	0%	11.1%
NOISE	0%	1.4%	83.1%	15.5%
F1 SCORE	0.65	0.80	0.91	

Figure 21: Covid-19 accuracy

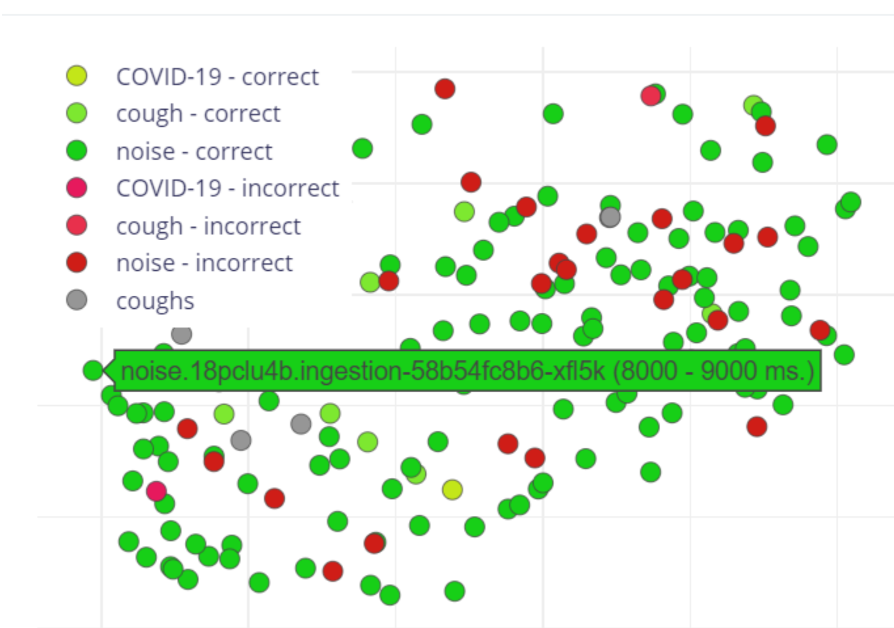

Figure 22:

3. Comparison of classification on the cloud (Edge Impulse) and on the embedded device to show the same accuracies are maintained

The machine learning model was optimized for performance on an embedded device so as to limit the need of connectivity during inferences. This reduces costs and latencies on the predictions. The performance of the model shows similar accuracies in comparison with the cloud-based inference. Figure 23 shows a sample output of the prediction on the embedded device.

TIMESTAMP	COVID-19	COUGH	NOISE
0	0.28	**0.60**	0.12
500	0.32	**0.61**	0.07
1000	0.28	**0.62**	0.10
1500	**0.54**	0.41	0.05
2000	0.45	**0.52**	0.04
2500	0.15	**0.70**	0.14
3000	0.16	**0.69**	0.15

Figure 23: On-device inference (1)

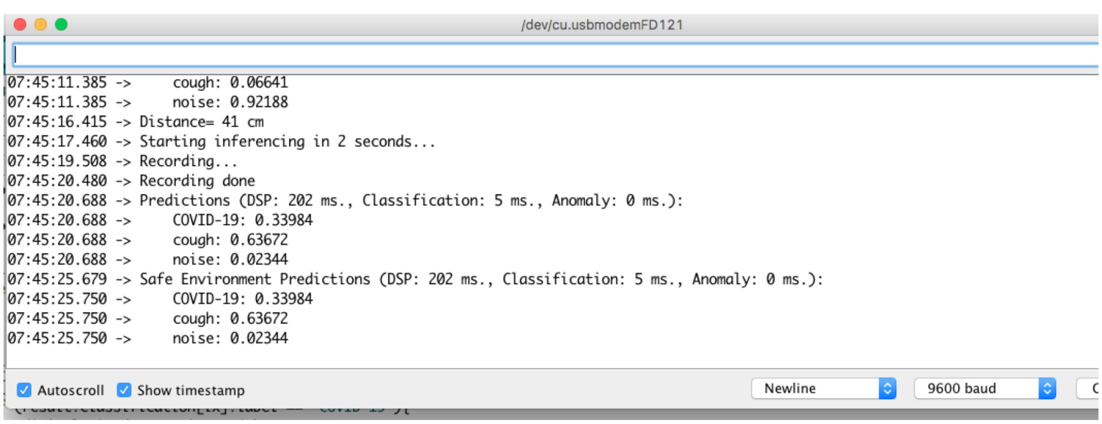

Figure 24: On-device inference (2)

