# CHAPTER 1

# INTRODUCTION

## 1.1 GENERAL

The intrusion of wildlife into agricultural lands near forested areas has become a significant challenge, leading to crop destruction and economic loss for farmers. To mitigate this, we propose a multi-level animal detection and deterrence system. This system uses ultrasonic sensors to detect animals at a certain distance and triggers an initial buzzer alert. If the animal continues to approach, an AI model identifies the species responsible, ensuring that only harmful animals are targeted. The system operates in three phases: an early warning signal, species identification, and, if necessary, activation of a shock circuit to deter the animal. This approach ensures the safety of crops while minimizing harm to wildlife, maintaining ecological balance, and providing farmers with an effective tool to safeguard their lands from wildlife-related damage.

## 1.2 SCOPE OF THE PROJECT

The scope of this project encompasses the development and integration of an IoT-based monitoring system within external fixation devices used for treating bone fractures. This system aims to provide real-time monitoring of the healing process, patient behaviour, and environmental factors affecting recovery. The project focuses on enhancing patient care by enabling healthcare professionals to access continuous data and insights, thus improving decision-making and treatment adjustments. The target audience for this technology includes patients of all ages, from children to the elderly, ensuring accessibility and ease of use without lrequiring nurse assistance. Additionally, the project aims to reduce complications associated with traditional fracture treatments by promoting patient compliance with prescribed post-operative behaviour’s. The

implementation of this IoT-enabled system is expected to lead to improved clinical outcomes, reduced healthcare costs, and increased efficiency in the treatment and management of bone fractures

## 1.3 EXSITING SYTEM

- **Animal Identification Algorithm:** Existing systems rely on manual or semi-automated methods to identify individual animals in camera-trap images, which often lack efficiency and scalability for large datasets of wildlife images.
- **Clustering and Verification:** Conventional clustering algorithms like k-medoids++ are used for animal identification, but they may not handle variability in images effectively, requiring additional post-clustering verification for better accuracy.

### 1.3.1 DRAWBACKS

- **Limited Scalability:** Existing systems struggle to handle large datasets efficiently, particularly with high-resolution images and a large number of individual animals, leading to increased computational costs and time.
- **Low Accuracy in Complex Scenarios:** Conventional clustering algorithms like k-medoids++ may fail to accurately identify animals due to variability in image quality, lighting conditions, and animal poses, necessitating manual verification.
- **Ineffective Clustering for Similar-Looking Animals:** Standard clustering methods may group animals that look similar, such as different leopards with similar features, leading to incorrect identifications without advanced post-clustering verification.
- **High Dependency on Preprocessing:** Existing systems often require extensive preprocessing, such as manual segmentation and image

enhancement, to improve clustering accuracy, which can be time-consuming and error-prone.

- **Inadequate Adaptation to Dynamic Environments:** These systems may not adapt well to varying environments, such as changes in the animal's appearance over time or diverse environmental conditions captured by camera traps.

# CHAPTER 2
# LITERATURE SURVEY

M. Ali and F. M. M. Iqbal, in their paper titled "Detection of Wildlife Animals using Deep Learning Approaches: A Systematic Review" (2022), provide an in-depth review of how deep learning models have been utilized in wildlife detection. The paper explores the implementation of convolutional neural networks (CNNs) and recurrent neural networks in automating wildlife monitoring processes. It emphasizes key challenges such as the variability in animal appearances, environmental conditions, and the dependency on large, annotated datasets. The study offers valuable insights into how these models have been applied in real-world scenarios, contributing to improved accuracy and efficiency in wildlife surveillance systems.

D. V. Smith and J. H. Davis, in their 2023 research paper "Automated Recognition of Wild Animal Species in Camera Trap Images Using Deep Learning Models", propose a system that uses deep learning to identify and categorize animal species from camera trap images. The authors tackle common obstacles such as image noise, poor lighting, and occlusion. By deploying convolutional neural networks, their model achieves higher accuracy and automation in species classification. This approach enhances traditional camera trap monitoring, making wildlife observation more scalable and less reliant on manual labor.

A. J. M. Hasan and R. K. Singla, in their paper "Real-Time Animal Classification for Camera Traps Using Convolutional Neural Networks" (2022), develop a real-time classification system using CNNs tailored for camera trap images. Their work focuses on optimizing the classification of multiple animal species despite the challenges of varied poses,

environmental lighting, and motion blur. The authors implement optimization techniques to reduce latency and improve system performance, making the solution suitable for deployment in dynamic wildlife environments.

L. J. Goodwin and S. K. Lee, in their study "A Novel Approach for Animal Detection in Forest Regions Using Machine Learning Techniques" (2021), introduce a detection system based on a hybrid of decision trees and deep learning models. Their system is designed to enhance the reliability and speed of detecting animals, especially rare species, in dense forest environments. This research highlights the potential of machine learning in reducing false detections and improving the scalability of surveillance systems in remote and inaccessible areas.

K. D. Thomas and M. P. Oliveira, in their 2023 paper "Application of AI in Animal Behavior Recognition from Camera Trap Images", investigate how AI can be employed to recognize animal behaviors and interactions. Their study focuses on movement tracking and behavioral classification to derive ecological insights, such as habitat usage and inter-species interactions. By applying computer vision and AI models, the system enables researchers to gain behavioral data without human intervention, making conservation studies more robust.

M. S. Norouzzadeh et al., in the paper "Automatically Identifying, Counting, and Describing Wild Animals in Camera-Trap Images with Deep Learning" (2018), propose a CNN-based approach for automatic identification and counting of animals in camera trap datasets. The authors highlight key challenges including occlusion, image variability, and environmental noise. Their work demonstrates how deep learning can automate the data collection process in ecology and reduce the time required

for manual labeling, thus supporting large-scale wildlife conservation efforts.

D. Tuia et al., in "Perspectives in Machine Learning for Wildlife Conservation" (2022), explore the broader role of AI and machine learning in conservation biology. The study summarizes how data-driven methods contribute to monitoring and protecting species. It emphasizes the impact of real-time data collection, predictive analytics, and AI-driven insights in improving conservation planning and wildlife management strategies.

M. Vidal, N. Wolf, B. Rosenberg, B. P. Harris, and A. Mathis, in their 2021 paper "Perspectives on Individual Animal Identification from Biology and Computer Vision", combine biological understanding with computer vision techniques to enhance individual animal recognition. They evaluate deep learning-based techniques alongside traditional manual methods, showing how AI systems can outperform older identification techniques, especially for species with subtle visual differences.

S. Schneider, G. W. Taylor, S. Linquist, and S. C. Kremer, in "Past, Present, and Future Approaches Using Computer Vision for Animal Re-Identification from Camera Trap Data" (2019), provide a comprehensive review of how animal re-identification has evolved using computer vision. Their work discusses key innovations in model architectures, challenges in long-term monitoring, and the scalability of such systems across different ecological zones and species.

S. Kumar and S. K. Singh, in "Visual Animal Biometrics: Survey" (2017), conduct an extensive survey on biometric identification techniques used in wildlife monitoring. Their paper covers techniques such as feature extraction, pattern matching, and deep learning-based species identification.

They also highlight how advances in visual biometrics can lead to more accurate and efficient monitoring systems, especially for endangered species.

E. Nepovinnykh, T. Eerola, H. Kälviäinen, and G. Radchenko, in their 2018 work "Identification of Saimaa Ringed Seal Individuals Using Transfer Learning", explore the use of transfer learning to identify individual ringed seals. The study demonstrates how pre-trained models can be fine-tuned to work on small, rare datasets, making it feasible to monitor endangered species like the Saimaa ringed seal with higher accuracy and less training data.

E. Nepovinnykh, T. Eerola, and H. Kälviäinen further proposed a 2020 system in "Siamese Network-Based Pelage Pattern Matching for Ringed Seal Re-Identification", where they implement a Siamese neural network to match pelage patterns for individual identification. Their approach significantly improves re-identification accuracy, contributing to long-term wildlife studies and automated conservation efforts.

S. Li, J. Li, H. Tang, R. Qian, and W. Lin, in their 2020 study "ATRW: A Benchmark for Amur Tiger Re-Identification in the Wild", present the ATRW dataset designed to aid in the development of AI models for tiger re-identification. The dataset facilitates more accurate tracking of individual Amur tigers in the wild and supports AI-powered conservation tools to protect this endangered species.

P. Chen et al., in "A Study on Giant Panda Recognition Based on Images of a Large Proportion of Captive Pandas" (2020), apply deep learning to the task of identifying giant pandas from a large dataset. The study focuses on

individual recognition, allowing for better management of captive populations and improving welfare monitoring through automated systems.

