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Research Thesis Title: Integrating Analog PIR Sensing with TinyML Inference for On-the-Edge Classification of Moving Objects

By:

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A research Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the Internet of Things – ECS

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AFRICAN CENTRE OF EXCELLENCE IN INTERNET OF THINGS

Research Thesis Title: Integrating Analog PIR Sensing with TinyML Inference for On-the-Edge Classification of Moving Objects

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

Submitted By

Marie Ritha UMUTONI (REF.NO:220019630)

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December 2022

Declaration

I Marie Ritha UMUTONI, a Master’s student from African Center of Excellence in internet of things, University of Rwanda. I declare that this research thesis is my original work and has never been presented anywhere in the world.

Marie Ritha UMUTONI

Ref: 220019630

Signed: ………………………….

Date: ……/……/……

Bonafide Certificate

This is to certify that the project entitled “Integrating Analog PIR Sensing with TinyML Inference for On-the-Edge Classification of Moving Objects” is a record of original work done by Marie Ritha UMUTONI with registration number 220019630 in partial fulfillment of the requirement for the award of master of sciences in the Internet of Things in College of Science and Technology, University of Rwanda, the Academic year 2020/2021

This work has been submitted under the guidance of Dr. Jimmy Nsenga and Prof Damien Hanyurwimfura.

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Abstract

Classification of moving objects plays an important role in different real-life applications, especially for security monitoring. Digital Passive InfraRed (PIR) devices are the most used solutions but fail to classify the type of moving objects. Furthermore, they rely on hardware logic which is not upgradable and evolutive. This thesis presents a Tiny machine learning (TinyML) research to classify moving objects in the surrounding environment based on reflected analog PIR wave patterns. The lack of a public dataset has driven this research to start by collecting primary analog PIR data of moving humans, dogs, goats, and windblown vegetables. Then, a TinyML classification model has been trained with the objective to deploy it on a resource-constrained embedded microprocessor for real-time classification inference. This edge-centric architecture design enables the preservation of both battery lifetime and wireless communication bandwidth of the prototyped smart analog PIR device. The pilot experimentation shows a performance accuracy of 90% which may be improved over time using reinforcement learning.

Keywords: Analog PIR, Deep Learning, TinyML

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LIST OF ACRONYMS

AI- Artificial Intelligence
DL Deep learning
DNN Deep Neuron Network
FoV Field of View
IoT – Internet of Things
ML- Machine Learning
NN- Neural Network
TinyML Tiny Machine Learning

CHAPTER 1

INTRODUCTION

1.1 Introduction

The integration of Internet of Things (IoT) and Machine Learning (ML) with inference at the edge enables the development of real-time applications that require 24h operations (always on); namely monitoring of moving objects in the surrounding environment, management of social distance with wearable devices, home intrusion surveillance, proximity detection in dangerous or unauthorized locations, monitoring construction sites, and so on [1,2].

Traditionally, cameras used to be the standard sensing technologies for such types of applications. However, camera sensors have several constraints that limit their use in many real-time applications. These constraints are mainly (1) high bandwidth and energy consumption for real-time monitoring and (2) lack of privacy (sensing information that is not necessary to the use case). Those challenges motivate the need for a low-cost solution to enable different existing and emerging privacy-sensitive and real-time resource-constrained use cases.

To overcome the limitations of using the camera as the sensing technology, some researchers proposed to detect moving objects by combining digital Passive InfraRed (PIR) sensor and camera, with the PIR first detecting the movement of the object and then the camera recording the movement of objects. They are many different technologies for detecting objects in proximity like RFID, Near Field Communication (NFC), Bluetooth or Bluetooth low energy, Ultrasonic, Ultra-Wideband, Zigbee, camera and Social Distancing Application Technologies based on AI, infrared or infrared camera, inertial sensors, thermal sensors, [3][4]. For instance, Choubisa et al. [5] created an optical camera combined with a digital PIR sensing device for external intruder detection and classification. In [6], authors developed a system that uses graph spectral clustering to detect moving objects targeting applications like video surveillance, security, enforcement, and self-driving cars. In [7] a sensor tower platform which is made of 8 PIR sensors is combined with the optical camera to classify and detect any intrusion in the outside environment. All the above solutions rely on a digital PIR which relies on hardware-coded logic to provide a binary response about whether a movement has been detected or not. However, the raw analog signal waves collected by PIR sensors feature a lot of patterns that may be used to classify moving objects.

Analog PIR has been used in various applications, [8] An activity recognition method was developed, based on analog output and PIR sensors that can track the user's precise movements to detect which activities are being performed using machine learning. a system with PIR sensors that can calculate resting heart rate (RHR), as an effective and affordable solution for heart rate monitoring is the analog PIR-based system [9]. In addition, a system based on a single PIR sensor for monitoring purposes was developed in [10], the system uses a PIR sensor integrated with machine learning to monitor human-related activities. in these systems, they showed how a single PIR sensor can be used in person monitoring, person counting, activity recognition, motion monitoring, and even for security purposes. A combination of low-cost PIR and Deep learning was applied to optimize the performance of human counting and localization for both one and multiple persons, two-stage networks were designed, one that uses signal separation for counting persons and another for determining their locations [11].

1.2 Problem Statement

Moving object detection using computer vision is a trending topic and has been used in many applications like robotics, security, and monitoring system but they are expensive, its data contains a lot of noise and has low resolution [7]. Despite the rapid applications of image classification and object detection. There is still an urgency for alternative human detection. Further machine learning applications has an advantage of extracting different patterns that can be useful for further process. Deep learning can be leveraged for training a model which can effectively tackle scenarios which may have not been defined in a certain predefined human scope. Therefore, the intelligence is exponentially increased rather than having a static model
Wireless transmission to the cloud in African settings. TinyML therefore, has a useful approach that includes machine learning architectures and can be implemented on low energy or memory systems, low bandwidth and real time response.

1.3 Research questions

1. How do we collect and organize PIR data to be used to classify moving objects using inexpensive IoT sensors and AI?
2. How do we develop an AI based system that can perform object detection with high accuracy?
3. How do we confirm that the integration of IoT and AI can provide an alternative working solution for moving object detection?

1.4 Study objectives

1.4.1 General objective

This project aims to present a solution that demonstrates how IoT can be integrated with machine learning on the edge. The research is done using the specific use case of PIR based IoT system data collection in effort to develop a dataset to be used for machine learning processes in order to not only detect objects in proximity; but to further use the model at the edge to classify targeted moving objects.

1.4.2 Specific objective

1. Determining the requirements of implementing your solution (IoT based, ML, functionalities)
2. Reviewing the existing works on object detection in order to identify and address their weaknesses and limitations
3. Design a hybrid IoT and ML based prototype to be used for both data collection and classification of moving objects using inexpensive IoT devices
4. Evaluating the developed solution in identifying and classifying objects in motion

1.5 Hypothesis

It is possible to train a machine learning model and optimize it for the classification of targeted moving objects using time series dataset collected via analog PIR sensor on an embedded device from environment to serve as an alternative to image processing.

1.6 Study Scope

This study is focused on detecting moving objects using PIR sensor to serve as an alternative to image processing by covering the following:

1. Design and manipulation of data. Due to time constraints, limited resources and lack of public datasets for training of an AI model, this research works covers the data collection and data engineering to be evaluated on 3 classes of moving objects which are humans, animals and wind-blown vegetation,

2. Use of machine learning model to detect objects using PIR data for a cheaper yet accurate object detection.
3. Generation of TinyML, deployment and testing on an embedded platform for object detection in real-time.

1.7 Significance of the Study

The system will be of benefit to the society and the whole country in general-in contexts that cover several applications like monitoring house security, proximity sensing. The advantage being that it is a cheaper PIR sensor combined with an AI model as software, therefore benefiting of the low cost to replicate and improve software. With respect to image-based technology, this one also allows preserving privacy, low price and only focus on the challenge at hand "classify moving object". This work is a cheaper solution in Rwanda for security and proximity sensing purpose, it can be affordable by majority of Rwandan’s citizen affordable for protecting their safety. In addition, poorer countries can protect their citizens from dangerous zone or places using this solution

1.8 Organization of the Study

The rest of the paper is organized as follows; Section 2 defines the requirements for edge classification of moving objects. Section 3 presents the design and prototyping of a TinyML-based analog PIR device for classification inference of moving objects at the edge. Section 4 presents the System Analysis and Design, Section 5 Analysis the result. Finally, future works and conclusions are presented in section 6.

1.9 Conclusion

This chapter presents the introduction of this research, problem statement, and justification of the research which aims at designing and prototyping a cost-effective and evolutive smart embedded device that classifies moving objects using deep learning of raw analog PIR time series data patterns. After training the DL model in the cloud, a compressed TinyML model is derived and deployed on the edge analog PIR device to infer the classification directly at the edge as a way to minimize wireless communication with the cloud, which decreases energy consumption and increases battery life

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This section reviews relevant literature to demonstrate the basis of the integration of IoT, machine learning, and edge computing for classification of moving objects. First moving object detection using camera was presented, then moving object using PIR sensor and machine learning was presented, the requirement of camera object detection and PIR object detection for moving object. the comparison and gap in existing systems were stated in the last paragraph.

