

# AI Smart Gun using ESP32 Cam

SR Sirish, Srinivas CK, TB Srishti, Yogitha Singh D, Deepika D Pai

Department of Electronics & Communication Engineering  
Vemana Institute of Technology, Koramangala, Bangalore, India

**Abstract:** *The creation of a smart gun using ESP32-Cam is accomplished using the surrounding data and Internet of Battlefield Things (IoBT) in conjunction with a server which is further connected to the ESP32-CAM for more precise identification of the enemies. The user receives information from the server, which serves as the main framework of the system. Here, the server that has the acquired data goes through several processes to provide precise information that is then given to the user. After the user receives the information from the server, the output of the information is shown on an OLED panel that is positioned on the equipment. The user receives directions from the OLED display, which in turn aids in enemy detection.*

**Keywords:** ESP32

## I. INTRODUCTION

The soldiers and their equipment are the most flexible and important information sources for the working of this concept. The soldier wearables and equipment are enabled with various sensors to collect multidimensional battlefield information in real time. This collected information has enormous potential to create Situational Awareness (SA), which is highly beneficial for critical battlefield operations. The real-time ground zero information of the battlefield is collected by a camera fitted on the gun and the IoT network connected to the soldiers and their equipment. These intelligence inputs are extremely beneficial to the AI engine for smart and accurate decision-making, which can significantly influence the operation outcome. Hence, collective analysis of this raw information results in important battlefield feedback like real-time enemy localizations.

### 1.1 Advantages:

- To avoid firing on one's army.
- Provides precise direction to the user.
- The equipment's trigger is turned off when the user is not nearby.

### 1.2 Objectives

- In the entire IoBT scenario, the soldiers and their equipment are the most flexible and important sources to provide information.
- To develop enemy location systems that can be useful to both police and military forces.
- To collect the data surrounding the user with the help of IoBT. To share the collected data to the server captured by the ESP32-Cam module for providing information to the user.

## II. LITERATURE SURVEY

[1] Gunshot Acoustic Component Localization With Distributed Circular Microphone Arrays - Sergei Astapov, Johannes Ehala, Julia Berdnikova, Jürjo-Sören Preden, 2015.

Gunshot acoustic localization for military and urban security systems has long been an important topic of research. In recent years the development of independent Unmanned Ground Sensors (UGS), interconnected through Wireless Sensor Networks (WSN), performing distributed cooperative localization, has grown in popularity. This paper considers a 2D Direction of Arrival (DOA) estimation method for compact circular array UGS, establishing gunshot direction at close range, and discusses problems, situated with gunshot acoustic component analysis. The proposed method is aimed at reducing the computational cost of DOA calculation for implementation on embedded hardware of WSN smart sensors. It is compared with the SRP-PHAT localization algorithm and is proven to provide adequate DOA

estimates while being more computationally effective. The proposed 2D DOA estimation method is proven to be effective for gunshot event positioning. The experiments have shown, that post-blast noise, which is usually omitted from the analysis, may be useful for hit area estimation. In the future other DOA estimation algorithms, e.g. MUSIC will be tested and the most promising ones — employed on different WSN nodes for mutual reassurance of final estimates. Also, different data fusion techniques for shooter positioning and bullet trajectory estimation will be tested.

[2] Gunshot Signal Enhancement for DOA Estimation and Weapon Recognition-Angelo M.C.R. Borzino, Jose A. Apolin Ario Jr., Marcello L.R. de Campos, and Carla L. Pagliari, 2013.

This paper proposes a deconvolution technique for gunshot signals aiming at improving the direction of arrival estimation and weapon recognition. When dealing with field-recorded signals, reflections degrade the performance of these tasks and a signal enhancement technique is required. Our scheme improves a gunshot signal by delaying and summing its reflections. Conventional blind deconvolution schemes are not reliable when applied to impulsive signals. While other techniques impose restrictions on the signal to ensure stability, the one presented herein can be used without such limitations. The results of the proposed technique were tested with real gunshot signals and both applications performed well. In our scheme, we first need to locate the reflections (copies) and this is carried out using correlation functions. An SW signal originated from a .308 IMBEL AGLC (Sniper) Rifle, recorded around 300 meters far from the shooter position. In this figure, we also observe its autocorrelation function, a reference SW signal (obtained by averaging five AGLC shockwaves), and the cross-correlation between the original signal and this reference. As seen in this figure, SW signals resemble the letter “N” and they are usually referred to as “N” waves. In this case, we can distinguish a peak on the left side of the original signal and its replica in some samples later. This replica is certainly a reflection of the direct wave and we want to eliminate it as well as any other that might exist.