C. V. Stewart, J. R. Parham, J. Holmberg, and T. Y. Berger-Wolf, in "The Animal ID Problem: Continual Curation" (2021), examine the evolving challenges in maintaining and updating animal identification models. The authors suggest continual learning methods and curated data pipelines to improve model accuracy over time, especially for species where visual traits change with age or season.

# CHAPTER 3

# THEORETICAL BACKGROUND

## 3.1 GENERAL

Agricultural lands near wildlife habitats face frequent animal intrusions, leading to significant crop loss and financial strain on farmers. To address this, our solution implements a multi-level animal detection and deterrence system, combining sensors and AI for precise threat identification and response.The system begins by using ultrasonic sensors to detect animals within a defined range. Upon detection, it follows a structured three-stage process. In the first stage, a buzzer alert is triggered to notify the farmer of a potential intrusion.

The second stage employs an AI-based model to identify the specific animal species, ensuring that only harmful animals are targeted while minimizing unnecessary disturbance to non-threatening wildlife. If the detected animal poses a persistent threat, the third stage activates a shock circuit as a deterrent, safely encouraging the animal to retreat without causing harm. This tiered approach enhances agricultural security while maintaining ecological balance. By integrating AI with automated deterrence mechanisms, the system provides an efficient, cost-effective, and humane solution to protect farmlands, reduce wildlife-related losses, and support sustainable farming practices.

## 3.2 PROPOSED SYSTEM

- **Multi-Level Animal Detection and Identification:** The system uses ultrasonic sensors to detect approaching animals. First, a buzzer alerts the farmer. Then, an AI model identifies the species, targeting only harmful animals while avoiding unnecessary disturbance.
- **Automated Deterrence Mechanism:** Upon identification of a harmful animal, the system proceeds to the third level, where an automatic shock

circuit is activated to deter the intruder from damaging the crops. This multi-tiered approach ensures effective crop protection, minimizes harm to wildlife, and enhances agricultural safety without relying on manual intervention.

### 3.2.1 ADVANTAGE

- **Efficient Crop Protection with Minimal Wildlife Harm:** The multi-level detection system offers early warning and targeted intervention, preventing crop damage while ensuring non-threatening wildlife remains undisturbed, preserving ecological balance
- **Automated and Cost-Effective Solution:** The system operates autonomously, minimizing human supervision and manual effort, making it a cost-effective solution for farmers. AI-driven deterrence ensures timely and accurate responses to wildlife threats, enhancing agricultural efficiency and safety.

## 3.3 ARCHITECTURE DIAGRAM

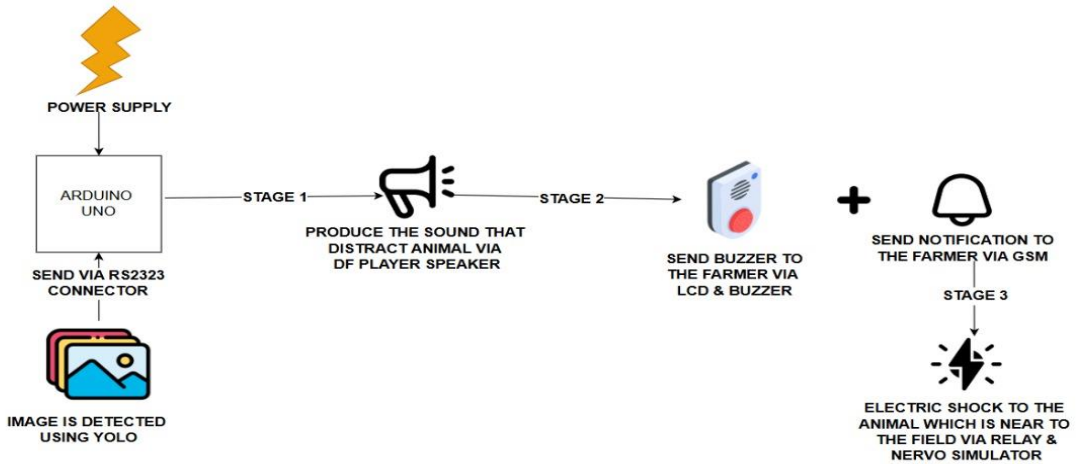


**Fig 3.1 Architecture Diagram**

## 3.4 USECASE DIAGRAM

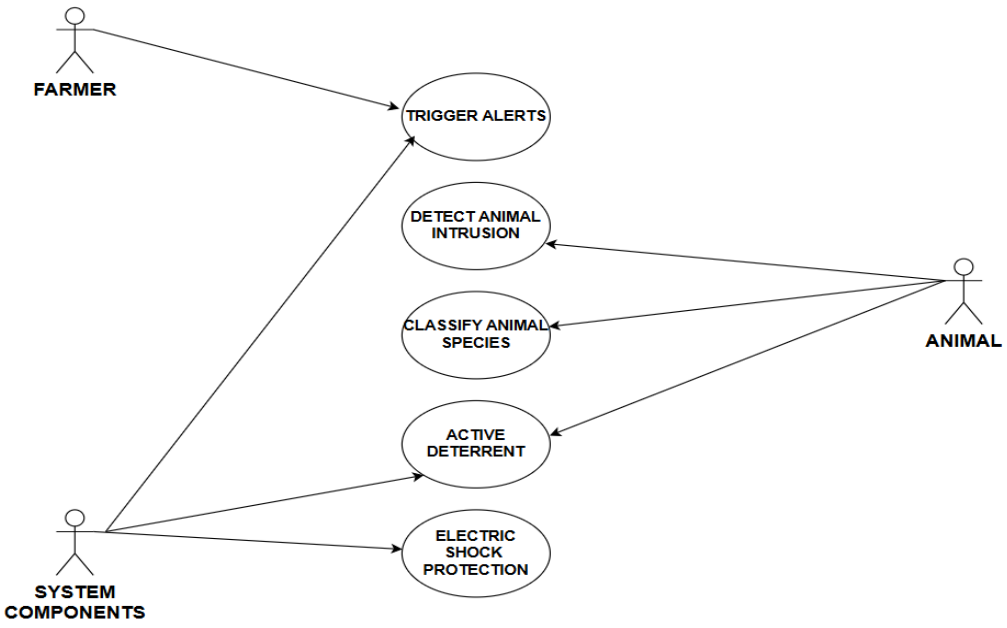


**Fig 3.2 Usecase Diagram**

The diagram represents an assistive technology system designed to enhance accessibility for individuals with visual, hearing, and speaking disabilities by providing multiple interaction methods. The system allows users to issue voice commands and gesture commands, which are processed to control various devices by turning them on or off as needed.

Additionally, the system is capable of storing data for future use, ensuring a more personalized and adaptive experience over time. A crucial safety feature integrated into the system is the emergency alert mechanism, which enables users to send notifications to a trusted person in case of urgent situations.

This is further reinforced by a safety buzzer, which acts as an immediate auditory warning signal for emergencies. By combining multiple input methods and emergency response functionalities, the proposed system makes everyday

interactions more seamless and efficient, ultimately improving the quality of life for individuals with disabilities.

Furthermore, the integration of artificial intelligence and smart automation enhances system responsiveness, allowing it to adapt to user preferences and environmental changes. The modular design also ensures scalability, enabling future upgrades with advanced sensors, machine learning models, and IoT-based functionalities for a more comprehensive assistive solution.