4. The on-device resources needed to show how the model fits on embedded devices

In order to ascertain whether the model could function as intended on an embedded device, the model's resource requirements on the device were examined. On an embedded device from the cloud training platform, the model's estimated on-device performance was 5.1 Kb of peak RAM utilization, 30.6 Kb of ROM usage, and an inference time of 1 ms. The findings indicate that just minimal resources are still needed. This demonstrates that a large number of commercially available embedded devices that have the necessary ARM cortex M4 processor may use the model.

Figure 25: on-device performance

5.2 Prototype results

1) Distance measurement

The idea is to delimit the working range of the device. So, we used an ultrasonic proximity sensor to measure the distance to the nearest person. The distance has to be less or equal to 2m for the device to sense. Distance measurement is shown below

```
11:11:16.436 -> Distance= 261 cm
11:11:17.491 -> Starting inferencing in 2 seconds...
```

Figure 26: Distance measurement

2) Temperature measurement

Once the distance condition is satisfied, the device takes the temperature in a contactless manner using an infrared temperature sensor.

```
11:20:38.011 -> Temperature= 31.81*C
```

Figure 27: Temperature measurement

Figure 28: on-device temperature measurement

3) Cough/noise/covid predictions

The goal is to predict the status of the environment based on symptoms (mainly cough). We developed a classification model where we classified sounds in three main classes: Covid-19, Cough and Noise. The model used existing datasets. We used a microphone (embedded on Arduino nano BLE sense) to record sound events from the environment and predict the status using the developed model.

```
11:22:58.985 -> Starting inferencing in 2 seconds...
11:23:01.036 -> Recording...
11:23:02.024 -> Recording done
11:23:02.232 -> Predictions (DSP: 191 ms., Classification: 5 ms., Anomaly: 0 ms.):
11:23:02.232 ->     COVID-19: 0.00391
11:23:02.232 ->     cough: 0.03125
11:23:02.232 ->     noise: 0.96484
11:23:07.231 -> Predictions (DSP: 191 ms., Classification: 5 ms., Anomaly: 0 ms.):
11:23:07.231 ->     COVID-19: 0.00391
11:23:07.231 ->     cough: 0.03125
11:23:07.231 ->     noise: 0.96484
11:23:12.251 -> Safe Environment Predictions (DSP: 191 ms., Classification: 5 ms., Anomaly: 0 ms.):
11:23:12.285 ->     COVID-19: 0.00391
11:23:12.285 ->     cough: 0.03125
11:23:12.285 ->     noise: 0.96484
```

Figure 29: Inferencing

Figure 30: On-device inferencing

Figure 31: on-device prediction

4) Sending data to the cloud

The last part was about sending the data collected from the device to the cloud for a remote-control purpose and for data driven decision making. For this, we used a GSM/GPRS module SIM800L. Below are results

Figure 32: On-device data sending

```
11:27:50.494 -> AT
11:27:50.494 -> OK
11:27:52.015 -> AT+CPIN?
11:27:52.015 -> +CPIN: READY
11:27:52.015 ->
11:27:52.015 -> OK
11:27:53.509 -> AT+CREG?
11:27:53.509 -> +CREG: 0,1
11:27:53.509 ->
11:27:53.509 -> OK
11:27:55.010 -> AT+CGATT?
11:27:55.010 -> +CGATT: 1
11:27:55.043 ->
11:27:55.043 -> OK
11:27:56.526 -> AT+CIPSHUT
```

Figure 33: Data sending (1)

```
11:27:56.526 -> AT+CIPSHUT
11:27:56.526 -> SHUT OK
11:27:59.033 -> AT+CIPSTATUS
11:27:59.033 -> OK
11:27:59.033 ->
11:27:59.033 -> STATE: IP INITIAL
11:28:01.552 -> AT+CIPMUX=0
11:28:01.552 -> OK
11:28:03.072 -> AT+CSTT="internet.mtn"
11:28:03.072 -> OK
11:28:06.558 -> AT+CIICR
11:28:06.558 -> OK
11:28:09.076 -> AT+CIFSR
11:28:09.076 -> 10.22.164.240
```