2.2 Object detection using camera

Developed an optical camera complement to a PIR sensor array for intrusion detection and classification in an outdoor environment where sensor tower platform (STP) for intrusion detection which made of 2STP have 8 PIR sensors with wise mote, camera and banana pi. collected data using PIR simulation of 3D animation tools. A low complexity classification algorithm based on energy and correlation features is implemented on a Wise mote running on Contiki Operating System (OS) , With supervised machine learning they were able to classify humans and animals as intruder and windblown vegetation so called clutter .in addition camera was used for missed detection and misclassification.[10]

Computer vision is the AI application of social distancing, Deep learning is an effective method to perform object detection. Deep Learning or Deep Neural Network refers to Artificial Neural Networks (ANN) with multi layers. One of the most popular deep neural networks is the Convolutional Neural Network (CNN). it has multiple layers; including convolutional layer, non-linearity layer, pooling layer and fully connected layer. The convolutional and fully- connected layers have parameters but pooling and non-linearity layers don't have parameters. The CNN has an excellent performance in machine learning problems, specially the applications that deal with image data, such as largest image classification data set (Image Net) and computer vision, It used in Implementing a real-time, AI-based, people detection and social distancing measuring system for Covid-19 [11][12].

In[23] they developed a system that can be used in many applications like video surveillance, security, enforcement, and self-driving cars as moving object detection for event-based vision using graph spectral clustering. they used bio-inspired sensors that do as human eyes work. unlike camera-based on conventional frames, sensors capture the stream of asynchronous events and have more advantages like high dynamic range, low latency, low power consumption, and reduced motion blur. but these come with, low resolution, a high cost, and data that contain more noise. they showed how an unsupervised graph spectral clustering technique can detect moving objects in event-based data

2.3 Moving object detection using PIR sensor and Machine Learning

The benefits of using analog PIR combined with AI compared to digital PIR was presented in [8], PIR sensor drawback it was not able to detect motionless human due to the lack of change in infrared radiation. To overcome this drawback of PIR sensors, two new methods was introduced which are motion induced PIR sensor and chest motion PIR sensor as systems for stationary human presence detection using a PIR sensor.

Using Wireless Multimedia Sensor Networks (WMSN) Similar to traditional sensor networks, with the recording of A wireless sensor network (WSN) multimedia device.
provide users with more meaningful data than only available on scalar sensor-based systems. but, production, storage, processing, analysis, transmission Multimedia data in sensor networks should be taken into account energy, computing power, Storage capacity and communication. Again, Multimedia sensors produce much more data than scalar sensors.
Analyzing multimedia data requires more manpower. To Overcoming these limitations and challenges was the aim of this study Propose a system architecture and set of methods
WMSN Facilitates Automatic Classification of Moving Objects Uses scalar and multimedia sensors. methods and standards of Detection, classification and transmission of moving objects as a result, it is described in detail. hardware for everyone the sensor node includes a built-in camera, passive infrared movement. sensor, vibration sensor, acoustic sensor. application
Developed using the suggested method and incorporated into multimedia sensor node. In addition, a sink station was installed, Data generated by the sensor network was collected by the sensor network server. The classification performance of the application is Tested with videos recorded by sensor nodes. effect of the proposed power consumption method was also tested and it was measured. Experimental results suggested This approach is lightweight enough for real world use surveillance application. [14][15][16]

To address the problem of person presence detection and tracking caused by the use of a single PIR sensor in monitoring applications, sharp alternative solutions have been developed. These systems used fixed learning and Data from Passive Infrared (PIR) sensors for uses in human surveillance.in these systems they showed how single PIR sensor can be used in persons monitoring, persons counting, activity recognition, motion monitoring and even for security purpose. Motion induced PIR produce infrared radiation shift required for precise detection of motionless peoples by actuator of robotic turning an analog PIR sensor, and chest motion using a single PIR sensor, PIR demonstrated accuracy at motionless person detection systems. To verify that the data collected is just from the chest motion, they used voltage threshold. These novel systems in order to succeed used statically learning for classification and regression. By distinguishing occupied and unoccupied spaces, they evaluated the performance of recurrent neural networks (RNN), long short time memories (LSTM), artificial neural networks (ANN), and convolutional neural networks (CNN). in addition, they classified some different activities of human-like laying in the bed, laying on the ground, walking, working at desk. These systems have indoor positioning which uses a regression model called gaussian process regression. They concluded by confirming that RNN with LSTM is the best classification model because there are used for time series data and these systems used analog PIR sensors which gave analog signals as raw voltage values, these signals were converted into digital and become time series.[17]

Combination of low cost PIR and Deep learning for localizing multiple humans were developed to enhance the performance of human counting and localization for both one and multiple persons, two-stage networks were designed, one that use signal separation for counting persons and another for determining their locations. A neuron network for PIR with biLSTM (as model used in sequential data) to localize single and multiple persons using 4 PIR sensors deployed in 4 corners. Raw signal decreased robust of the trained network. High person counting and human localization accuracy was achieved by using preprocessed data as input by utilizing inverse filter to process the raw input, normalization and data augmentation to reduce the noise in counting human and localization performance in deep learning.[18]

Moving Objects have been used in different applications like object detection, intrusion detection, social distancing and security systems. In [5],they developed a PIR sensor array with an optical camera as a backup for outdoor intruder detection and categorization where sensor tower platform for intrusion detection which made of 8 PIR sensors with wise mote, camera and banana pi. Collected data using simulation of 3D animation tools. With supervised machine learning they were able to classify humans and animals based on (Mondal et al. 2021) energy and correlation features.in addition it uses camera for correcting misclassification.

Social distancing there are many applications of moving objects where researchers were developing systems that can remind peoples to maintain distance in case, they are in crowded environment.in addition peoples have to be constantly reminded whenever they come in close proximity with other peoples or objects. AI inexpensive intelligent device to detect the COVID-19 infection and warn of WHO recommendations for social distancing. They proposed a smart device based on big data and machine learning that can detect covid 19 and alert the user on social distancing. They used PIR sensor that helped to collect temperature data in proximity. When temperature reading went beyond 37 degrees Celsius it activates the alarm. As it exceeds the range of normal human being temperature. So this can be one of the covid19 symptoms .They wanted to look at how to alert any mobile device that is in that close area [19]. For Covid 19, a brand-new cheap social distancing clever device as a wearable device that can be able to recognize a distance between peoples and then alerting the user. This device is using PIR sensor to detect the users and other individuals in proximity. This device is measuring also heat of the person in the range. Using machine learning they are able to know if the person has covid symptoms or not[20]. the increase of social distance through the use of ultrasonic and radio frequency communication as a wearable device that can notify a user in proximity of 6 feet. In order to work it requires everyone to wear the device[21].

A combination of low-cost PIR and Deep learning for multi-person localization was developed in [22] To improve the performance of these two networks, two-stage networks were designed, one that uses signal separation for counting persons and another for determining their locations. A neuron network for PIR to localize multiple people, where they achieved high localization accuracy by deep analyzing analog PIR signals and. PIR sensors were deployed in 4 corners to detect persons, they used preprocessing and data augmentation to increase the performance of deep learning.

Infrared sensors for vehicle traffic control that are both passive and active were developed for monitoring and detecting vehicle road traffic. For active systems, they used lasers and detectors that can operate in the infrared spectral range which is near while for the passive system they used detectors that can work in the region of thermal infrared. All these systems use techniques of correlation and signal processing which are computerized so that Vehicle availability, increased traffic, measuring vehicle speed, and length classification can be determined[23].

2.4 Requirements for edge classification of moving objects

Classification of moving objects is a requirement for several real-life applications especially the ones related to security. Before using PIR-based sensors, camera-based solutions were the dominant solutions but encountered several limitations such as privacy invasion, high bandwidth, and high energy consumption [8],[9]. Later on, a PIR-based solution emerged to overcome some of the problems of a camera-based solution as summarized in the table.

Table 1: Comparison of object detection between the camera and analog PIR

Object detection using the camera	Object detection using analog PIR
Intrusion of privacy	No intrusion of privacy
High power consumption	Low power consumption
Low resolution caused by low light condition	Doesn’t affected by light condition
Expensive hardware	Cheap hardware
Long set-up time in case of deploying	Short setup time for deploying
Camera capture many things in the environment	Analog PIR detects the targeted objects

Many researchers who try to address this issue but there are still gaps .With the existing moving objects monitoring and detection ,some systems cameras for objects detection like in [23][24] while others combined PIR for detecting objects and classify them and handle misclassification using camera [11]. Using cameras in objects detection has different drawbacks which are a high cost, as the event camera data typically contains more noise and has low resolution and invasion of privacy[7].This study propose an intelligent device which can detect objects in motion using analog PIR sensors and build a model that can run at the edge to classify them.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter provides the study materials and procedures. The high-level system architecture is presented in the first part. A thorough embedded system-level design that includes a system block diagram, Original Equipment Manufacturer (OEM) components and a data collection campaign is then presented. A pipeline for efficient edge AI prototyping is also described. The embedded system's modeling and layout are then provided.