## 3.5 BLOCK DIAGRAM

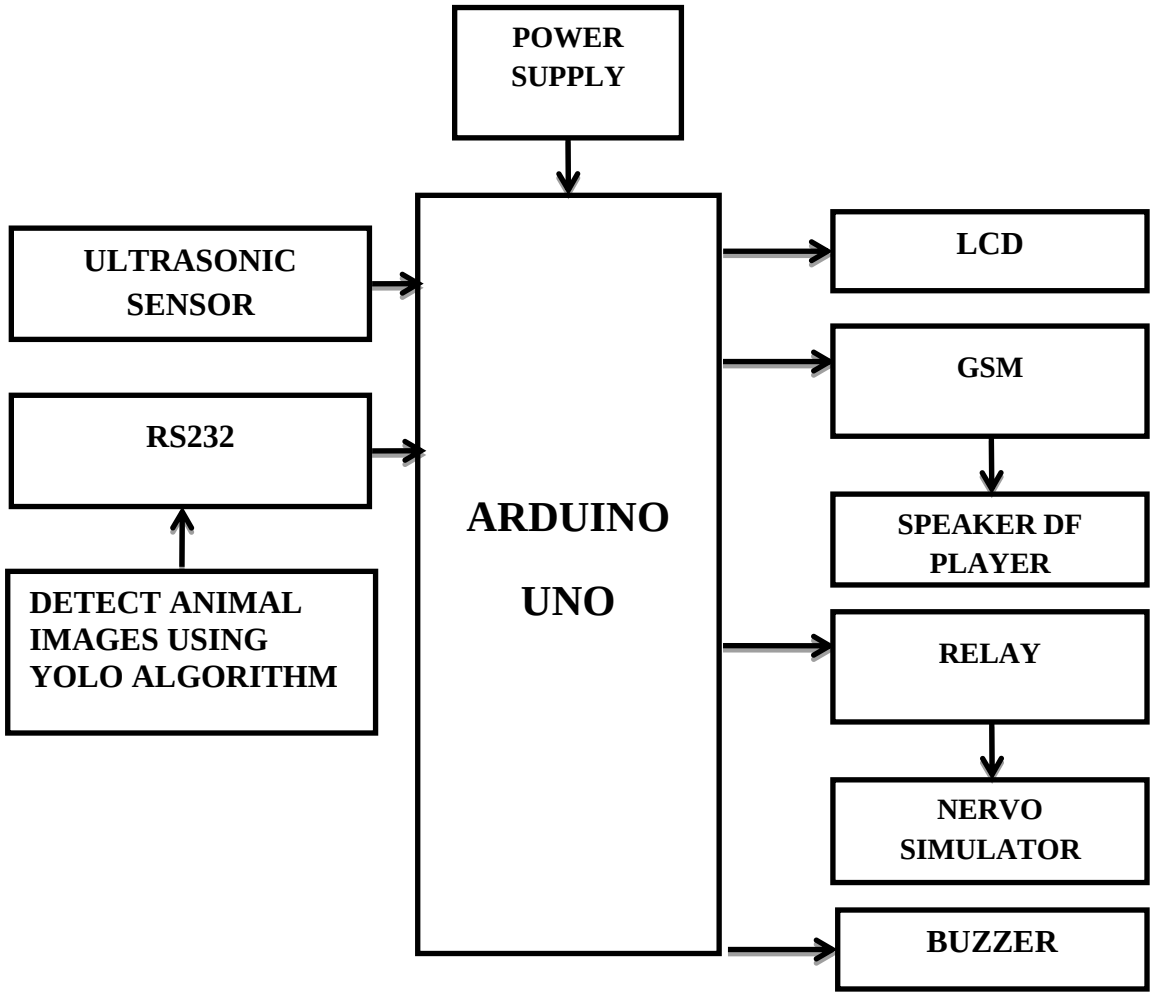


**Fig 3.3 Block Diagram**

## 3.6 BLOCK DIAGRAM WORKING

The proposed system integrates three essential modules to provide an effective and automated solution for protecting agricultural land from wildlife intrusions. It begins with ultrasonic sensors that continuously monitor the surroundings and detect approaching animals within a predefined range. Upon detection, the system triggers a buzzer alert, immediately notifying the farmer of potential threats. In the next stage, a camera module captures real-time images, which are analyzed using an AI-powered YOLO algorithm to identify the species of the detected animal.

This intelligent classification ensures that only harmful animals are targeted, preventing unnecessary disturbances to non-threatening wildlife. If the identified animal poses a risk and continues approaching the farmland, the system activates a deterrent mechanism. A relay is triggered to turn on a shock circuit, delivering a mild, non-lethal electric pulse to discourage the animal from further intrusion.This tiered approach ensures an efficient balance between agricultural security and ethical wildlife management.

By leveraging AI-driven automation, the system minimizes human intervention, enhances farm protection, and reduces crop losses. Additionally, its non-lethal deterrence mechanism promotes sustainable farming by preventing damage without harming animals, making it an environmentally responsible and cost-effective solution for farmers.

## 3.7 MODULES NAME

- OBJECT DETECT IN THAT RANGE
- ANIMAL IDENTIFICATION USING AI
- SHOCK MECHANIMS ON PROCESS

### 3.7.1 MODULE DESCRIPTION

- **OBJECT DETECT IN THAT RANGE**

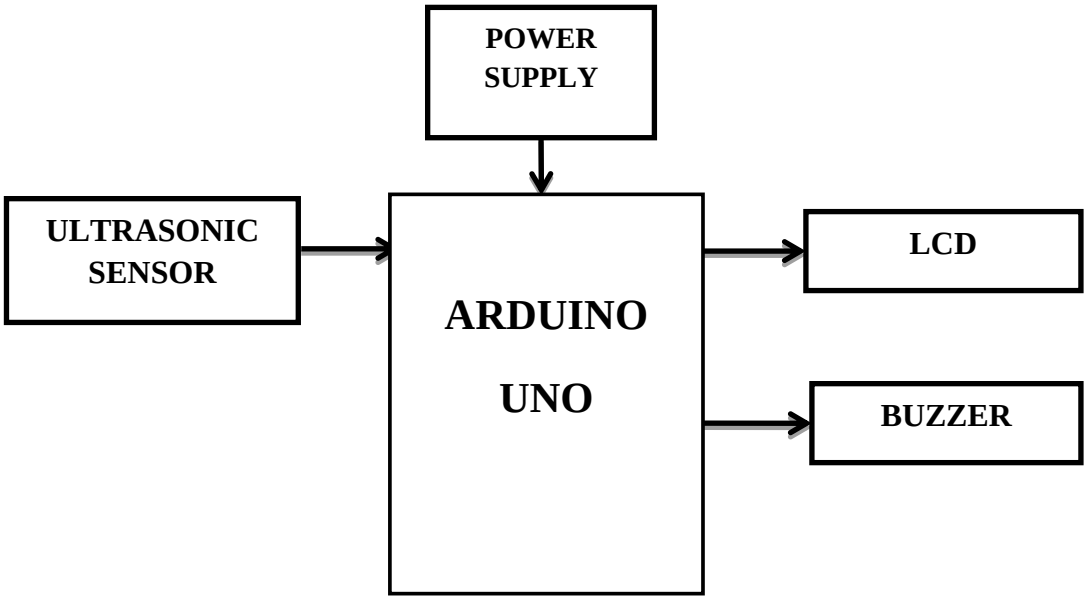


**Fig 3.4 Object Detect In That Range**

The proposed system utilizes ultrasonic sensors positioned at the front range of the agricultural land to detect any approaching animals. Once an animal is detected, the sensor triggers a buzzer alert to notify the farmer of a potential threat. The heart of the system is the Arduino Uno controller, which processes the sensor data and manages the alert mechanism. The Arduino Uno coordinates the detection process, ensuring the timely activation of the buzzer and facilitating the smooth operation of the entire system. This setup allows for real-time monitoring and early warning of animal intrusion, providing an efficient and automated method for safeguarding crops.

## ➢ ANIMAL IDENTIFICATION USING AI

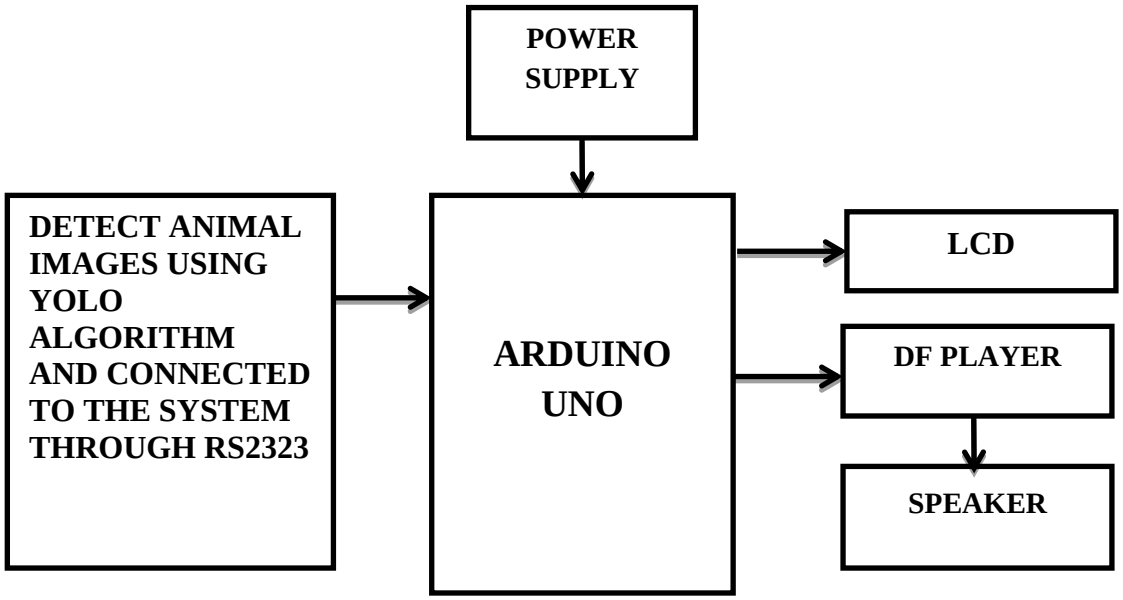


**Fig 3.5 Animal Identification Using AI**

The system incorporates an AI model using the YOLO (You Only Look Once) algorithm to identify the species of animals detected by the ultrasonic sensors at the front of the land. Once an animal is detected, the YOLO algorithm analyzes the visual data to determine the specific species. If the identified animal is deemed harmful or a threat to the crops, the system then triggers a distraction mechanism, where an ultrasonic sound is produced from a speaker to deter the animal from approaching further. This combination of real-time detection and AI-driven species identification ensures that the system responds appropriately to wildlife threats, providing a targeted and effective deterrent while minimizing unnecessary disruption to non-threatening animals.