Figure 34: Data sending (2)

```
11:28:09.672 -> AT+CIPSPRT=0
11:28:09.672 -> OK
11:28:12.207 -> AT+CIPSTART="TCP","api.thingspeak.com","80"
11:28:12.207 -> OK
11:28:12.207 ->
11:28:12.207 -> CONNECT OK
11:28:16.722 -> AT+CIPSENDGET https://api.thingspeak.com/update?api_key=MEMT7F39ONUDAEN1&field1=Savanna&field2=32.75&field3=31&field4=0
11:28:20.283 -> GET https://api.thingspeak.com/update?api_key=MEMT7F39ONUDAEN1&field1=Savanna&field2=32.75&field3=31&field4=0
11:28:23.773 ->
11:28:23.773 ->
11:28:23.773 -> SEND OK
```

Figure 35: data sending (3)

5.3 Cloud dashboard results

All data collected from the device are sent to the cloud. We used ThingSpeak platform. We had a channel with 4 fields where field1 is for the device id, field2 for temperature measurements, field3 for distance measurements, and field4 for predictions.

A. Distance

The measured distance is sent to the cloud as shown below

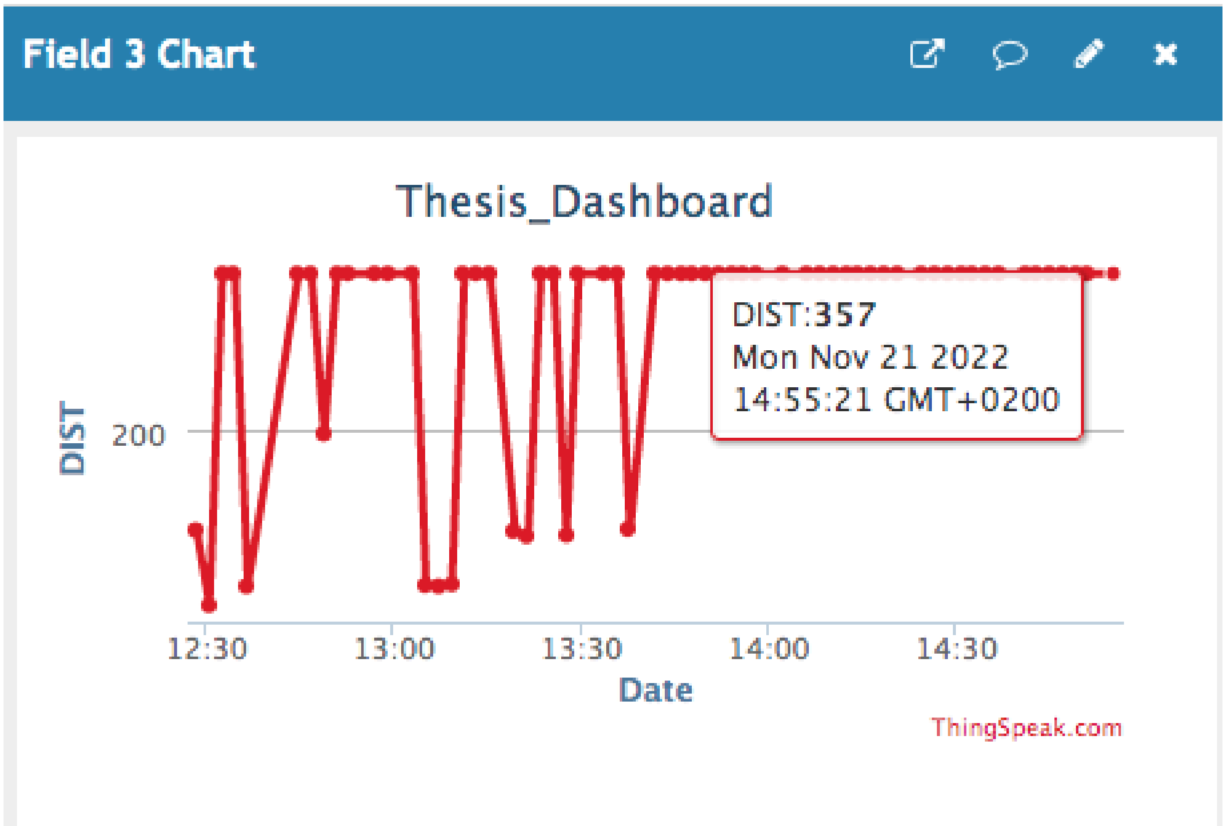

Figure 36: Distance on the cloud

Each data point includes the distance value and the exact time the data was sent

B. Temperature

The figure below shows the temperature on the cloud, each data point including the temperature value and the exact time when it was sent.

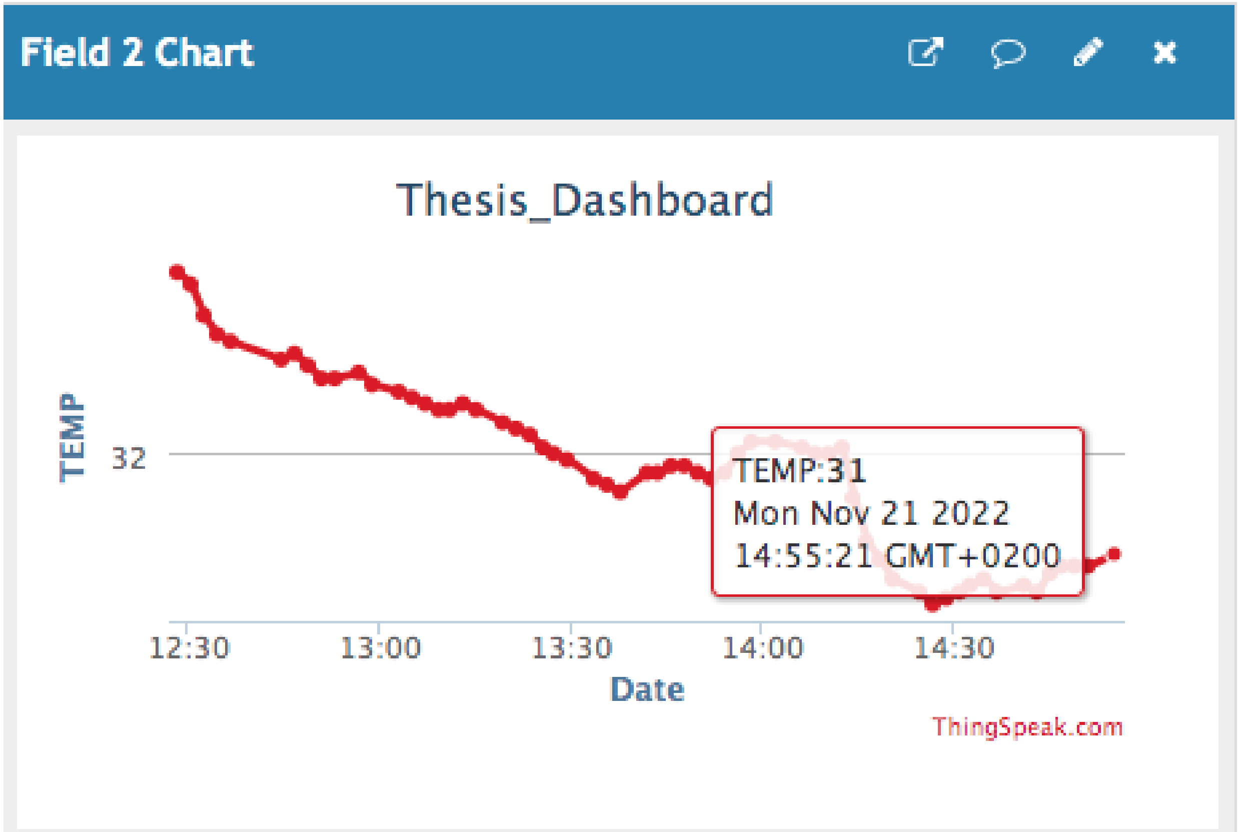

Figure 37: Temperature on the cloud

C. Predictions

For the prediction, we are sending either 0, 1 or 2. 0 is associated to Noise sound, 1 to normal Cough and 2 for COVID-19 related cough as shown below