3.2 System Architecture

3.2.1 High level System Architecture

To be able to capture the information, a prototype will be developed using different analog PIR sensors, ARM Cortex-M0+ processor (133 MHz), and LCD. With a prototype system, signals generated by humans, animals and windblown vegetation motion are analyzed to build a model that can be able to classify Huma, animals, vegetables and other objects like cars. Proximity sensors will be used to detect moving objects that will be classified.

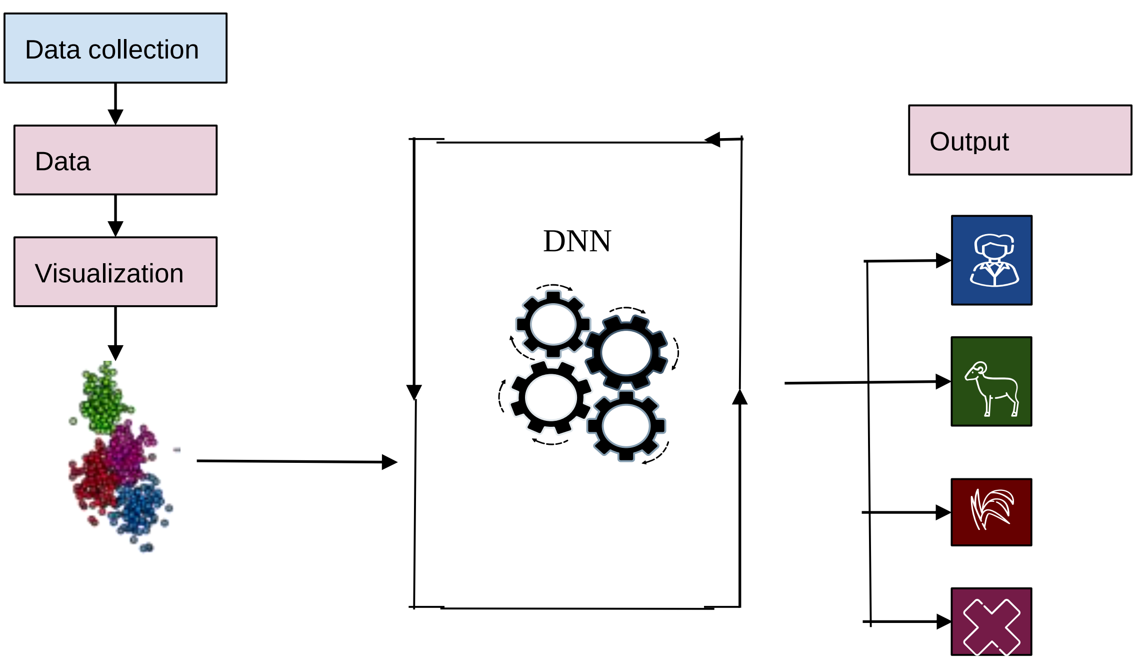


Figure 1 System architecture

3.3 Machine Learning Process

theorizing about and creating computer systems that can carry out tasks that would typically need human intelligence, like speech recognition, visual perception, decision-making, and interpretation [30]. Machine learning (ML) is a very evolving procedure, and ML models are trained by examining historical data as well as past events. Figure 2 illustrates a machine process of learning.

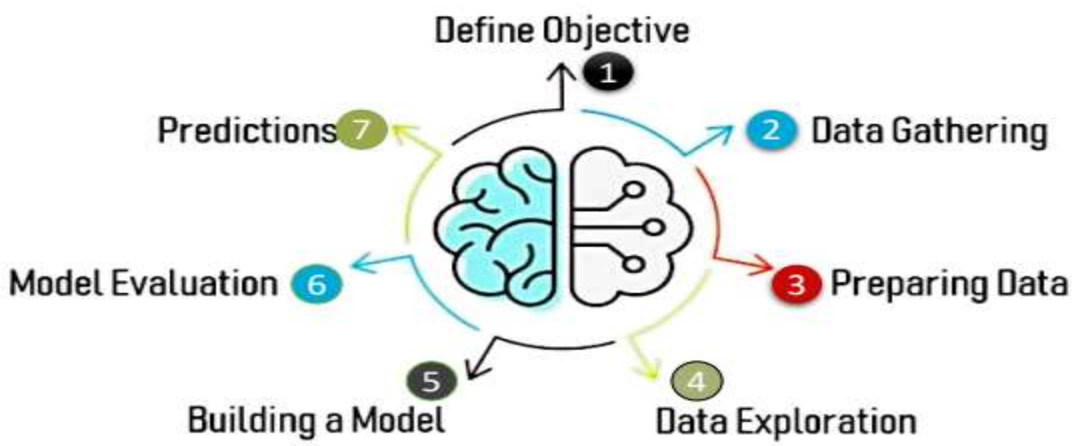


Figure 2. Machine learning process

Step1: **The first step is to define the problem's goal**

(Problem solution?) of the problem's goal (Problem solution?).

- What do you want to predict?
- What characteristics are the targets?
- What data required are there?
- What kind of issue are we dealing with?
    - Regression, Clustering, and Binary Classification

Step2: Data Gathering

- What sort of information is required to resolve this issue?
- Is this information available?
- If the information is available, where can I acquire it and how can I receive it?
- Consider the machine learning process's more time-consuming steps
- What kind of data is required for moving object classification?

- ❖ Timeseries data from analog PIR sensor,

Step 3: Data Preparation (Cleaning of Data)

- entails eliminating data discrepancies such missing values or superfluous variables.
-
- Convert data to the required format:
- Cleaning Data
    1. Missing Values
    2. Damaged data
    3. Delete pointless information

Step4: Exploration Data Analysis

- Involves comprehending the trends and patterns in the data. At this point,
- All pertinent conclusions have been reached, and the relationships between the variables are understood.

Step5: Predictions

After parameter adjusting and enhancing the model's precision, the outcome is projected.

Step6: Model Evaluation & Optimization

• The model's effectiveness is assessed, and any potential improvements are put into practice. The Model is evaluated by using the test dataset

- The model's accuracy is determined.
- Utilizing strategies like parameter tuning and cross validation approaches, the model is further improved.

In Chapter 4, we will be answering all this questions and how we went through on all this machine learning process.

3.3.1 Artificial Neural Network (ANN)

ML model with inspiration from the human brain:

- Algorithms that simulate the human brain.
- Synaptic connection strengths among neurons are employed to store the learned information in this massively parallel, distributed system of basic processing units (neurons).
- Through a learning process, the network picks up knowledge from its surroundings.

Two types of Stacking Perceptron:

1. Parallel
2. Sequential

Deep learning (DL) Using a hierarchy of several layers, algorithms try to learn (multiple levels of) representation. Deep learning is a type of machine learning in which features and tasks are directly learned from data. Recent substantial developments in voice, natural language processing, and image processing have been made. (See in Figure 3 the difference between DL and ML)
High performance computing and Big data.
If you feed the system a ton of data, it starts to comprehend it and react in helpful ways.

A method of machine learning called "DL" learns tasks and characteristics directly from data.

- ❖ Inputs are run through "neural networks".
- ❖ Neural Network have hidden layers.

• Deep learning applications employ an artificial neural network, which is a layered framework of algorithms.

In figure 3 we are going to see in summary relationship and difference between machine learning and deep learning.