[3] Estimating Direction Of Arrival Of Long Range Gunshot Signals - Angelo M.C.R. Borzino, Jose A. Apolin Ario Jr., Marcello L. R. de Campos, 2014.

Information obtained from recorded gunshot signals can be useful for law enforcement agencies and defense forces. The direction of arrival estimation of a gunshot is an important issue in shooter localization. As the distance between the firing position and the sensor increases, the signal-to-noise ratio decreases and this estimation degrades. In that case, some sort of preprocessing of the firing acoustic signal before the application of direction of arrival estimation algorithms becomes necessary. This paper shows that applying spectral subtraction to enhance the signal improves the results. Moreover, it is shown that further improvement is attained when employing a recently proposed data selection algorithm. The tests were carried out with simulated directions by delaying copies of a real gunshot signal and also with real gunshot signals recorded by a microphone array.

[4] A Novel Approach For The Detection Of Gunshot Events Using Sound Source Localization Techniques - Ajay Kumar Bandi, Maher Rizkalla, and Paul Salama, 2012.

Acoustic detection of gunshots has many applications in the field of security and the military. This paper deals with the detection of gunshots, using microphone sensor arrays placed in different locations which are processed using MATLAB. The time difference of arrivals of acoustic signals at different sensors is used to determine the direction of arrival, elevation, and the location of the shooter. The project aims to develop a high-speed, low-power sensor array that can be used for both military and civilian safety along with efficient network security. A mathematical model will be developed and five microphone systems will be used in localizing the gunshot. A mathematical model for gunshot detection has been designed. A high-speed, low-power sensor array of five microphones was developed for localizing the gunshot. This is an efficient method to find the shooter’s location precisely, which is why it can be incorporated into military and civilian safety applications. Further improvement can be made to the system by integrating this method with other efficient network security methods.

[5] Bearings-Only Aerial Shooter Localization Using A Microphone Array Mounted On A Drone -Rigel P. Fernandes and Jose A. Apolin ´ Mario Jr., Antonio L. L. Ramos, 2017.

Estimating the direction of arrival (DoA) of an audio signal from an aerial platform gives way to estimating the localization of the source. This paper addresses the problem of airborne shooter localization using an array of microphones mounted on a drone. In such a scenario, noise from the propellers poses a great challenge in estimating the DoA of gunshot signals. This, combined with the fact that drones, in general, have small payload and fly without precise control over their coordinates, have discouraged their use for shooter localization. Based on real gunshot signals

recorded at a shooting site, we explore the advantages and limitations of using a drone for the task of audio surveillance and gunshot detection and localization. This work shows that, within limitations, bearings estimated through exhaustive search can be applied successfully to estimate shooter localization using an array of microphones mounted on a quadcopter. The accuracy of the shooter localization estimation depends on the number of measurements, the distance between the array and the shooter, and the trajectory. Moreover, the number of necessary measurements must increase with the distance to maintain the same mean localization error. The results for shooter localization using a drone are a compromise between the distance (from microphone array to shooter) and the drone trajectory.

[6] Analysis Of Acoustic Signatures Of Small Firearms For Gun Shot Localization - Pathrose Nimmy, K Raveendran Nair, R Murali, K R Rajesh, Mathew Nimmy, S Vishnu, 2016.