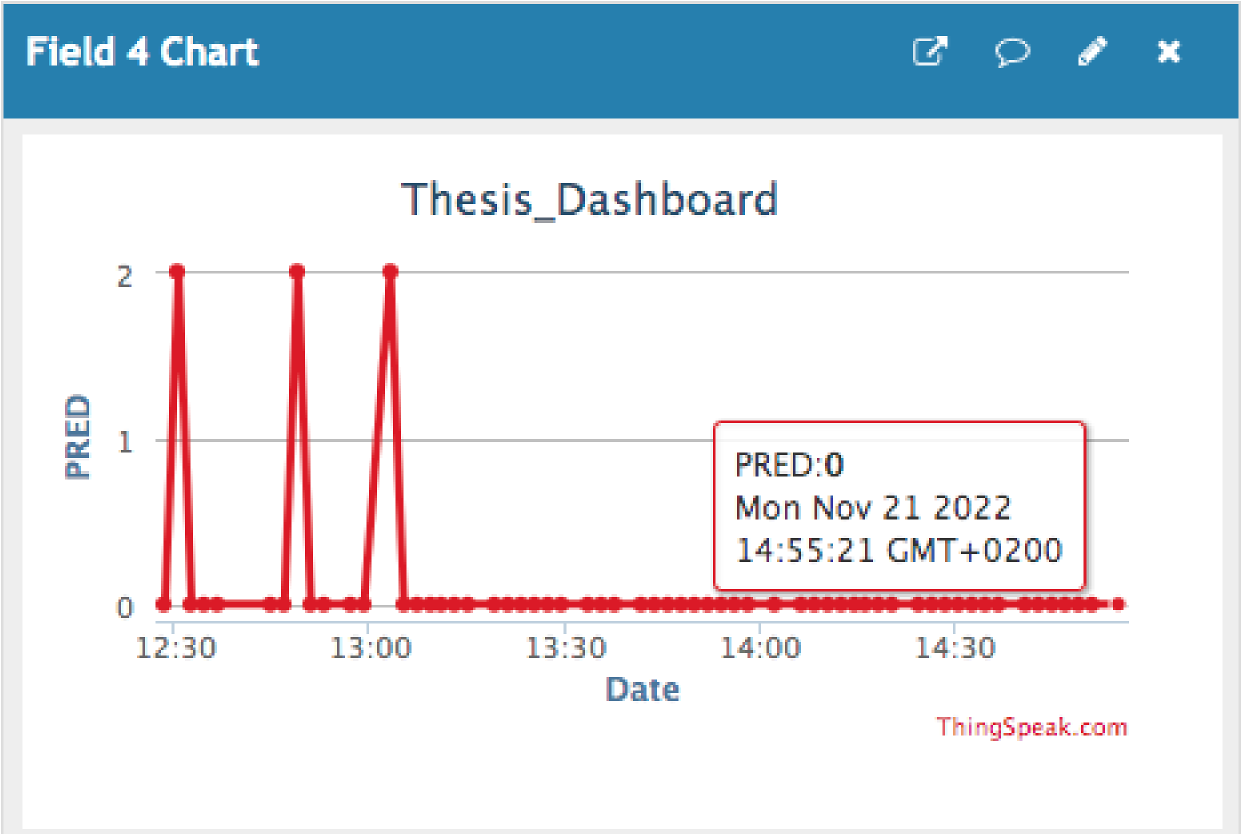

Figure 38: Predictions on the cloud

CONCLUSION

According to the world health organization respiratory diseases are one of the causes of deaths across the globe. There have been increasing attempts to use latest technologies as a solution to early detection and thus prevent fatalities. Some of the technologies that are increasingly being used involve the integration of IoT and AI technologies to enable real-time predictions. From a review of the related works its was noted that existing solutions are built around a cloud-based architecture. Due to connectivity and cost constraints in Africa such solutions have been difficult to adopt across the continent.