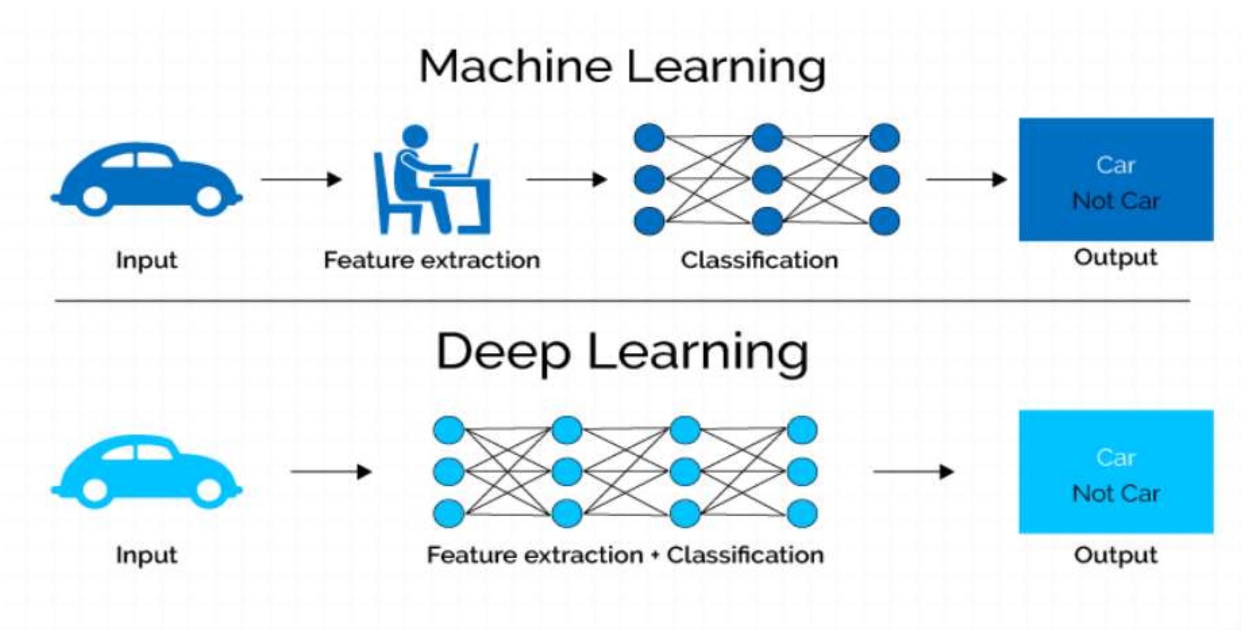


Figure 3: ML vs DL

3.3 Data acquisition

The data collection phase was targeting our architecture. As defined in our design, the following time series dataset was the one of interest in this study**:** a stream of analog signals which made of 1 seconds to 10 seconds. The data acquired as sampled Signals that represent measurements of actual physical situations will be transformed into digital numeric values for subsequent processing [23].Primary data were collected from different IoT devices for example PIR sensors in different locations like home and schools for collecting human related data, farms and homes for collecting animals, windblown vegetation and other objects. After collecting data, the result was a rich dataset, 1287 observations for each class in the csv format and json format were collected for the first phase of training. The data collection phase took an estimated 3 month. See in Figure 4 the system level design for data collection.

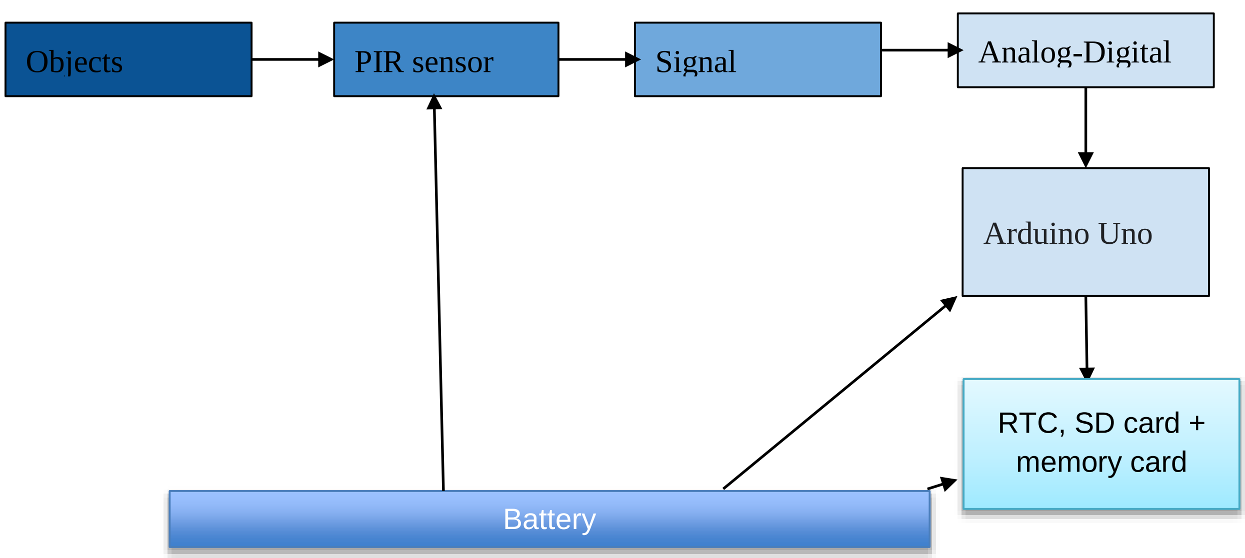


Figure 4: Data acquisition system

3.4 Prototype design

Figure 5 represents system block diagram, embedded of sensors, software, actuators, devices like battery and other technologies with the purpose of connecting and sharing data. We have AMN12242 as analog PIR sensor for collecting data, processing unit to handle edge processing of data collected from sensor using Arduino nano Ble sense 33, display the results using Oled 0.96.

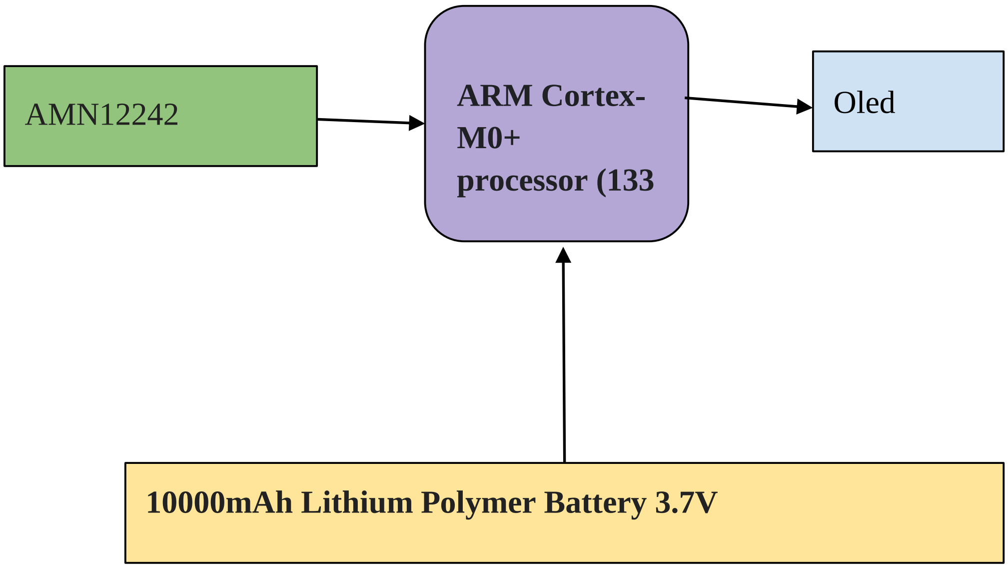


Figure 5: System block diagram

3.4.1 System components

Analog PIR sensor

Panasonic AMN24112 PIR sensor: Infrared (IR) light emanating from objects in its range of view is measured by an analog sensor. (FoV). According to the manufacturer, we use the analog Panasonic AMN24112 PIR sensor, which has a 93-degree horizontal and 110-degree vertical field of view use the analog Panasonic AMN24112 PIR sensor, which has a 93-degree horizontal and 110-degree vertical field of view according to the manufacturer. Additionally, the vendor states that when used as a conventional motion sensor, the maximum detection distance is 10 meters. The Panasonic AMN24112 PIR sensor was selected due to its ability to produce analog outputs and its comprehensive datasheet of these measurable properties. The Fresnel lens contained with the Panasonic AMN24112 gadget is the outer, white shell with the hexagonal marks shown in Figure 6.[27]

Figure 6: analog PIR

Arduino Nano BLE sense

The Arduino Nano 33 BLE sense is built upon the nRF52840 microcontroller. It runs on ARM Mbed OS making it appropriate for solutions that involve embedded machine learning. In addition, it has an integrated Bluetooth low energy module and a variety of sensors including temperature and humidity sensors [28]. Figure 7 shows the pin layout for the board. This processor is the best choice for small and portable devices because:

1. It has the possibility of running Edge Computing applications (AI) on it using TinyML
2. With TensorFlow Lite Micro library version, it can be possible to run machine learning models, that can detect people in images, or recognize gestures and voices.
3. It uses low power
4. Low cost

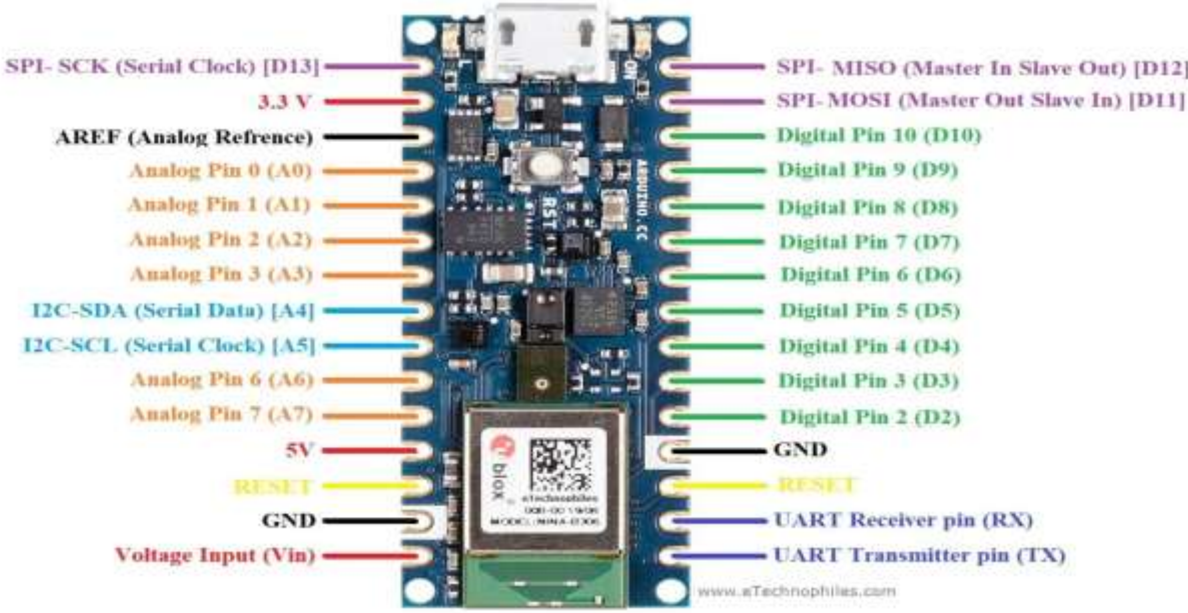


Figure 7: Arduino Nano BLE Sense pin layout

OLED

OLEDs are the displays of the future because they outperform both LCDs and LEDs, the two most widely used display technologies today. The fact that OLED displays don't require a backlight like traditional LCD/LED panels is what makes them so appealing to use. When stimulated by a current or an electric field, the organic material's inherent feature known as electroluminescence (EL) enables it to "light." Outstanding displays that save energy![29]