## ➢ SHOCK MECHANISM ON PROCESS

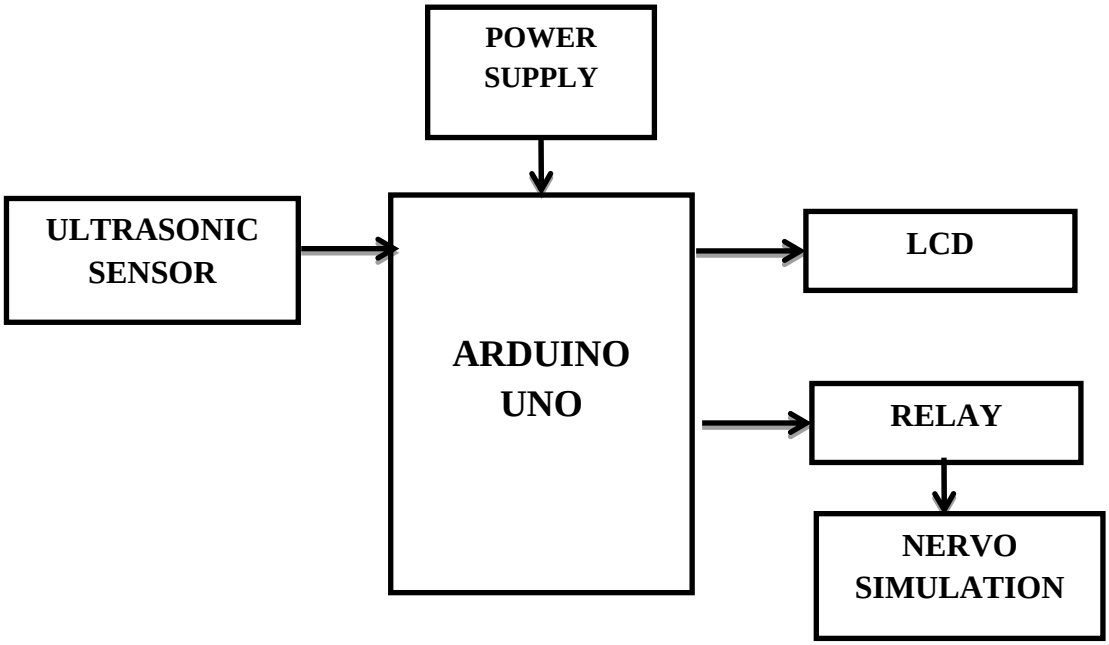


**Fig 3.6 Shock Mechanism On Process**

The system uses ultrasonic sensors to monitor the range of animals approaching the land. When an animal comes within a predefined distance, the sensor detects its proximity and sends a signal to a relay. If the animal is too close to the land and is deemed a threat, the relay activates the shock circuit, providing a deterrent to prevent further intrusion. This automated response ensures that the crops are protected from damage without requiring manual intervention, offering an efficient and reliable solution to manage wildlife interactions on agricultural land.

## 3.8 HARDWARE REQUIREMENT

### 3.8.1 ARDUINO

Arduino is an open-source electronics platform based on easy-to-use hardware and software. Arduino boards are able to read inputs - light on a sensor, a finger on a button, or a Twitter message - and turn it into an output - activating a motor, turning on an LED, publishing something online. You can tell your board what to do by sending a set of instructions to the microcontroller on the board.

Over the years Arduino has been the brain of thousands of projects, from everyday objects to complex scientific instruments. A worldwide community of makers - students, hobbyists, artists, programmers, and professionals - has gathered around this open-source platform, their contributions have added up to an incredible amount of accessible knowledge that can be of great help to novices and experts alike.

Arduino was born at the Ivrea Interaction Design Institute as an easy tool for fast prototyping, aimed at students without a background in electronics and programming. As soon as it reached a wider community, the Arduino board started changing to adapt to new needs and challenges, differentiating its offer from simple 8-bit boards to products for IoT applications, wearable, 3D printing, and embedded environments. All Arduino boards are completely open-source, empowering users to build them independently and eventually adapt them to their particular needs. The software, too, is open-source, and it is growing through the contributions of users worldwide.

#### 3.8.1.1 WHY ARDUINO

Thanks to its simple and accessible user experience, Arduino has been used in thousands of different projects and applications. The Arduino software is easy-

to-use for beginners, yet flexible enough for advanced users. It runs on Mac, Windows, and Linux. Teachers and students use it to build low cost scientific instruments, to prove chemistry and physics principles, or to get started with programming and robotics. Designers and architects build interactive prototypes, musicians and artists use it for installations and to experiment with new musical instruments. Makers, of course, use it to build many of the projects exhibited at the Maker Faire, for example. Arduino is a key tool to learn new things. Anyone - children, hobbyists, artists, programmers - can start tinkering just following the step by step instructions of a kit, or sharing ideas online with other members of the Arduino community.

There are many other microcontrollers and microcontroller platforms available for physical computing. Parallax Basic Stamp, Netmedia's BX-24, Phidgets, MIT's Handyboard, and many others offer similar functionality. All of these tools take the messy details of microcontroller programming and wrap it up in an easy-to-use package. Arduino also simplifies the process of working with microcontrollers, but it offers some advantage for teachers, students, and interested amateurs over other systems:

- **Inexpensive** - Arduino boards are relatively inexpensive compared to other microcontroller platforms. The least expensive version of the Arduino module can be assembled by hand, and even the pre-assembled Arduino modules cost less than $50.

- **Cross-platform** - The Arduino Software (IDE) runs on Windows, Macintosh OSX, and Linux operating systems. Most microcontroller systems are limited to Windows.

- **Simple, clear programming environment** - The Arduino Software (IDE) is easy-to-use for beginners, yet flexible enough for advanced users to take advantage of as well. For teachers, it's

conveniently based on the Processing programming environment, so students learning to program in that environment will be familiar with how the Arduino IDE works.

- **Open source and extensible software** - The Arduino software is published as open source tools, available for extension by experienced programmers. The language can be expanded through C++ libraries, and people wanting to understand the technical details can make the leap from Arduino to the AVR C programming language on which it's based. Similarly, you can add AVR-C code directly into your Arduino programs if you want to.

- **Open source and extensible hardware** - The plans of the Arduino boards are published under a Creative Commons license, so experienced circuit designers can make their own version of the module, extending it and improving it. Even relatively inexperienced users can build the breadboard version of the module in order to understand how it works and save money.

### 3.8.2 ARDUINO UNO

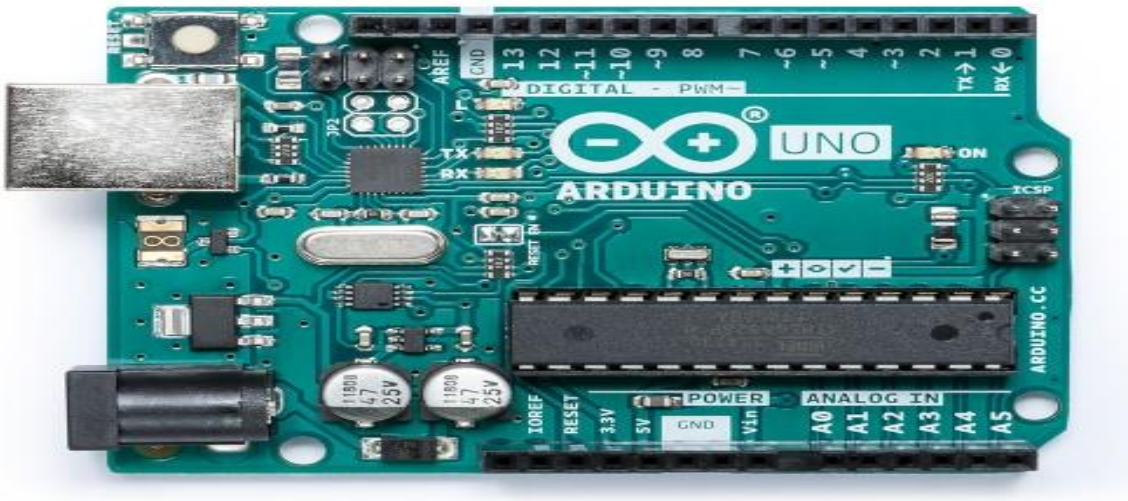


**Fig 3.7 Arduino Uno**

**Arduino Uno** is a microcontroller board based on the ATmega328P (datasheet). It has 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz quartz crystal, a USB connection, a power jack, an ICSP header and a reset button. It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with a AC-to-DC adapter or battery to get started. You can tinker with your UNO without worrying too much about doing something wrong, worst case scenario you can replace the chip for a few dollars and start over again.