During an ambush, it is very important to identify the direction of attack for retaliation. A gunshot localizer in this scenario can alert the troops of the incoming bullet. The firing of a gun produces a high sound pressure which can be used for locating the shooting position. Such devices also find applications in high-security areas to listen for any probable attacks. For detecting and localizing a gunshot, an array of microphones connected to a Data Acquisition and Processing Unit is employed. The microphones listen to acoustical events and the associated system continuously looks for any signal of interest. Following the signal detection Time Difference of Arrival of the sound at the different microphones is processed to extract the positional information of a gunshot. The positional information comprises the Azimuth, Elevation, and Range of the source of gunfire relative to the sensor array. The authors at CDAC, Trivandrum have developed an Acoustic Gun Shot Detector for small firearms and extensive field trials were conducted for system evaluation at firing ranges. This paper presents an analysis of the Acoustical Characteristics of small firearms based on the recorded data and test results of field trials.

[7] Consistent DOA Estimation Of Heavily Noisy Gunshot Signals Using A Microphone Array - Angelo Marcio Cardoso Ribeiro Borzino<sup>1</sup>, José Antonio Apolinário Jr.1, Marcello Luiz Rodrigues de Campos, 2016.

Direction of arrival (DOA) estimation of a gunshot is an important issue in shooter localization. As the distance between the firing position and the sensor array increases, the signal-to-noise ratio decreases, which degrades the accuracy of the DOA estimation. Strong noise may lead to false peaks in cross-correlation functions, which may result in spurious time difference of arrival (TDOA) estimates and hence spurious DOA estimates. The proposed gunshot DOA estimation algorithm [exhaustive search- searching consistent fundamental loop (ES-SCFL)] reduces this problem by combining the methods of standard estimation, ES, and SCFL. The ES-SCFL method looks for the best set of microphone pairs and the correct peaks of their cross-correlation functions and uses the time lags of these peaks as the TDOA estimates for DOA estimation. The performance of the proposed algorithm is evaluated using real gunshot data recorded from a field experiment.

### III. DESIGN METHODOLOGY

#### 3.1 Block Diagram

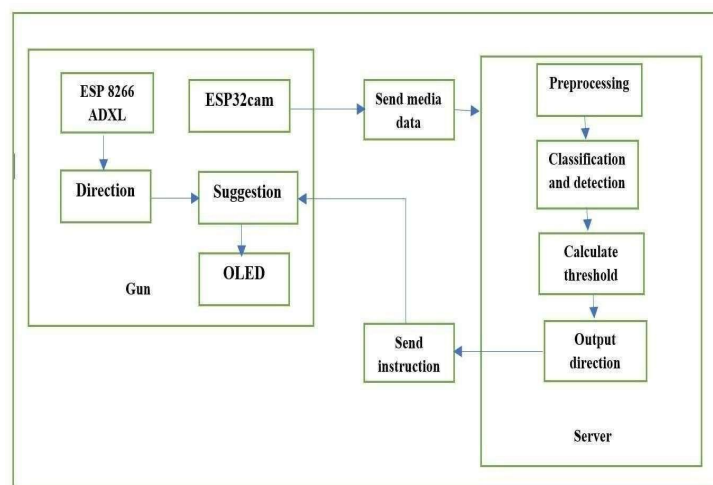


Fig 3.1 Block Diagram of Overall Process

The two main blocks present here are the server block and the gun block. The four steps of the server block are pre-processing, classification and detection, and calculating threshold and output direction. The gun block is made up of five parts: an ESP 8266, an ESP32 Cam, a direction block, a suggestion block, and an OLED display.

- ESP8266: This low-cost microchip includes a microcontroller as well as TCP/IP networking capabilities.
- ESP-32 Cam: An ESP32-based camera module with a small size and low power consumption.
- Direction block: This block generates directions that direct the user to the appropriate adversary.
- Suggestion block: This block provides information with the use of the output provided by the server block which is combined with the direction block and provides the user with the adversary's location.
- The OLED display: This is employed as an output device where the user reads the output on this display, The enemy's direction is the output in this situation.

**Working off the above block diagram:**

The ESP-8266 ADXL, which is installed on the user's equipment and monitors user movements, along with the ESP-32cam which is present on the front of the gun. This is how the block diagram above functions. The data in front of the user is read by the ESP-32 Cam, collected, and transferred to the server (through the send media block). The data is sent through several processes by the server.