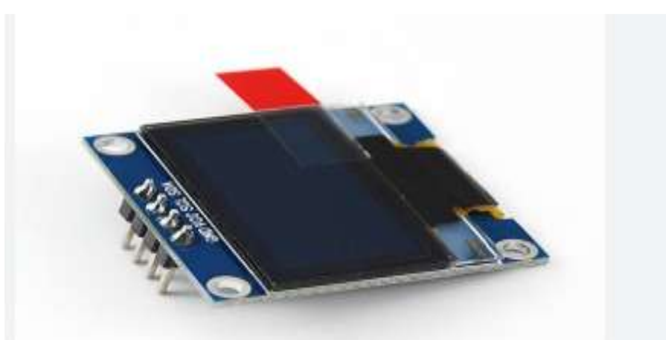


Figure 8*: OLED*

3.4.2 Components for data collection prototype

Analog PIR sensor was one of the devices used for collecting raw data (see in system components part).

Arduino UNO

An open-source microcontroller board called the Arduino Uno was developed by Arduino and originally made accessible in 2010. It is built around the ATmega328P microprocessor from Microchip. The board features set of analog and digital pins that can be connected to other boards, devices, and expansions.[30]

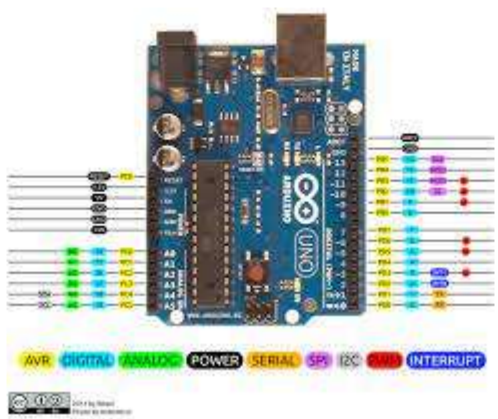


Figure 9: Arduino Uno

Arduino RTC

Real-time clock is referred to as RTC. The current date and time can be seen by opening the serial monitor screen. The serial monitor is located in the top right corner of the Arduino IDE program. Two of its pins (GND and VCC) are used for power, and the remaining two are used for data (SDA and SCL).[31]

Figure 10: Arduino RTC

Arduino SD card

Particularly helpful for tasks that call for data logging is the SD card module The microcontroller may create a file on an SD card to write and store data by using the SD library.. The SPI communication protocol is used by several models from various providers, although they all function similarly.[32]

Figure 11: Arduino SD card

14500 1300mah 3.7 V lithium ion rechargeable battery COM32

High-performance lithium-ion batteries like the ICR 1200mAh 14500 are ideal for demanding electronics like tactical LED torches. These batteries have a top-notch 1200mAh capacity and 3.7 Volts of power, which will enable them to run high drain electronics for longer than alternative power sources. The ICR 14500 is one of the best offers when it comes to li-ion power because of its dependable manufacturing quality and bulk discount pricing.[33]

Figure 12: chargeable battery

CHAPTER 4

SYSTEM ANALYSIS AND DESIGN

4.1 Introduction

The use case of classifying moving objects has been tested in the evaluation. This part first provides the creation of dataset in an evaluation utilizing the collected raw data, then talks about the training architecture for our edge AI Tiny Model, and finally shows the outcomes of an inference simulation on an actual and virtualized embedded board. The experimental classification of moving objects using artificial data in the context of large time series datasets.

4.2 Data collection campaign

Raw analog PIR time series data was required for ML to find features that are hidden and allowed to detect the different moving objects. The biggest challenge presented finding open-source datasets in public repositories. Therefore, primary data was collected using an IoT device (see Figure 13) made up of an AMN24112 analog PIR sensor working at 166 HZ, RTC, SD card, Arduino Uno boards, switch buttons, and LED. The device was used to collect human-related data, animals (dogs, goats), windblown vegetation, and analog readings where there was no object detected. The data collection process took three months. Since the quality of the data was a big concern, the data was collected in the different scenario but the ones which were more accurate to the use case was chosen.

During the data collection process, it has been found that the strength of the signal from analog PIR sensors can change with environmental contexts. For example, when the temperature changes the range of signals also changes. In addition, the data collected from highly populated areas like churches, have a different signal range from quiet areas like homes or schools. In addition to the lesson learned, there were various challenges including (1) the availability of targeted objects for example presence of wind, (2) forcing animals to move, and (3) the presence of noise (movement of the not targeted object). After overcoming some of the challenges, a dataset was formed with 213760 rows collected in each of the four classes. In each class, 1287 observations were produced, totaling 5148 observations for all 4 classes. See in Figure.14 how 1000 samples from a class animal. In Figure. 15, Raw data from a person class was shown in one observation of 166 rows, as number 37 in the class.

Figure 13. Device developed for collecting analog PIR time series dataset

Figure 14. collecting data for animal class

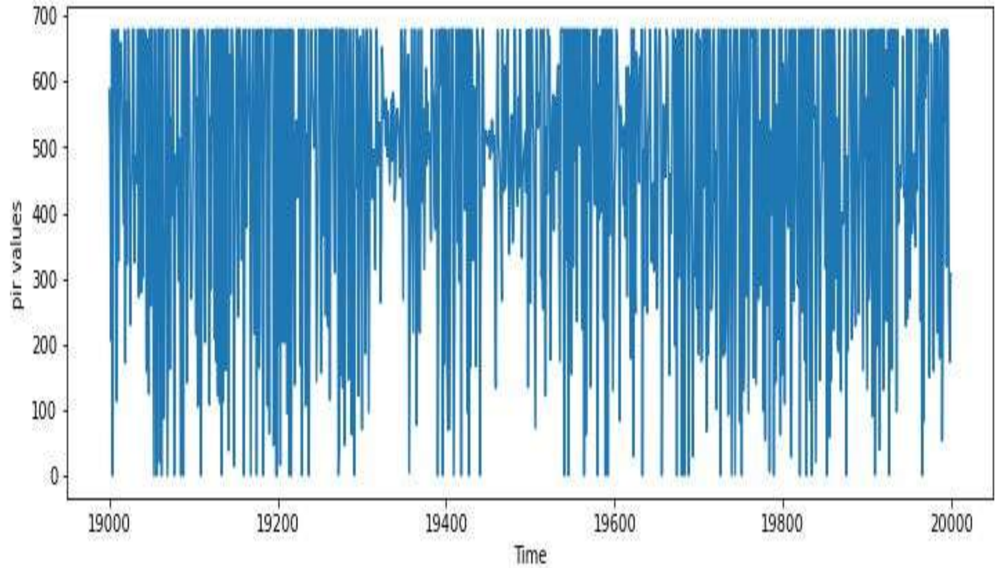
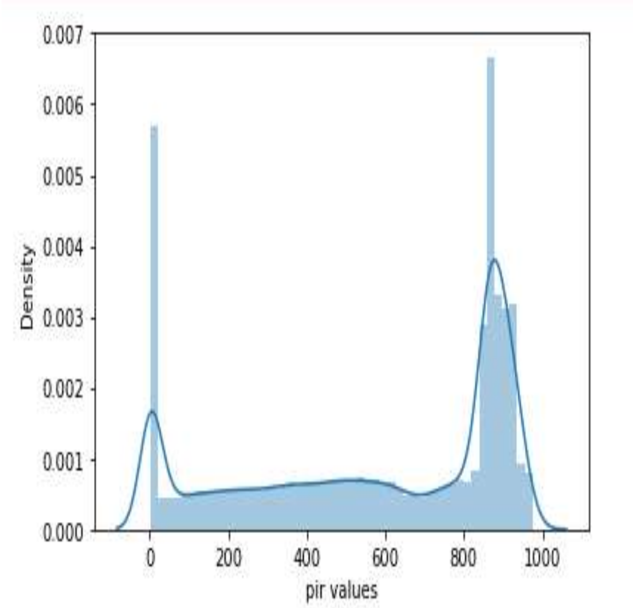