"Uno" means one in Italian and was chosen to mark the release of Arduino Software (IDE) 1.0. The Uno board and version 1.0 of Arduino Software (IDE) were the reference versions of Arduino, now evolved to newer releases. The Uno board is the first in a series of USB Arduino boards, and the reference model for the Arduino platform; for an extensive list of current, past or outdated boards see the Arduino index of boards.

### 3.8.2.1 TECHNICAL SPECIFICATIONS

| | |
|---|---|
| **Microcontroller** | ATmega328P |
| **Operating Voltage** | 5V |
| **Input Voltage (recommended)** | 7-12V |
| **Input Voltage (limit)** | 6-20V |
| **Digital I/O Pins** | 14 (of which 6 provide PWM output) |
| **PWM Digital I/O Pins** | 6 |

| | |
|---|---|
| **Analog Input Pins** | 6 |
| **DC Current per I/O Pin** | 20 mA |
| **DC Current for 3.3V Pin** | 50 mA |
| **Flash Memory** | 32 KB (ATmega328P) of which 0.5 KB used by boot loader |
| **SRAM** | 2 KB (ATmega328P) |
| **EEPROM** | 1 KB (ATmega328P) |
| **Clock Speed** | 16 MHz |
| **LED_BUILTIN** | 13 |
| **Length** | 68.6 mm |
| **Width** | 53.4 mm |
| **Weight** | 25 g |

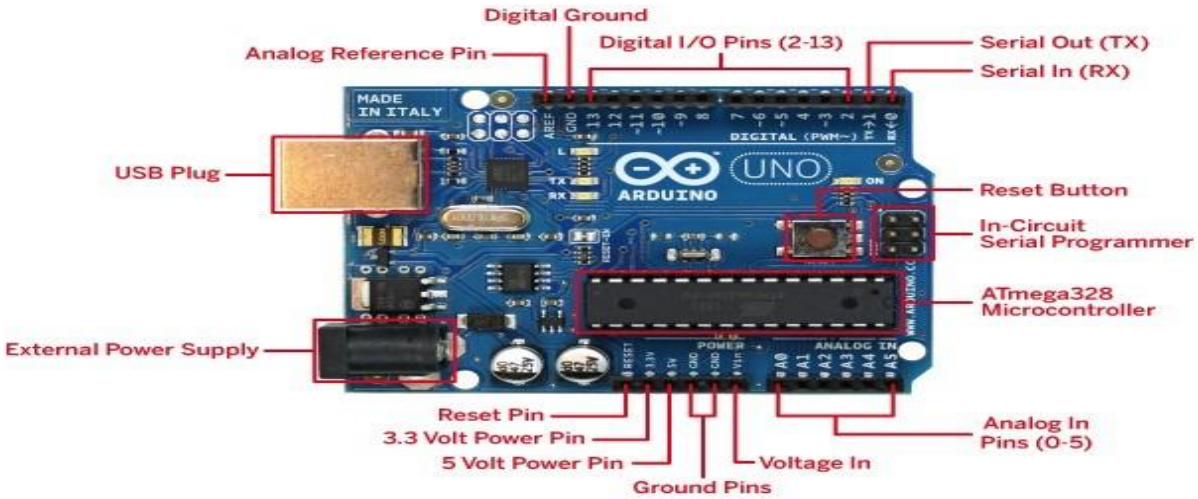


**Fig 3.8 Arduino Uno Technical Specification**

### 3.8.2.2 HARDWARE

Arduino is an open-source hardware platform with reference designs available under a Creative Commons Attribution Share-Alike 2.5 license. While the hardware and software are freely accessible, the Arduino name is exclusive to the official product, preventing unauthorized use in derivative works. Many Arduino-compatible products exist, often using names ending in "-duino" to differentiate themselves while maintaining similar functionality.

Most Arduino boards feature an Atmel 8-bit AVR microcontroller (ATmega8, ATmega168, ATmega328, ATmega1280, ATmega2560) with varying amounts of flash memory, pins, and features. The 32-bit Arduino Due, introduced in 2012, is based on the Atmel SAM3X8E microcontroller. Boards typically use single or double-row pins and female headers for easy connections to external circuits, including add-on modules known as shields. These shields can be stacked and addressed individually via an I²C serial bus, expanding Arduino's functionality. Most boards include a 5V linear regulator and a 16 MHz crystal oscillator, while some models, such as the LilyPad, operate at 8 MHz without an onboard voltage regulator due to form-factor constraints.

Arduino microcontrollers are preloaded with a bootloader, simplifying program uploads to on-chip flash memory. Programs are transferred via a serial connection, often through USB-to-serial adapters like the FTDI FT232 or an integrated AVR chip running USB-to-serial firmware. Some variants, such as the Arduino Mini and Boarduino, use detachable adapters, Bluetooth, or other methods for programming. Traditional

microcontroller tools can be used with standard AVR in-system programming (ISP).

Arduino boards expose the microcontroller's I/O pins for external use. The Diecimila, Duemilanove, and Uno models provide 14 digital I/O pins, six of which support pulse-width modulation (PWM), along with six analog inputs that can also function as digital I/O. These pins are accessible via female headers, while some models, such as the Nano, use male header pins for direct breadboard compatibility. Several plug-in shields are commercially available, offering additional functionality such as motor control, Wi-Fi, and GPS integration.

Numerous Arduino-compatible and derived boards exist, with some designed for specific applications such as education, robotics, and industrial automation. Some boards maintain full compatibility with Arduino shields, while others modify form factors or use alternative processors with varying degrees of compatibility. The Arduino ecosystem continues to grow, providing a versatile platform for hobbyists, educators, and professionals in embedded system development.

### 3.8.2.3 PROGRAMMING

The Arduino Uno can be programmed with the (Arduino Software (IDE)). Select "Arduino/Genuino Uno from the Tools > Board menu (according to the microcontroller on your board). For details, see the reference and tutorials.

The ATmega328 on the Arduino Uno comes preprogrammed with a boot loader that allows you to upload new code to it without the use of an

external hardware programmer. It communicates using the original STK500 protocol (reference, C header files).

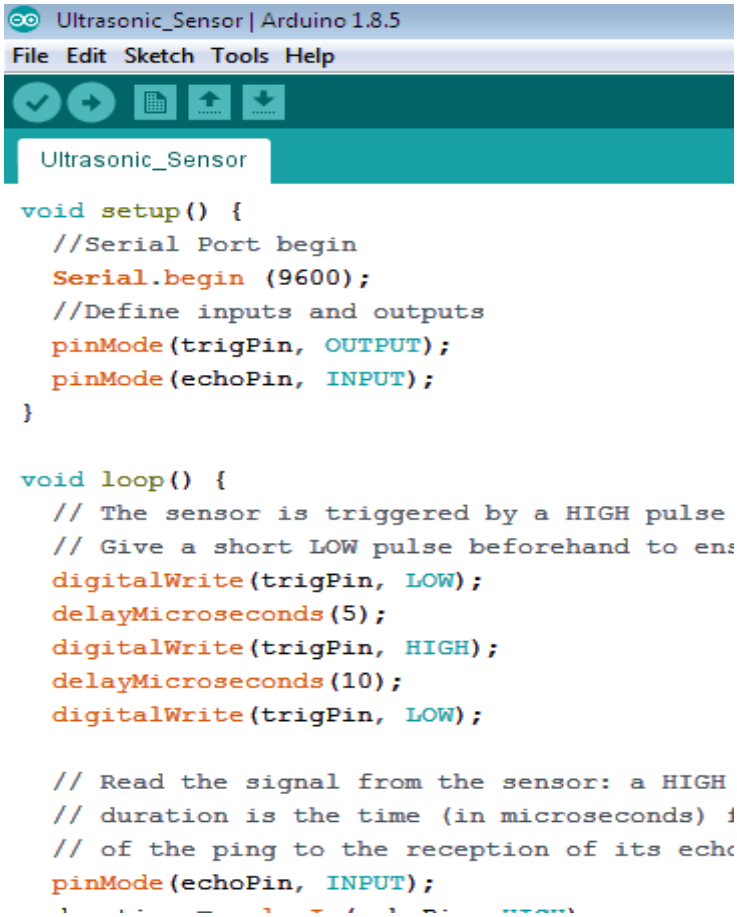


**Fig 3.9 Arduino Programming**

You can also bypass the boot loader and program the microcontroller through the ICSP (In-Circuit Serial Programming) header using Arduino ISP or similar; see these instructions for details.