This study therefore proposed the use of edge-based IA technologies to enable prediction of how safe an environment is from respiratory diseases without the need for connectivity. In the proposed solution sound, temperature and proximity sensors are used to collect data from the environment and TinyML being applied to predict if an environment is COVID 19 contaminated or not with the user getting appropriate alerts.

The model was trained using open datasets with the results showing it is possible to indeed detect if a person in a crowded place is safe or not.

The use of this solution will help to limit the spread of communicable respiratory diseases in public settings.

Future works will involve improving on the model and collecting more data for other diseases

REFERENCES

[1] “Estimating the burden of respiratory diseases - Practical Approach to Lung Health - NCBI Bookshelf.” https://www.ncbi.nlm.nih.gov/books/NBK310631/ (accessed Jul. 05, 2022).

[2] “Causes of Death: The Most Common Diseases in Rwanda.” https://borgenproject.org/common-diseases-in-rwanda/ (accessed Jul. 05, 2022).

[3] “Chronic respiratory diseases.” https://www.who.int/health-topics/chronic-respiratory-diseases#tab=tab_1 (accessed Jul. 05, 2022).

[4] G. Rathee, A. Sharma, H. Saini, R. Kumar, and R. Iqbal, “https://www.who.int/health-topics/coronavirus#tab=tab_1,” *Multimedia Tools and Applications*, 2020.

[5] WHO, “Coronavirus disease (COVID-19): How is it transmitted?,” *Q&A Detail*, no. July 2020. 2020.

[6] “WHO Coronavirus (COVID-19) Dashboard | WHO Coronavirus (COVID-19) Dashboard With Vaccination Data.” https://covid19.who.int/ (accessed May 17, 2022).

[7] P. P. Ray, “A survey on Internet of Things architectures,” *Journal of King Saud University - Computer and Information Sciences*, vol. 30, no. 3. 2018. doi: 10.1016/j.jksuci.2016.10.003.

[8] A. Panesar, *Machine Learning and AI for Healthcare: Big Data for Improved Health Outcomes*. 2019. doi: 10.1007/978-1-4842-3799-1.

[9] “IOT AND AI IN HEALTHCARE: A SYSTEMATIC LITERATURE REVIEW,” *Issues In Information Systems*, 2018, doi: 10.48009/3_iis_2018_33-41.

[10] T. Panch, H. Mattie, and L. A. Celi, “The ‘inconvenient truth’ about AI in healthcare,” *npj Digital Medicine*, vol. 2, no. 1, 2019, doi: 10.1038/s41746-019-0155-4.

[11] S. Chakkor, M. Baghouri, Z. Cheker, A. el Oualkadi, J. A. el Hangouche, and J. Laamech, “Intelligent network for proactive detection of COVID-19 disease,” *Colloquium in Information Science and Technology, CIST*, vol. 2020-June, pp. 472–478, Jun. 2020, doi: 10.1109/CIST49399.2021.9357181.

[12] S. O. Ooko, M. Muyonga Ogore, J. Nsenga, and M. Zennaro, “TinyML in Africa: Opportunities and Challenges,” *2021 IEEE Globecom Workshops, GC Wkshps 2021 - Proceedings*, 2021, doi: 10.1109/GCWKSHPS52748.2021.9682107.

[13] J. Portilla, G. Mujica, J. S. Lee, and T. Riesgo, “The Extreme Edge at the Bottom of the Internet of Things: A Review,” *IEEE Sensors Journal*, vol. 19, no. 9, 2019, doi: 10.1109/JSEN.2019.2891911.

[14] D. L. Dutta and S. Bharali, “TinyML Meets IoT: A Comprehensive Survey,” *Internet of Things (Netherlands)*, vol. 16. 2021. doi: 10.1016/j.iot.2021.100461.

[15] “Infectious diseases - Symptoms and causes - Mayo Clinic.” https://www.mayoclinic.org/diseases-conditions/infectious-diseases/symptoms-causes/syc-20351173 (accessed May 14, 2022).

[16] K. A. Hacker, P. A. Briss, L. Richardson, J. Wright, and R. Petersen, “COVID-19 and Chronic Disease: The Impact Now and in the Future,” *Preventing Chronic Disease*, vol. 18, 2021, doi: 10.5888/PCD18.210086.