Figure 15. Output raw data from a class person made of 1000 samples

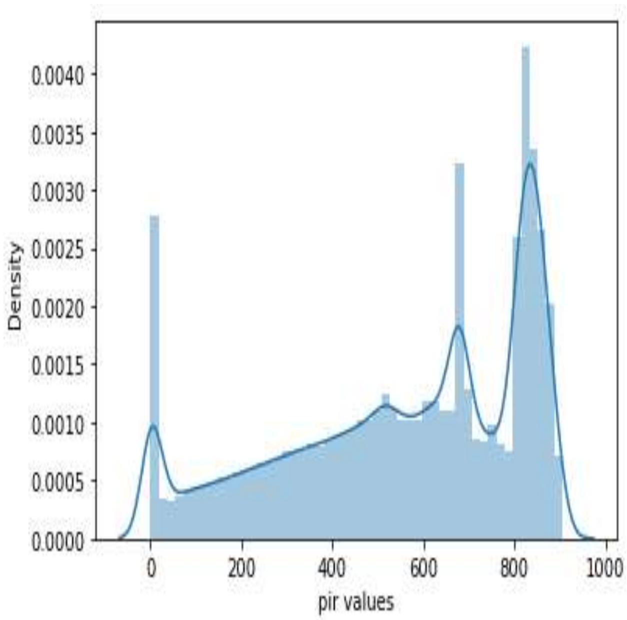
After data collection, the data was preprocessed, by cleaning them and removing null values. Then check the relationship between different classes wind and human using different ways on of them was skewness. See in figure 16 and 17.




```
wind.describe()
```

	timestamp	pir values
count	2.137590e+05	213759.000000
mean	6.412740e+05	578.426925
std	3.702423e+05	331.872367
min	0.000000e+00	2.000000
25%	3.206370e+05	291.000000
50%	6.412740e+05	687.000000
75%	9.619110e+05	872.000000
max	1.282548e+06	974.000000

Figure 16. skewness and description of wind class




```
human.describe()
```

	timestamp	pir values
count	2.137590e+05	213759.000000
mean	6.412740e+05	558.893600
std	3.702423e+05	263.863238
min	0.000000e+00	0.000000
25%	3.206370e+05	372.000000
50%	6.412740e+05	618.000000
75%	9.619110e+05	811.000000
max	1.282548e+06	906.000000

Figure 17. skewness and description of human class

In Figure 18, there is an observation which made of 166 records or of analog PIR values from class of animals which is taken as one sample to show how time series dataset.

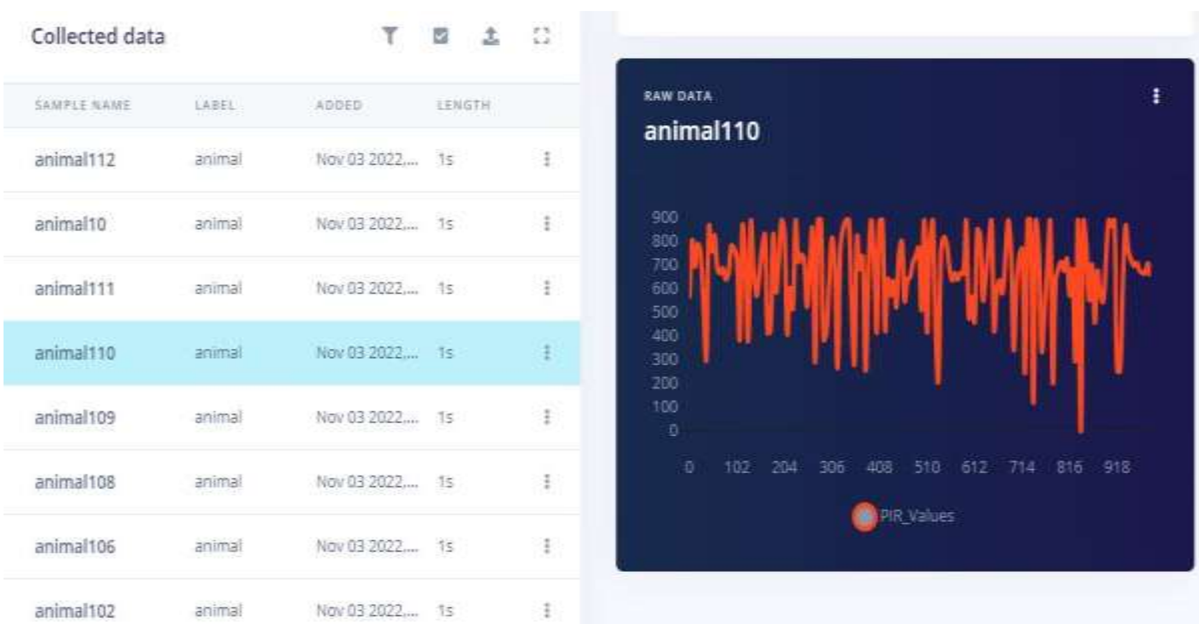


Figure 18. Raw data from person class, observation number 37

4.3 Machine Learning Training

Training data is the process which come after data preprocessing. the dataset on which used to train the model. The model will be built used Machine Learning algorithm for classification and handle misclassification using reinforcement learning.

The moving object classification model was trained using the following steps:

1. After data collection, data were pre-processed by cleaning through the removal of null values
2. Data transformation - Data was converted from raw values to a time series dataset. Fast Fourier transform as a further step is used to decompose the data into frequency components.
3. Dataset is then dividing into 80% set for training / validation and 20% set for testing.

Digital Signal Processing (DSP) is used to manipulate time series data acquired from our analog signal for analysis Through extensive experimentation with different settings, DNNs were able to determine important features that work s best., such as the output from the block of spectral features, which include: PIR Values RMS, PIR Values Skewness, PIR Values Kurtosis, PIR Values Spectral Power 5.21 - 15.62 Hz, PIR Values Spectral Power 15.62 - 26.04 Hz, PIR Values Spectral Power 26.04 - 36.46 Hz, PIR Values Spectral Power 36.46 - 46.88 Hz. The proposed model was trained using deep neural network architecture as shown in Figure. 19 and 20, at a learning rate 0f 0.0005, input layer (11 features), dense layer (48 neurons), dense layer (20 neurons), and 4 classes of the output layer.