- Pre-processing: In this phase, the information gathered by the ESP-32 Cam is sorted into categories and reduced to the enemy's basic colors or outfits.
- Classification and detection: At this phase, the data has been filtered by the pre-processing block to identify friends and adversaries and to detect the target present within the provided data.
- Calculation of the threshold: The identified adversary is taken as the primary object in this stage, and the user's distance from the adversary is calculated, shown, and marked.
- Output direction: After the adversary has been identified in the previous phase if the user is not exactly aligned with the adversary, the adversary's direction is delivered in this step. This is the server block's primary output.

When the server block has finished producing its output, it sends it to the gun's suggestion block. The ESP8266 provides the output containing the direction or movement of the gun, which is used by the suggestion block. These two act as inputs to the suggestion block, which sends the output signal to the OLED display. The output is displayed as visual data on the OLED display. Because the user recognizes this visual information, the output is used to either identify the adversary or lead the user to identify them as a friend.

**3.2 Flow Chart**

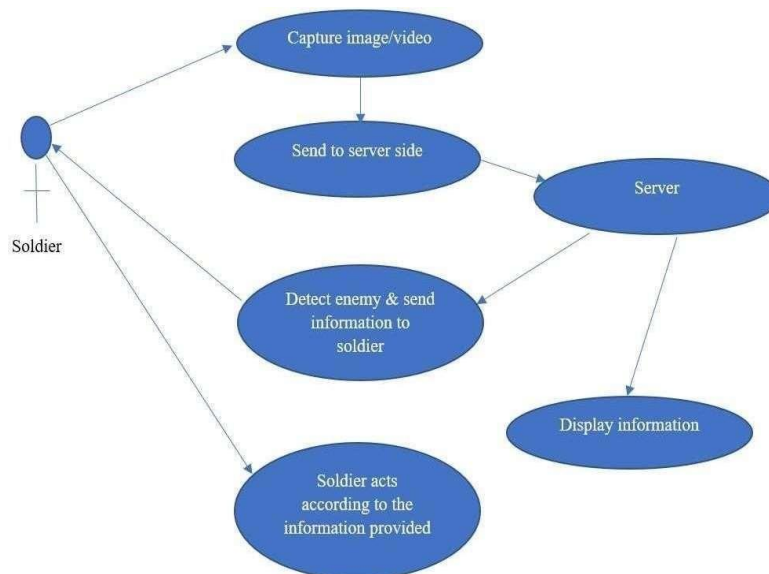


Fig 3.2 Flow Chart of Process Operation

DOI: 10.48175/IJAR SCT-9681

### 3.3 CNN Algorithm Overview

A convolutional neural network (CNN/Conv Net) is a class of deep neural networks, most commonly applied to analyze visual imagery. Consider a neural network it talks about matrix multiplications but that is not the case with Conv Net. It uses a special technique called Convolution. The application of convolutional layers consists in convolving a signal or an image with kernels to obtain feature maps. So, a unit in a feature map is connected to the previous layer through the weights of the kernels. The weights of the kernels are adapted during the training phase by backpropagation, to enhance certain characteristics of the input. Since the kernels are shared among all units of the same feature maps, convolutional layers have fewer weights to train than dense FC layers, making CNN easier to train and less prone to overfitting. Moreover, since the same kernel is convolved over all the images, the same feature is detected independently of the locating-translation invariance. By using kernels, information on the neighborhood is taken into account, which is a useful source of context.

#### A. Network Architecture

##### Image-Input Layer

An image Input Layer is a place you initialize the size of the input image, here, 128 -by-128-by-1 is used. These numbers represent the height, width, and number of channels. In this case, the input data is a grayscale image, hence the number of channels is 1.

##### Convolutional Layer

Input arguments for this layer are filtering size, the number of filters, and padding. Here, the filter of size 10 is used, which determines the 10 x 10 filter. The number of channels used is 10, which means 10 neurons are connected. A padding of 1 specifies that the size of the output image is the same as that of an input image.

##### ReLU Layer

ReLU (rectified linear unit) layer is a batch normalization layer, which is placed after initializing a nonlinear activation function. The importance of this layer is to decrease the sensitivity and increase the pace of the training.