[17] “People with Certain Medical Conditions | CDC.” https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/people-with-medical-conditions.html (accessed May 14, 2022).

[18] M. Ajebli *et al.*, “Chronic Diseases and COVID-19: A Review,” *Endocrine, Metabolic & Immune Disorders - Drug Targets*, vol. 21, no. 10, 2020, doi: 10.2174/1871530320666201201110148.

[19] M. R. Nahimana *et al.*, “A population-based national estimate of the prevalence and risk factors associated with hypertension in Rwanda: Implications for prevention and control,” *BMC Public Health*, vol. 18, no. 1, 2017, doi: 10.1186/s12889-017-4536-9.

[20] “If we are to ‘live with’ COVID-19, we must decide what we really value | openDemocracy.” https://www.opendemocracy.net/en/oureconomy/covid-19-future-live-with-virus/ (accessed May 14, 2022).

[21] Y. E. Erdoğan and A. Narin, “COVID-19 detection with traditional and deep features on cough acoustic signals,” *Computers in Biology and Medicine*, vol. 136, 2021, doi: 10.1016/j.compbiomed.2021.104765.

[22] “Rapid Tests: MedlinePlus Medical Test.” https://medlineplus.gov/lab-tests/rapid-tests/ (accessed May 14, 2022).

[23] “Reduced Lung-Cancer Mortality with Low-Dose Computed Tomographic Screening,” *New England Journal of Medicine*, vol. 365, no. 5, pp. 395–409, Aug. 2011, doi: 10.1056/NEJMOA1102873/SUPPL_FILE/NEJMOA1102873_DISCLOSURES.PDF.

[24] W. C. Black *et al.*, "Cost-effectiveness of CT screening in the National Lung Screening Trial," *N Engl J Med*, vol. 371, no. 19, pp. 1793–1802, Nov. 2014, doi: 10.1056/NEJMOA1312547.

[25] "iOS - Research App - Apple." https://www.apple.com/ios/research-app/ (accessed Jul. 25, 2022).

[26] "Grantee: Har Zindagi | UNICEF Office of Innovation ." https://www.unicef.org/innovation/stories/grantee-har-zindagi (accessed Jul. 26, 2022).

[27] D. Yang, K. Li, D. Mingwei Chua, Y. Song, C. Bai, and C. A. Powell, "Application of Internet of Things in Chronic Respiratory Disease Prevention, Diagnosis, Treatment and Management," *Clinical eHealth*, vol. 5, pp. 10–16, Dec. 2022, doi: 10.1016/J.CEH.2021.08.001.

[28] Y. F. Y. Chan *et al.*, "The Asthma Mobile Health Study, a large-scale clinical observational study using ResearchKit," *Nat Biotechnol*, vol. 35, no. 4, pp. 354–362, Apr. 2017, doi: 10.1038/NBT.3826.

[29] J. C. Tsai *et al.*, "Design and Implementation of an Internet of Healthcare Things System for Respiratory Diseases," *Wireless Personal Communications 2020 117:2*, vol. 117, no. 2, pp. 337–353, Nov. 2020, doi: 10.1007/S11277-020-07871-5.

[30] A. Raji, P. Kanchana Devi, P. Golda Jeyaseeli, and N. Balaganesh, "Respiratory monitoring system for asthma patients based on IoT," *Proceedings of 2016 Online International Conference on Green Engineering and Technologies, IC-GET 2016*, May 2017, doi: 10.1109/GET.2016.7916737.

[31] K. Kumar, N. Kumar, and R. Shah, "Role of IoT to avoid spreading of COVID-19," *International Journal of Intelligent Networks*, vol. 1, pp. 32–35, Jan. 2020, doi: 10.1016/J.IJIN.2020.05.002.

[32] R. Ani, S. Krishna, N. Anju, A. M. Sona, and O. S. Deepa, "IoT based patient monitoring and diagnostic prediction tool using ensemble classifier," *2017 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2017*, vol. 2017-January, pp. 1588–1593, Nov. 2017, doi: 10.1109/ICACCI.2017.8126068.