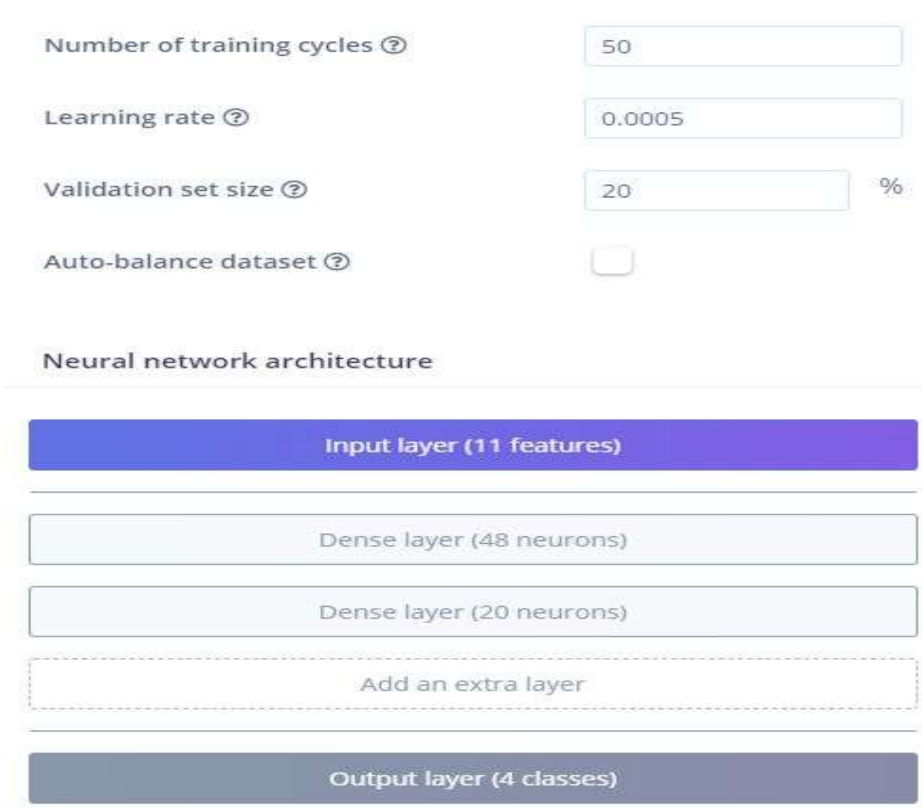


Figure 19. Deep Neural network architecture

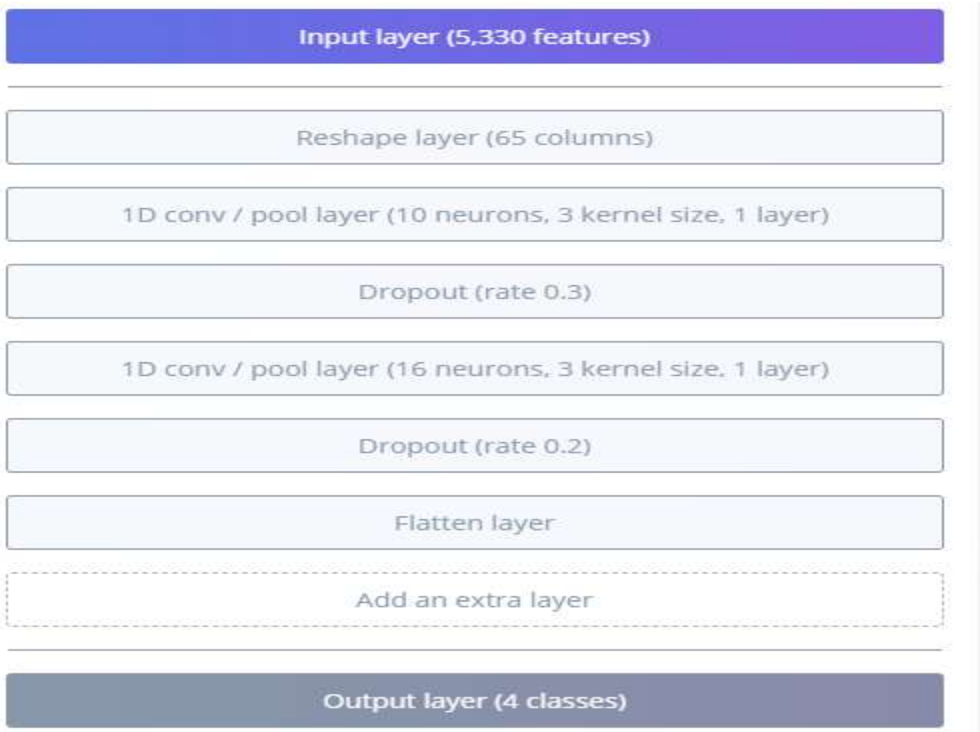


Figure 20. Convolutional Neural network architecture

The Timeseries dataset was done using different time intervals of observation from 10 seconds to 1 second. The dataset for 10-second time intervals has 128 observations while 1 second has 1287observations.dataset of 1-second observations was chosen since it has proven that it has more accuracy than others, see in Fig.5, and also analog PIR sensor was used was able to detect an object in 6milleseconds.

Table 2. Time interval and their corresponding number of observations

Time interval	Number of observations
10 seconds	128
9 seconds	143
8 seconds	160
7 seconds	183
6 seconds	214
5 seconds	256
4 seconds	320
3 seconds	427
2 seconds	640
1 second	1287

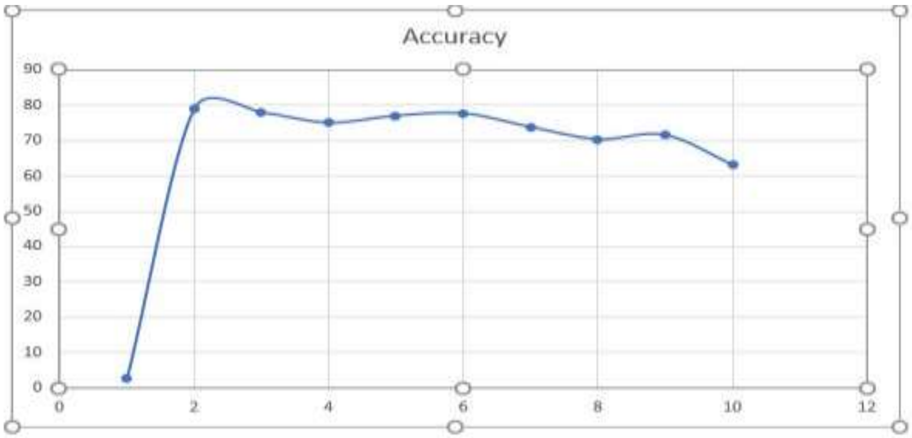


Figure 21. the accuracy of all-time intervals from 1 second to 10 seconds.

Table 3. Comparison of DSP block parameter's performance

DSP block parameters	Input layers	Accuracy	Loss
Raw Values	166	24.8%	1.38
Flatten	7	79.8%	0.70
Spectral analysis	11	80.8%	0.47
Spectrogram	10715	92.9%	0.21

4.4 Detecting Anomalies

We employ a K-means was used for detecting anomaly learning block for anomaly identification as shown in Figure 22. With this, the features that have been chosen are utilized and made normal using a common scaler. Then, using the specified number of clusters, a K-means cluster is performed across this feature space. For each cluster found, the center and radius are calculated. Anomaly detection was included to locate outliers, which is proven good for identifying unidentified states and completing classifiers [31].

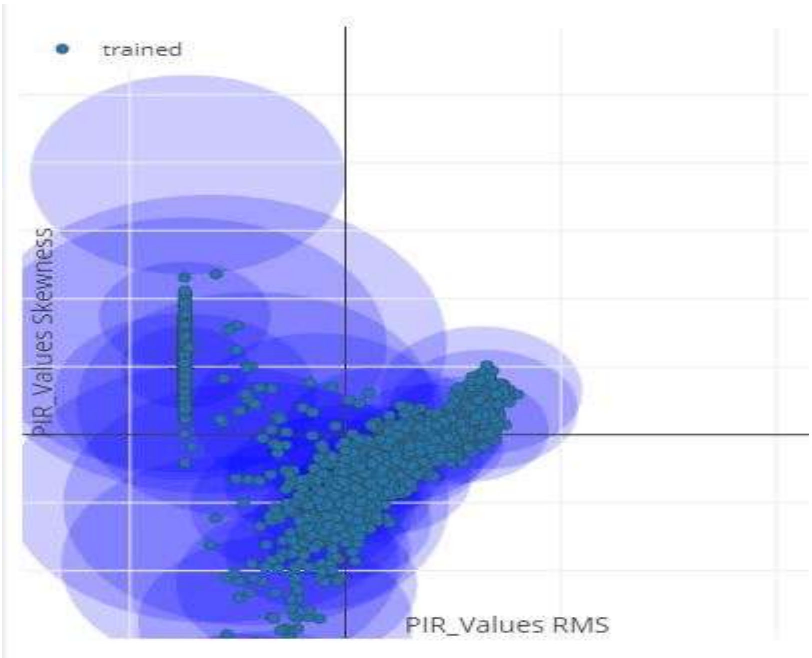


Figure 22. Training data for anomalies

4.5 CLASSIFICATION PERFORMANCE ANALYSIS

Classification performance was analyzed based on the following requirements: input features, target, and prediction. For training set classification using spectral analysis, the TinyML model that designed to classify moving objects, and the following results were obtained: animals are correctly classified with 80.1%, animals and humans are 17.5%, animals and no object are 0.9% related, and animals and wind are 1.4%related. humans are correctly classified with 75.4%, humans and no object are 0% related, human and wind 4.4% related.no object and animal are 0% related, no object and Human are 0% related, no objects are 100% correctly classified, no object and wind are 0% related, wind and animal are 4.9% related. Wind and human are 27.2% related, wind and no object are 0% related, and the wind is 68% correctly classified. So, the F1 score as one of the significant evaluation metrics in ML was used, where the animal has 78%, the human has 68%, no object has 100% and wind has 78% as it is shown in Figure 10.

While training set classification using spectrogram, the following results were obtained animals are correctly classified with 93.6%, animals and humans are 5.9% related, animal and no objects are 0.5%, animal and wind 0%. Human and animal are 17.1% related, humans are correctly classified with 77.3%, human and no object is 0% related, human and wind 0.5% related.no object and animal are 0% related, no object and Human are 0% related, no objects are 100% correctly classified, no object and wind are 0% related. wind and animal are 2.9% related. Wind and human are 6.3% related, wind and no object 0% related, and the wind is 90.8% correctly classified. So, the F1 score has 87% for animals, 82% for humans, 100%for no object, 93%for wind as it is shown in Figure 11.