##### Max Pooling Layer

The Max pooling layer is one of the down-sampling techniques which is used for convolutional layers. In this architecture, the pool size is set to 3 and the training function's step size is 3.

##### Fully Connected Layer

Fully connected layers follow the max pooling layer. In this layer, all the neurons of all layers are interconnected to the previous layer. This layer's input argument is 10, which indicates 10 classes.

##### Softmax Layer

Fully connected layers are followed by a softmax layer, which is a normalization technique. This layer generates positive numbers as the output such that the sum of numbers is one. The classification layer uses these numbers for classification.

##### Classification Layer

The classification layer is the final layer of the architecture. This layer classifies the classes based on probabilities obtained from the softmax layer and also calculates the cost function.

##### Training Options

The maximum number of epochs is set to 100 and the initial learning rate is 0.001.

#### B. VGG16 Architecture (ImageNet)

The input dimensions of the architecture are fixed to the image size, (224 × 224). In a pre-processing step, the mean RGB value is subtracted from each pixel in an image.

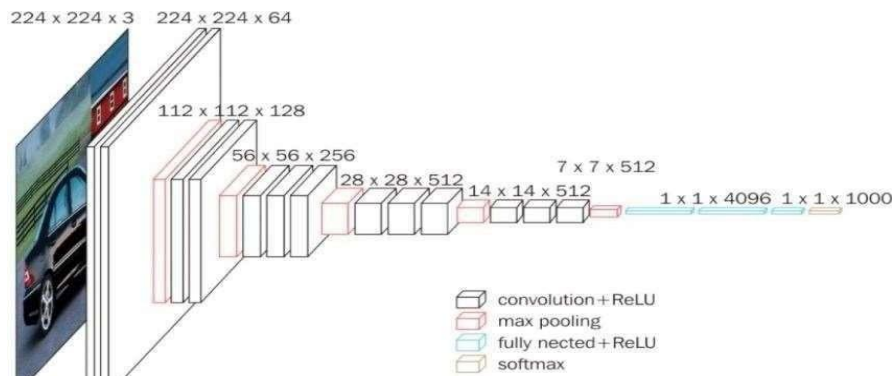


Fig 3.3 Architecture of Neural network (VGG16)

Advantages of the algorithm

- Minimize computation compared to a regular neural network.
- They are great at handling image classification.
- Execution time is less.
- High prediction accuracy.

### Working on the Algorithm

#### Step 1: Convolutional Neural Networks

Convolutional Neural Networks have a different architecture than regular Neural Networks. Regular Neural Networks transform an input by putting it through a series of hidden layers. Every layer is made up of a set of neurons, where each layer is fully connected to all neurons in the layer before. Finally, the final fully-connected layer, the output layer, represents the predictions.

CNN is composed of two major parts:

- **Feature-Extraction:** In this part, the network will perform a series of convolutions and pooling operations during which the features are detected. If you had a picture of a zebra, this is the part where the network would recognize its stripes, two ears, and four legs.
- **Classification:** Here, the fully connected layers will serve as a classifier on top of these extracted features. They will assign a probability for the object on the image being what the algorithm predicts it is.

#### Step 2: Feature Extraction: Convolution

Convolution in CNN is performed on an input image using a filter or a kernel. To understand filtering and convolution you will have to scan the screen starting from top left to right and moving down a bit after covering the width of the screen and repeating the same process until you are done scanning the whole screen.


#### Step 3: Feature Extraction: Padding

There are two types of results to the operation — one in which the convoluted feature is reduced in dimensionality as compared to the input, and the other in which the dimensionality is either increased or remains the same. This is done by applying Valid Padding or the Same Padding in the case of the latter.