The ATmega16U2 (or 8U2 in the rev1 and rev2 boards) firmware source code is available in the Arduino repository. The ATmega16U2/8U2 is loaded with a DFU boot loader, which can be activated by:

- **On Rev1 boards:** connecting the solder jumper on the back of the board (near the map of Italy) and then reseing the 8U2.

- **On Rev2 or later boards:** there is a resistor that pulling the 8U2/16U2 HWB line to ground, making it easier to put into DFU mode.

You can then use Atmel's FLIP software (Windows) or the DFU programmer (Mac OS X and Linux) to load a new firmware. Or you can use the ISP header with an external programmer (overwriting the DFU boot loader). See this user-contributed tutorial for more information.

### 3.8.2.4 WARNINGS

The Arduino Uno has a resettable polyfuse that protects your computer's USB ports from shorts and overcurrent. Although most computers provide their own internal protection, the fuse provides an extra layer of protection. If more than 500 mA is applied to the USB port, the fuse will automatically break the connection until the short or overload is removed.

### 3.8.2.5 DIFFERENCES WITH OTHER BOARDS

The Uno differs from all preceding boards in that it does not use the FTDI USB-to-serial driver chip. Instead, it features the Atmega16U2 (Atmega8U2 up to version R2) programmed as a USB-to-serial converter.

### 3.8.2.6 POWER

The Arduino Uno board can be powered via the USB connection or with an external power supply. The power source is selected automatically.

External (non-USB) power can come either from an AC-to-DC adapter (wall-wart) or battery. The adapter can be connected by plugging a

2.1mm center-positive plug into the board's power jack. Leads from a battery can be inserted in the GND and Vin pin headers of the POWER connector.

The board can operate on an external supply from 6 to 20 volts. If supplied with less than 7V, however, the 5V pin may supply less than five volts and the board may become unstable. If using more than 12V, the voltage regulator may overheat and damage the board. The recommended range is 7 to 12 volts.

The power pins are as follows:

- **Vin**. The input voltage to the Arduino/Genuino board when it's using an external power source (as opposed to 5 volts from the USB connection or other regulated power source). You can supply voltage through this pin, or, if supplying voltage via the power jack, access it through this pin.
- **5V**.This pin outputs a regulated 5V from the regulator on the board. The board can be supplied with power either from the DC power jack (7 - 12V), the USB connector (5V), or the VIN pin of the board (7-12V). Supplying voltage via the 5V or 3.3V pins bypasses the regulator, and can damage your board. We don't advise it.
- **3V3**. A 3.3 volt supply generated by the on-board regulator. Maximum current draw is 50 mA.
- **GND**. Ground pins.
- **IOREF**. This pin on the Arduino/Genuino board provides the voltage reference with which the microcontroller operates. A properly configured shield can read the IOREF pin voltage and

select the appropriate power source or enable voltage translators on the outputs to work with the 5V or 3.3V.

### 3.8.2.7 MEMORY

The ATmega328 has 32 KB (with 0.5 KB occupied by the boot loader). It also has 2 KB of SRAM and 1 KB of EEPROM (which can be read and written with the EEPROM library).

### 3.8.2.8 INPUT AND OUTPUT

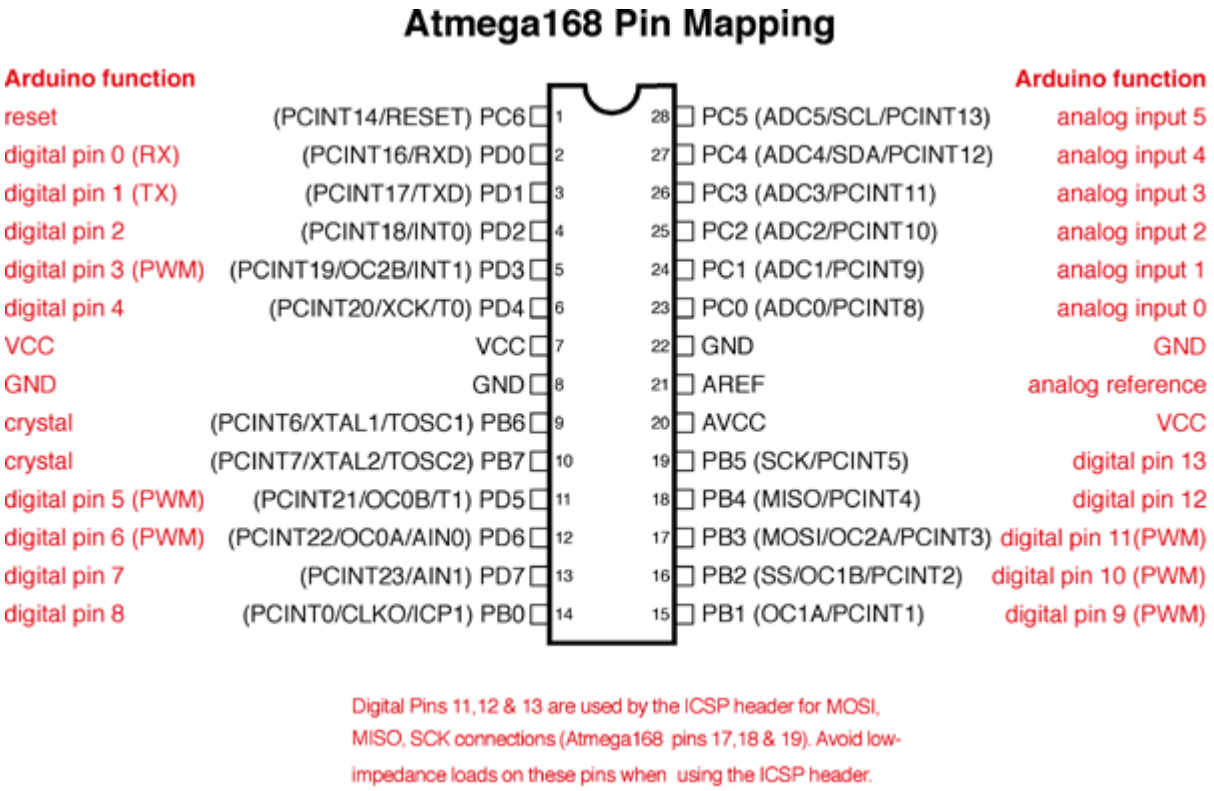


**Fig 3.10 Input And Output Of Arduino Pin**

Each of the 14 digital pins on the Uno can be used as an input or output, using **pinMode()**, **digitalWrite()**, and **digitalRead()** functions. They operate at 5 volts. Each pin can provide or receive 20 mA as recommended operating condition and has an internal pull-up resistor

(disconnected by default) of 20-50k ohm. A maximum of 40mA is the value that must not be exceeded on any I/O pin to avoid permanent damage to the microcontroller.

In addition, some pins have specialized functions:

- **Serial:** 0 (RX) and 1 (TX). Used to receive (RX) and transmit (TX) TTL serial data. These pins are connected to the corresponding pins of the ATmega8U2 USB-to-TTL Serial chip.
- **External Interrupts:** 2 and 3. These pins can be configured to trigger an interrupt on a low value, a rising or falling edge, or a change in value. See the **attachInterrupt()** function for details.
- **PWM:** 3, 5, 6, 9, 10, and 11. Provide 8-bit PWM output with the **analogWrite()** function.
- **SPI:** 10 (SS), 11 (MOSI), 12 (MISO), 13 (SCK). These pins support SPI communication using the SPI library.
- **LED:** 13. There is a built-in LED driven by digital pin 13. When the pin is HIGH value, the LED is on, when the pin is LOW, it's off.
- **TWI:** A4 or SDA pin and A5 or SCL pin. Support TWI communication using the Wire library.

The Uno has 6 analog inputs, labeled A0 through A5, each of which provide 10 bits of resolution (i.e. 1024 different values). By default they measure from ground to 5 volts, though is it possible to change the upper end of their range using the AREF pin and the **analogReference()** function. There are a couple of other pins on the board:

- **AREF**. Reference voltage for the analog inputs. Used with **analogReference()**.