Thus, the model A achieved 80% with the loss of 0.47 for both training and testing classification for targeted classes: animals, humans, no objects, and wind (windblown vegetation) and anomaly

detection shows that all inputs for model inference are valid for the targeted moving object. While model B achieved 92% set for training and 88% set for testing.
Comparing the last two model to check the best one for training side:


Last training performance (validation set)

ACCURACY 80.8%

LOSS 0.47

Confusion matrix (validation set)

	ANIMAL	HUMAN	NOBJECT	WIND
ANIMAL	80.1%	17.5%	0.9%	1.4%
HUMAN	20.2%	75.4%	0%	4.4%
NOBJECT	0%	0%	100%	0%
WIND	4.9%	27.2%	0%	68.0%
F1 SCORE	0.78	0.68	1.00	0.78

Figure 23 Confusion matrix for training performance spectral analysis


Last training performance (validation set)

ACCURACY 92.9%

LOSS 0.21

Confusion matrix (validation set)

	ANIMAL	HUMAN	NOBJECT	WIND
ANIMAL	95.4%	4.6%	0%	0%
HUMAN	7.6%	84.8%	1.1%	6.5%
NOBJECT	0%	0%	100%	0%
WIND	3.2%	7.4%	0%	89.5%
F1 SCORE	0.93	0.86	1.00	0.91

Figure 24. Confusion matrix for training performance spectrogram using CNN

Comparing the last two model to check the best one for testing side:

Model testing results

ACCURACY
80.45%

	ANIMAL	HUMAN	NOBJECT	WIND	ANOMALY	UNCERTA
ANIMAL	74.6%	11.7%	1.6%	0%	0.8%	11.3%
HUMAN	0%	99.2%	0%	0%	0%	0.8%
NOBJECT	0%	0%	99.6%	0%	0.4%	0%
WIND	0.4%	21.9%	0%	48.4%	0%	29.3%
ANOMALY	-	-	-	-	-	-
F1 SCORE	0.85	0.85	0.99	0.65	0.00	

Figure 25. Confusion matrix for testing performance spectral analysis

Model testing results

ACCURACY
88.78%

	ANIMAL	HUMAN	NOBJECT	WIND	UNCERTAIN
ANIMAL	92.9%	1.6%	1.6%	0%	3.9%
HUMAN	4.7%	87.4%	0%	0%	7.9%
NOBJECT	0%	0%	100%	0%	0%
WIND	3.1%	11.0%	0%	74.8%	11.0%
F1 SCORE	0.93	0.87	0.99	0.86	

Figure 26. Confusion matrix for training performance spectrogram using CNN

After cross validation for two models, the one model(A) which has 80.8 accuracy for training and 80.45 accuracy for testing with loss of 0.47 and another model(B) which has 90% accuracy for training and 85% accuracy for testing with loss of 0.28.Thus,model B is the Best model since it has a higher accuracy and low loss.

CHAPTER 5

RESULTS AND ANALYSIS

5.1 **Inferencing on edge Analog PIR sensor**

The TinyML model's performance during the training phase was measured at first using a cloud-based run-time environment as shown in Figure 29. This part is the first step towards deployment focusing on an edge run-time environment. We had to ensure that the model works properly before converting it to TinyML.

The TinyML model for the NN classifier developed in the machine learning training section was optimized and compressed into the Arduino library designed to run on Arm-based development boards on device inference which was done on different moving objects. After integrating the library model and uploading analog PIR codes to Arduino-nano-33-ble-sense run inference see Figure 23. We defined our DSP block size to schedule our inferencing intervals. Based on the frequency of the sensor, we feed 166 values which are equivalent to one observation then proceed to perform inference. Thus, the inference happens every minute, as shown in Figure 27.

```
19:09:19.609 -> run_classifier returned: 0
19:09:19.609 -> Predictions (DSP: 27 ms., Classification: 0 ms., Anomaly: 4 ms.):
19:09:19.609 -> animal: 0.87891
19:09:19.609 -> human:  0.12109
19:09:19.609 -> nobject:        0.00000
19:09:19.609 -> wind:   0.00000
19:09:19.609 -> anomaly:        -0.427
19:10:59.031 -> run_classifier returned: 0
19:10:59.031 -> Predictions (DSP: 27 ms., Classification: 0 ms., Anomaly: 4 ms.):
19:10:59.031 -> animal: 0.84766
19:10:59.031 -> human:  0.15234
19:10:59.031 -> nobject:        0.00000
19:10:59.031 -> wind:   0.00000
19:10:59.031 -> anomaly:        -0.307
19:12:38.483 -> run_classifier returned: 0
```

Figure 27. On-device inferencing targeting animal class.

Random tests were performed test the device. As shown in figure 28, we set up our experiment to prove our working hypothesis, output for this particular case as per figure 29 shows output from the device for objects in figure 28 and we noted an accuracy of 0.87 which far exceeds the threshold of 0.7. Other experiments showed that the device places objects in correct classes with accuracies ranging in the 80th and 90th percentile.

Figure 28.0n device used in inferencing.

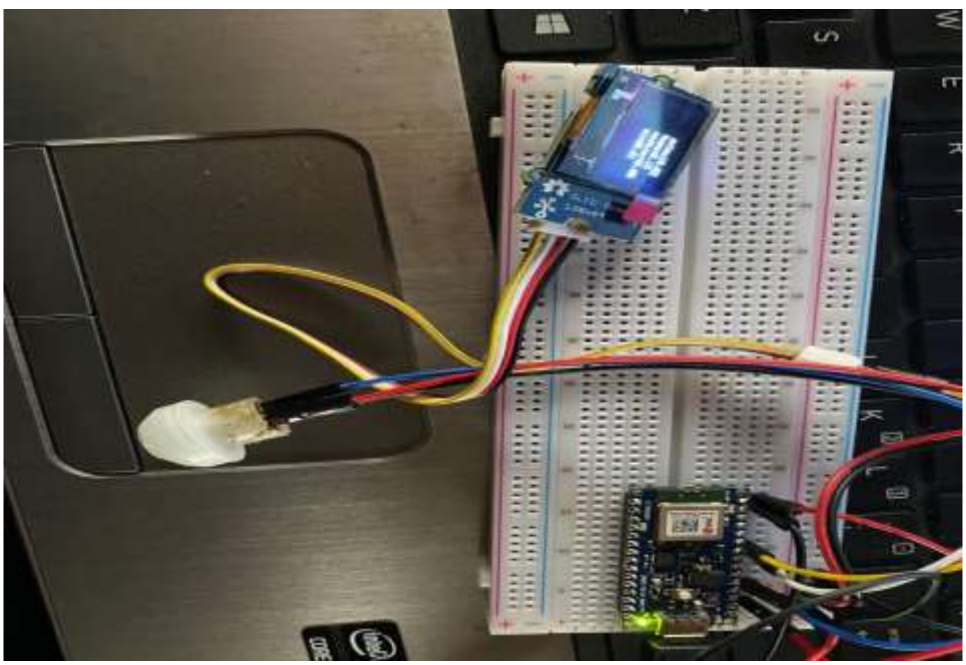


Figure 29.Results displayed on Oled

On Figure 28 shows how the system is classifying on the field dogs which were passing and on the figure 29 shows the results, a few samples are taken to classify into the prototype device, and samples of their moving objects are collected. From this, it is inferred whether or not the objects are animals, winds or humans.

The AI model exhibits comparable While using both embedded CPUs and the cloud, inference accuracy, according compare the outcomes of inference simulation and the outcomes of inference produced by the TinyML cloud platform. It's interesting to see that our model correctly identified air samples as an abnormality. We draw the conclusion from the data that TinyML model is useful in classifying whether a moving object are humans, animals and windblown or not objects.
The random observation was taken which tends to be 730 from the class of humans from the testing dataset to inference as presented in Figure 30., it was predicted as human.

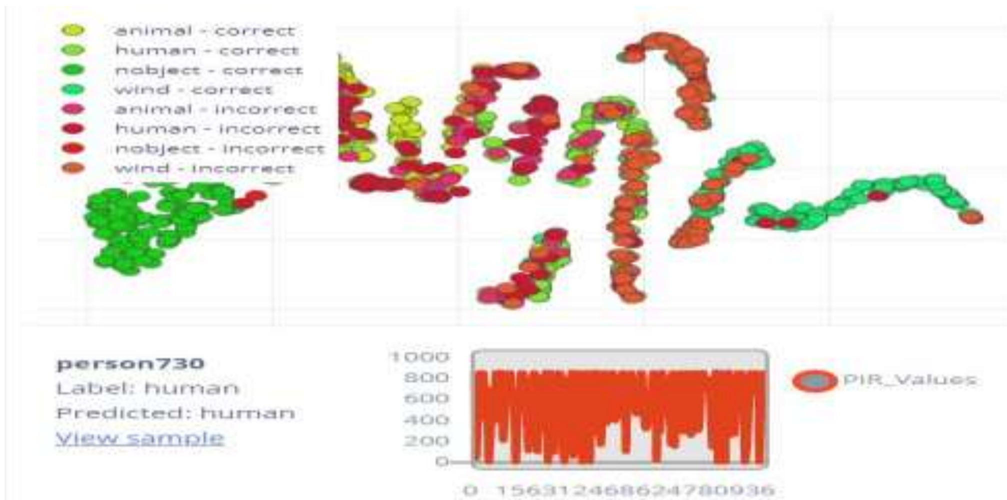


Figure 30. online inference

CONCLUSION

This thesis developed a cost-effective solution that performs the detection of moving objects at the edge by minimizing resources such as processing while relying on cheap analog passive infrared (PIR) sensors and AI to classify moving objects based on patterns of PIR signals bounced back from different objects. This solution has the potential to be used on different types of applications requiring non-invasive sensing such as "monitoring house security, eligible moving objects at a given place, and proximity sensing. The main contribution of this thesis is (1)constructing a dataset of analog PIR time series data for humans, dogs, goats, windy vegetables, and no moving objects which can be used for other research and (2) The pilot experimentation of the developed TinyML analog PIR device which detects, classify and differentiate moving objects achieved an accuracy of 90%.

FUTURE WORKS

Future works will focus on improving the accuracy of moving objects, add more moving objects like cars, different kind of animals like cows, chicken, mouse. This accuracy will be improved over time using reinforcement learning and the study will be extended to detect many complex moving objects.

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