#### Step 4: Feature Extraction: Non-Linearity

After sliding our filter over the original image the output which we get is passed through another mathematical function which is called an activation function. The activation function usually used in most cases in CNN feature extraction is ReLU which stands for Rectified Linear Unit. Which simply converts all of the negative values to 0 and keeps the positive values the same:

1	14	-9	4
-2	-20	10	6
-3	3	11	1
2	54	-2	80



1	14	0	4
0	0	10	6
0	3	11	1
2	54	0	80

Fig 3.4 CNN feature extraction with ReLu

After passing the outputs through ReLu functions they look like this:

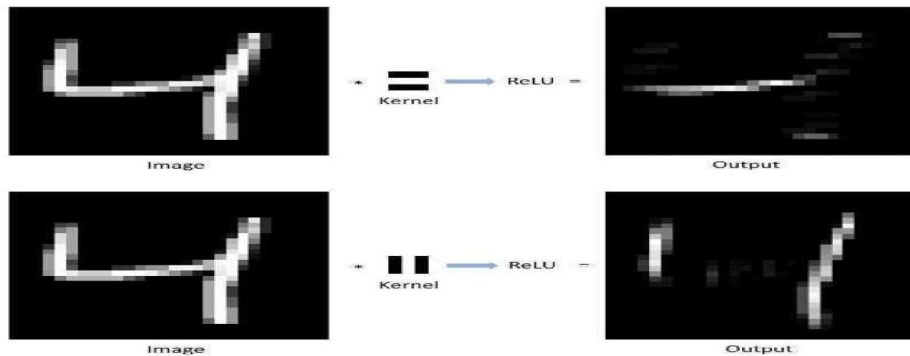


Fig 3.5 Input image after filters with ReLu

**Step 5: Feature Extraction: Pooling**

It is common to add a pooling or a sub-sampling layer in CNN layers. The Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to decrease the computational power required to process the data through dimensionality reduction. Pooling shortens the training time and controls over-fitting.

There are two types of Pooling:

Max Pooling and Average Pooling. Max Pooling returns the maximum value from the portion of the image covered by the Kernel. Max Pooling also performs as a Noise Suppressant. Average Pooling returns the average of all the values from the portion of the image covered by the Kernel. Average Pooling simply performs dimensionality reduction as a noise-suppressing mechanism. Hence, we can say that Max Pooling performs a lot better than Average Pooling.

**Step 6: Classification - Fully Connected Layer (FC Layer)**

Adding a Fully-Connected layer is a reasonable way of learning non-linear combinations of the high-level features as represented by the output of the convolutional layer. The Fully-Connected layer is learning a possibly non-linear function in that space.

**IV. DESIGN IMPLEMENTATION**

**4.1 Hardware Requirements**

- Processor: Intel i5
- RAM: 8 GB and above
- System type: 64-bit Operating system
- Hard disk: 500 GB
- ESP32 Wifi camera
- ESP8266 (Node MCU)
- GY-271
- OLED Display

**A. ESP32 Wi-Fi Camera**

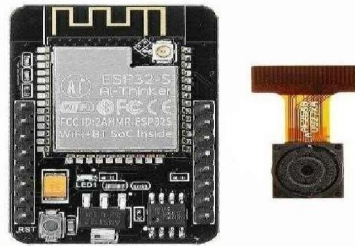


Fig 4.1 ESP32 Wi-Fi Camera

The ESP32 CAM Wi-Fi Module Bluetooth with OV2640 Camera Module 2MP For Object Recognition has a very competitive small-size camera module that can operate independently as a A minimum system with a footprint of only 40 x 27 mm; a deep sleep current of up to 6mA and is widely used in various IoT applications. It is suitable for home smart devices, industrial wireless control, wireless monitoring, and other IoT applications.

**Specifications:**

- Input Voltage: 5V,
- RAM : 520KB SRAM + 4MB PSRAM.3. Wi-fi: 802.11 b/g/n.
- Image Output Format: JPEG, BMP, GRAYSCALE.
- Spectrum Range: 2412 ~ 2484MHz.
- Dimensions : 8 x 6 x 2 cm.

**B. ESP8266 (Node MCU)**

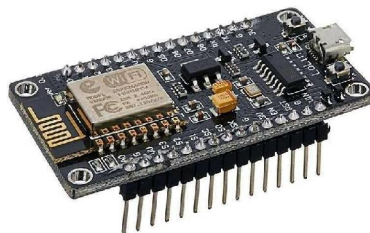


Fig 4.2 ESP8266

Node MCU is a low-cost open-source IoT platform. It initially included firmware that runs on the ESP8266 Wi-Fi SoC from Express if Systems and hardware that was based on the ESP-12 module.