- **Reset**. Bring this line LOW to reset the microcontroller. Typically used to add a reset button to shields which block the one on the board.

### 3.8.2.9 COMMUNICATION

The Arduino/Genuino Uno supports multiple communication methods with computers, other Arduino boards, and microcontrollers. The ATmega328 provides UART TTL (5V) serial communication on digital pins 0 (RX) and 1 (TX), while an ATmega16U2 channels this over USB, appearing as a virtual COM port. No external driver is needed, except for a .inf file on Windows. The Arduino IDE includes a serial monitor for sending and receiving data, with RX and TX LEDs flashing during USB communication. A Software Serial library enables serial communication on any digital pin. The ATmega328 also supports I2C (TWI) and SPI, with dedicated Wire and SPI libraries for simplified use.

### 3.8.2.10 AUTOMATIC (SOFTWARE) RESET

Rather than requiring a physical press of the reset button before an upload, the Arduino/Genuino Uno board is designed in a way that allows it to be reset by software running on a connected computer. One of the hardware flow control lines (DTR) of the ATmega8U2/16U2 is connected to the reset line of the ATmega328 via a 100 nanofarad capacitor. When this line is asserted (taken low), the reset line drops long enough to reset the chip.

The Arduino Software (IDE) uses this capability to allow you to upload code by simply pressing the upload button in the interface toolbar. This means that the boot loader can have a shorter timeout, as the lowering of DTR can be well-coordinated with the start of the upload.

This setup has other implications. When the Uno is connected to either a computer running Mac OS X or Linux, it resets each time a connection is made to it from software (via USB). For the following half-second or so, the boot loader is running on the Uno. While it is programmed to ignore malformed data (i.e. anything besides an upload of new code), it will intercept the first few bytes of data sent to the board after a connection is opened.

If a sketch running on the board receives one-time configuration or other data when it first starts, make sure that the software with which it communicates waits a second after opening the connection and before sending this data.

The Uno board contains a trace that can be cut to disable the auto-reset. The pads on either side of the trace can be soldered together to re-enable it. It's labeled "RESET-EN". You may also be able to disable the auto-reset by connecting a 110 ohm resistor from 5V to the reset line; see this forum thread for details.

Some terminal programs allow users to toggle the DTR line, enabling or disabling the reset functionality programmatically. This provides additional flexibility for advanced users working on custom applications.

The Arduino community offers extensive discussions, forum threads, and alternative methods for managing the auto-reset feature. These resources help users troubleshoot and customize their boards according to specific project requirements.

Another way to disable auto-reset is by connecting a 110-ohm resistor between the 5V pin and the reset pin. This method prevents the reset signal from taking effect, allowing uninterrupted serial communication.

### 3.8.3 LIQUID CRYSTAL DISPLAY

An LCD screen is a widely used electronic display module, with the 16*2 LCD being a common choice in various devices and circuits. It is preferred over seven-segment and multi-segment LEDs due to its affordability, programmability, and ability to display special characters, custom symbols, and animations. A 16*2 LCD can display 16 characters per line across two lines, with each character shown in a 5*7 pixel matrix. It has two registers: the Command register, which stores instructions for tasks like initialization, clearing, and cursor positioning, and the Data register, which holds ASCII values of characters to be displayed.

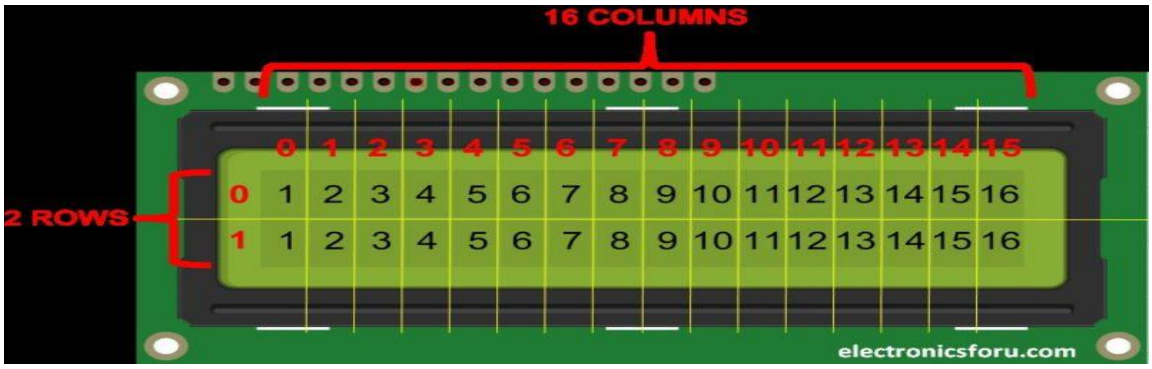


**Fig 3.11 LCD Diagram**

An LCD is an electronic display module which uses liquid crystal to produce a visible image. The 16*2 LCD display is a very basic module commonly used in projects. The 16*2 translates to a display 16 characters per line in 2 such lines. In this LCD each character is displayed in a 5*7 pixel matrix.

The 16×2 LCD module operates using an HD44780 controller, which simplifies communication with microcontrollers like Arduino, Raspberry Pi, and other embedded systems. It can function in both 4-bit and 8-bit modes, allowing flexibility in data transmission. The display has built-in registers to store

commands and data, enabling tasks such as cursor movement, text scrolling, and custom character creation.

### 3.8.3.1 16*2 LCD PINOUT DIAGRAM

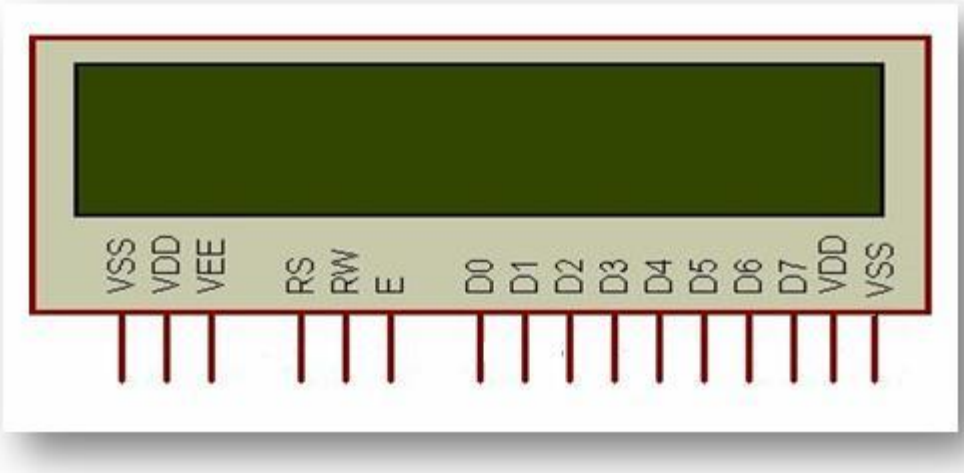


**Fig 3.12 16*2 LCD Pinout Diagram**

| PIN NO. | FUNCTION | NAME |
|---|---|---|
| 1 | Ground (0V) | Ground |
| 2 | Supply voltage; 5V (4.7V – 5.3V) | VCC |
| 3 | Contrast adjustment; the best way is to use a variable resistor such as a potentiometer. The output of the potentiometer is connected to this pin. Rotate the potentiometer knob forward and backwards to adjust the LCD contrast. | Vo / VEE |
| 4 | Selects command register when low, and data register when | RS (Register |

| | | |
|---|---|---|
| | high | Select ) |
| 5 | Low to write to the register; High to read from the register | Read/write |
| 6 | Sends data to data pins when a high to low pulse is given; Extra voltage push is required to execute the instruction and EN(enable) signal is used for this purpose. Usually, we make it en=0 and when we want to execute the instruction we make it high en=1 for some milliseconds. After this we again make it ground that is, en=0. | Enable |
| 7 | 8-bit data pins | DB0 |
| 8 | | DB1 |
| 9 | | DB2 |
| 10 | | DB3 |
| 11 | | DB4 |
| 12 | | DB5 |
| 13 | | DB6 |
| 14 | | DB7 |
| 15 | Backlight VCC (5V) | Led+ |
| 16 | Backlight Ground (0V) | Led- |