[33] E. Mekov, M. Miravitlles, and R. Petkov, "Artificial intelligence and machine learning in respiratory medicine," *https://doi.org/10.1080/17476348.2020.1743181*, vol. 14, no. 6, pp. 559–564, Jun. 2020, doi: 10.1080/17476348.2020.1743181.

[34] A. Kaplan *et al.*, "Artificial Intelligence/Machine Learning in Respiratory Medicine and Potential Role in Asthma and COPD Diagnosis," *J Allergy Clin Immunol Pract*, vol. 9, no. 6, pp. 2255–2261, Jun. 2021, doi: 10.1016/J.JAIP.2021.02.014.

[35] C. I. Alvarez-Mendoza, A. Teodoro, A. Freitas, and J. Fonseca, "Spatial estimation of chronic respiratory diseases based on machine learning procedures—an approach using remote sensing data and environmental variables in quito, Ecuador," *Applied Geography*, vol. 123, p. 102273, Oct. 2020, doi: 10.1016/J.APGEOG.2020.102273.

[36] G. Chambres, P. Hanna, and M. Desainte-Catherine, "Automatic detection of patient with respiratory diseases using lung sound analysis," *Proceedings - International Workshop on Content-Based Multimedia Indexing*, vol. 2018-September, Oct. 2018, doi: 10.1109/CBMI.2018.8516489.

[37] E. A. Paraschiv and C. M. Rotaru, "Machine Learning Approaches based on Wearable Devices for Respiratory Diseases Diagnosis," *2020 8th E-Health and Bioengineering Conference, EHB 2020*, Oct. 2020, doi: 10.1109/EHB50910.2020.9280098.

[38] B. Aljaddouh and D. Malathi, "Trends of using machine learning for detection and classification of respiratory diseases: Investigation and analysis," *Materials Today: Proceedings*, vol. 62, pp. 4651–4658, Jan. 2022, doi: 10.1016/J.MATPR.2022.03.120.

[39] R. Palaniappan, K. Sundaraj, and N. U. Ahamed, "Machine learning in lung sound analysis: A systematic review," *Biocybernetics and Biomedical Engineering*, vol. 33, no. 3, pp. 129–135, Jan. 2013, doi: 10.1016/J.BBE.2013.07.001.

[40] S. O. Ooko, M. Muyonga Ogore, J. Nsenga, and M. Zennaro, "TinyML in Africa: Opportunities and Challenges," *2021 IEEE Globecom Workshops, GC Wkshps 2021 - Proceedings*, 2021, doi: 10.1109/GCWKSHPS52748.2021.9682107.

[41] V. Tsoukas, E. Boumpa, G. Giannakas, and A. Kakarountas, "A Review of Machine Learning and TinyML in Healthcare," *ACM International Conference Proceeding Series*, pp. 69–73, Nov. 2021, doi: 10.1145/3503823.3503836.

[42] P. P. Ray, "A review on TinyML: State-of-the-art and prospects," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 4, pp. 1595–1623, Apr. 2022, doi: 10.1016/J.JKSUCI.2021.11.019.

[43] A. Rana, Y. Dhiman, and R. Anand, "Cough Detection System using TinyML," pp. 119–122, Jun. 2022, doi: 10.1109/IC3P52835.2022.00032.

[44] S. O. Ooko, D. Mukanyiligira, J. P. Munyampundu, and J. Nsenga, “Edge AI-based Respiratory Disease Recognition from Exhaled Breath Signatures,” *2021 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology, JEEIT 2021 - Proceedings*, pp. 89–94, 2021, doi: 10.1109/JEEIT53412.2021.9634140.

[45] “TensorFlow Lite | ML for Mobile and Edge Devices.” https://www.tensorflow.org/lite (accessed Aug. 01, 2022).

[46] “IoT Analytics - ThingSpeak Internet of Things.” https://thingspeak.com/ (accessed Jul. 26, 2022).

[47] D. Ibrahim, “Microcontroller-Based Project Development Cycle,” *ARM-Based microcontroller projects using MBED*, pp. 9–23, 2019, doi: 10.1016/B978-0-08-102969-5.00002-1.