**Specifications:**

- Operating Voltage: 3.3V.
- Input Voltage: 7-12V.
- Digital I/O Pins (DIO): 16.
- Analog Input Pins (ADC):

**C. GY-271 Compass**

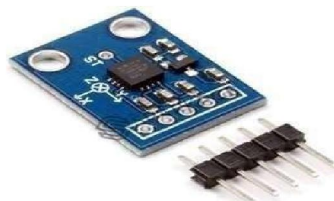


Fig 4.3 GY-271



An accelerometer is an electromechanical device that will measure acceleration forces. It shows acceleration, only due to the cause of gravity i.e. g force. It measures acceleration in g units. The GY-271 gives a complete 3-axis acceleration measurement. This module measures acceleration within the range  $\pm 3$  g in the x, y, and z-axis. The output signals of this module are analog voltages that are proportional to the acceleration.

#### Specifications:

- 3V-6V DC Supply Voltage.
- On-board LDO Voltage regulator.
- It can be interfaced with a 3.3V or 5V Microcontroller.
- Ultra-Low Power: 40uA in measurement mode, 0.1uA in standby at 2.5V.

#### D. OLED Display



Fig 4.4 OLED Display

An organic light-emitting diode (OLED or organic LED), also known as an organic electroluminescent (organic EL) diode, is a light-emitting diode (LED) in which the emissive electroluminescent layer is a film of organic compound that emits light in response to an electric current. OLEDs are used to create digital displays in devices such as television screens, computer monitors, and portable systems such as smartphones.

#### 4.2 Software Requirements

- Coding Language: Python, C
- Operating system: Windows 11
- Tool: Anaconda Navigator IDE 3.7.4, (Jupyter Notebook)

##### A. Python

Python is a popular programming language. It was created by Guido van Rossum, and released in 1991. It is used for web development (server-side), software development, mathematics, and system scripting. It can be used alongside software to create workflows. It can connect to database systems. It can also read and modify files. Python can be used for rapid prototyping or production-ready software development. Python works on different platforms (Windows, Mac, Linux, Raspberry Pi, etc). It has a simple syntax similar to the English language. Contains a syntax that allows developers to write programs with fewer lines than some other programming languages. Python can be treated in a procedural way, an object-oriented way, or a functional way. The most recent major version of Python is Python 3, which we shall be using in this tutorial. However, Python 2, although not being updated with anything other than security updates.

##### B. C

C is a general-purpose programming language created by Dennis Ritchie at the Bell Laboratories in 1972. It is a very popular language, despite being old. C is strongly associated with the UNiplexed Information Computing System (UNIX), as it was developed to write the UNIX operating system. It is one of the most popular programming languages in the world. C is very fast, compared to other programming languages, like Java and Python. C is very versatile and it can be used in both applications and technologies

**C. Anaconda Navigator**

Anaconda Navigator is a desktop graphical user interface that comes with the Anaconda distribution and allows us to run programs and manage Anaconda packages, environments, and channels without having to use command-line commands. Packages can be found on Anaconda.org or in a local Anaconda Repository using Navigator. It's compatible with Windows, Mac OS X, and Linux. Many scientific packages rely on certain versions of other programs to run. Anaconda is a package and environment manager that can be run from the command line. This assists data scientists in ensuring that each version of each package has all of the dependencies it needs and functions properly. Navigator is a point-and-click interface for working with packages and environments that eliminates the need to type anaconda instructions into a terminal window. We may use it to search packages, install them in an environment, execute them, and update them all from within the navigator.

**4.3 Test Cases**

Test Case: 01

Name of Test	Digital Compass sensor
Expected Result	We are using a Digital Compass sensor to find the gun's direction.
Actual output	Same as expected.
Remarks	Successful

Test Case: 02

Name of Test	Node MCU
Expected Result	We are using a node MCU device to connect with the server.
Actual output	Same as expected.
Remarks	Successful

Test Case: 03

Name of Test	Esp32 cam
Expected Result	In Esp32 cam, we are using the Arduino C program. Esp32 cam connects with the server.
Actual output	Same as expected.
Remarks	Successful

Test Case: 04

Name of Test	Image /video transfer
Expected Result	Esp32 cam captures images/ video, after that it will send to the server.
Actual output	Same as expected.
Remarks	Successful

Test Case: 05

Name of Test	Enemy Detection
Expected Result	The server should detect enemies using deep learning model
Actual output	Same as expected.
Remarks	Successful

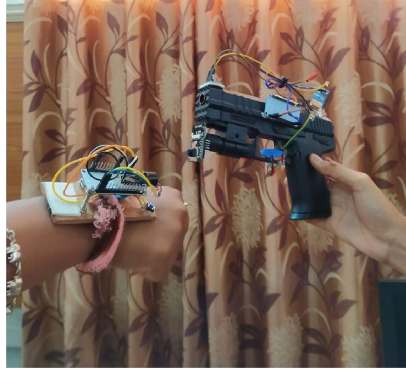


Fig 4.5 AI Smart Gun

### V. RESULT AND DISCUSSION

Our module, which is based on visual features and also gives the user instructions, has proved successful in detecting enemies. Additionally, we have implemented a safety feature that prevents access to the equipment when the user is not nearby which used a simple concept of WiFi.

```

right
Image successfully Downloaded: 1.png
1/1 [=====] - 1s 660ms/step
class_names ['H', 'V', 'W']
Detected classes ['W', 'H']
No Vest
status h@1
Image successfully Downloaded: 1.png
1/1 [=====] - 1s 678ms/step
class_names ['H', 'V', 'W']
Detected classes ['W', 'V', 'H']
status h@v
Enemy Detected
(768, 1024)
Originalframe of X: 500

Originalframe of y: 401

x_min 81
diff 419
right
Image successfully Downloaded: 1.png
1/1 [=====] - 1s 708ms/step
class_names ['H', 'V', 'W']
Detected classes ['H', 'W']
No Vest
status h@1

```

Fig 5.1 Enemy Detection through Server



Fig 5.2 Direction on equipment



Fig 5.3 Enemy Detection through Equipment

#### Applications

- Provides the soldier access to situational awareness while they are on the battlefield.
- Provides the precise location of the enemy and can be utilized to gather information about the enemy.
- Enables the soldier to distinguish whether the opponent is an adversary or a friend

#### REFERENCES

- [1]. Sergei Astapov, Johannes Ehala, Julia Berdnikova, Jürjo-Sören Preden . “Gunshot Acoustic Component Localization With Distributed Circular Microphone Arrays” Page: 1186-1190, 2015.
- [2]. Angelo M.C.R. Borzino, Jose A. Apolin Ario Jr., Marcello L.R. de Campos, and Carla L. Pagliari, “ Gunshot Signal Enhancement For DOA Estimation And Weapon Recognition” Page :1985-1989, 2013.
- [3]. Angelo M.C.R. Borzino, Jose A. Apolin Ario Jr., Marcello L. R. de Campos “Estimating Direction Of Arrival Of Long Range Gunshot Signals” Page:1965-1969, 2014.
- [4]. Ajay Kumar Bandi, Maher Rizkalla, and Paul Salama, “A Novel Approach For The Detection Of Gunshot Events Using Sound Source Localization Techniques” Page:494-497, 2012.
- [5]. Rigel P. Fernandes and Jose A. Apolin ´ Mario Jr., Antonio L. L. Ramos “Bearings-Only Aerial Shooter Localization Using A Microphone Array Mounted On A Drone” Page:886-890, 2017.
- [6]. Pathrose Nimmy, K Raveendran Nair, R Murali, K R Rajesh, Mathew Nimmy, S Vishnu “Analysis Of Acoustic Signatures Of Small Firearms For Gun Shot Localization” Page: 2 2 8 - 2 3 1 , 2016.
- [7]. Angelo Marcio Cardoso Ribeiro Borzino<sup>1</sup>, José Antonio Apolinário Jr.<sup>1</sup>, Marcello Luiz Rodrigues de Campos, “Consistent DOA Estimation Of Heavily Noisy Gunshot Signals Using A Microphone Array” Page:1856-1865, 2016.