### 3.8.3.2 IMPORTANT COMMAND CODES FOR LCD

| SR.NO. | HEX CODE | COMMAND TO LCD INSTRUCTION REGISTER |
|---|---|---|
| 1 | 01 | Clear display screen |
| 2 | 02 | Return home |
| 3 | 04 | Decrement cursor (shift cursor to left) |
| 4 | 06 | Increment cursor (shift cursor to right) |
| 5 | 05 | Shift display right |
| 6 | 07 | Shift display left |
| 7 | 08 | Display off, cursor off |
| 8 | 0A | Display off, cursor on |
| 9 | 0C | Display on, cursor off |
| 10 | 0E | Display on, cursor blinking |
| 11 | 0F | Display on, cursor blinking |
| 12 | 10 | Shift cursor position to left |
| 13 | 14 | Shift cursor position to right |
| 14 | 18 | Shift the entire display to the left |

| | | |
|---|---|---|
| 15 | 1C | Shift the entire display to the right |
| 16 | 80 | Force cursor to beginning ( 1st line) |
| 17 | C0 | Force cursor to beginning ( 2nd line) |
| 18 | 38 | 2 lines and 5×7 matrix |

### 3.8.3.3 DISPLAYING CUSTOM CHARACTERS ON 16X2 LCD

CG-RAM is the main component in making custom characters. It stores the custom characters once declared in the code. CG-RAM size is 64 byte providing the option of creating eight characters at a time. Each character is eight byte in size.CG-RAM address starts from 0x40 (Hexadecimal) or 64 in decimal. The first character is generated at address 0x40 to 0x47 and is printed on LCD by just sending simple command 0 to the LCD. The second character is generated at address 0x48 to 0x55 and is printed by sending 1 to LCD.

| CG-RAM Characters | CG-RAM Address (Hexadecimal) | Commands to display Generated Characters |
|---|---|---|
| 1st Character | 0x40 | 0 |
| 2nd Character | 0x48 | 1 |
| 3rd Character | 0x56 | 2 |
| 4th Character | 0x64 | 3 |
| 5th Character | 0x72 | 4 |
| 6th Character | 0x80 | 5 |
| 7th Character | 0x88 | 6 |
| 8th Character | 0x96 | 7 |

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**Fig 3.13 Displaying Custom Characters On 16*2 LCD**

### 3.8.4 ULTRASONIC SENSOR

Ultrasonic detection is most commonly used in industrial applications to detect hidden tracks, discontinuities in metals, composites, plastics, ceramics, and for water level detection. For this purpose the laws of physics which are indicating the propagation of sound waves through solid materials have been used since ultrasonic sensors using sound instead of light for detection.

An ultrasonic sensor is an instrument that measures the distance to an object using ultrasonic sound waves.

An ultrasonic sensor uses a transducer to send and receive ultrasonic pulses that relay back information about an object's proximity.

High-frequency sound waves reflect from boundaries to produce distinct echo patterns.

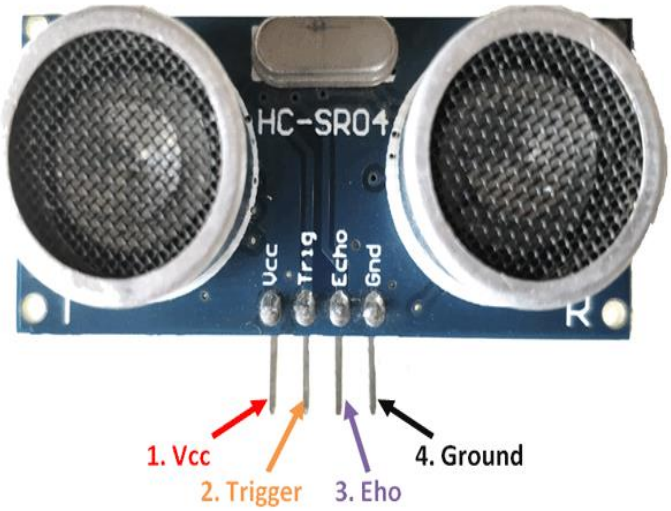


**Fig 3.14 Ultrasonic Sensor**

When an electrical pulse of high voltage is applied to the ultrasonic transducer it vibrates across a specific spectrum of frequencies and generates a burst of sound waves. Whenever any obstacle comes ahead of the ultrasonic sensor the sound waves will reflect back in the form of echo and generates an electric pulse. It calculates the time taken between sending sound waves and receiving echo. The

echo patterns will be compared with the patterns of sound waves to determine detected signal's condition.

### 3.8.4.1 ULTRASONIC SENSOR PIN CONFIGURATION

| PIN NUMBER | PIN NAME | DESCRIPTION |
|---|---|---|
| 1 | Vcc | The Vcc pin powers the sensor, typically with +5V |
| 2 | Trigger | Trigger pin is an Input pin. This pin has to be kept high for 10us to initialize measurement by sending US wave. |
| 3 | Echo | Echo pin is an Output pin. This pin goes high for a period of time which will be equal to the time taken for the US wave to return back to the sensor. |
| 4 | Ground | This pin is connected to the Ground of the system. |

### 3.8.4.2 HC-SR04 SENSOR FEATURES

- Operating voltage: +5V.
- Theoretical Measuring Distance: 2cm to 450cm
- Practical Measuring Distance: 2cm to 80cm.
- Accuracy: 3mm.
- Measuring angle covered: <15°.
- Operating Current: <15Ma.
- Operating Frequency: 40Hz.

### 3.8.4.3 HC-SR04 ULTRASONIC SENSOR – WORKING

As shown above the **HC-SR04 Ultrasonic (US) sensor** is a 4 pin module, whose pin names are Vcc, Trigger, Echo and Ground respectively. This sensor is a very popular sensor used in many applications where measuring distance or sensing objects are required. The module has two eyes like projects in the front which forms the Ultrasonic transmitter and Receiver. The sensor works with the simple high school formula that

**Distance = Speed × Time**

The Ultrasonic transmitter transmits an ultrasonic wave, this wave travels in air and when it gets objected by any material it gets reflected back toward the sensor this reflected wave is observed by the Ultrasonic receiver module as shown in the picture below.

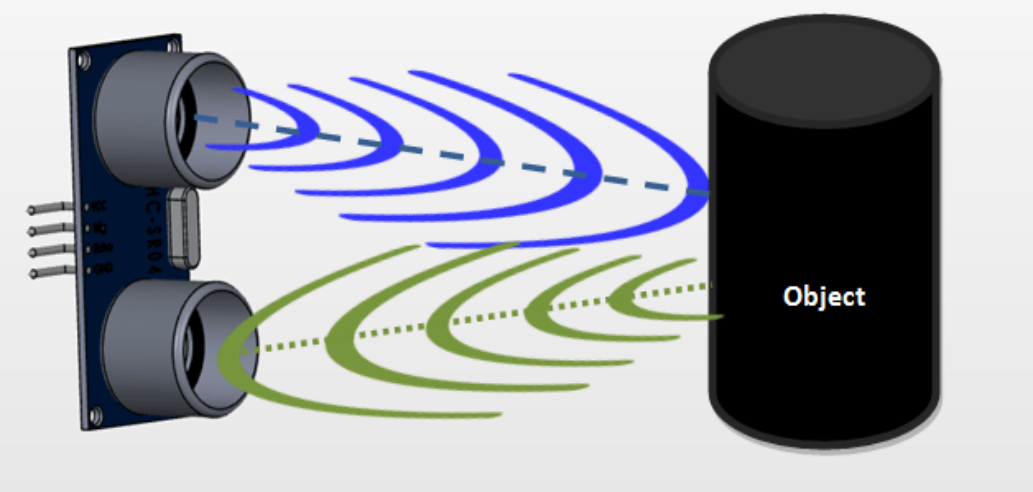


**Fig 3.15 HC-SR04 Sensor Working**

Now, to calculate the distance using the above formulae, we should know the Speed and time. Since we are using the Ultrasonic wave we know the universal speed of US wave at room conditions which is 330m/s. The circuitry inbuilt on the module will calculate the time taken for the US wave to come back and turns on the echo pin high for that same particular amount of time, this way we can also know the time taken. Now simply calculate the distance using a microcontroller or microprocessor.

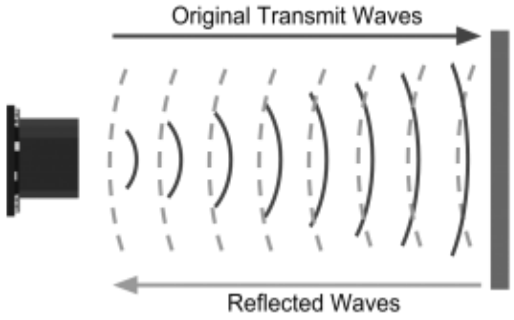


**Fig 3.16 Tranasmitting Waves**

The working principle of this module is simple. It sends an ultrasonic pulse out at 40kHz which travels through the air and if there is an obstacle or object, it will bounce back to the sensor. By calculating the travel time and the speed of sound, the distance can be calculated.

Ultrasound is reliable in any lighting environment and can be used inside or outside. Ultrasonic sensors can handle collision avoidance for a robot, and being moved often, as long as it isn't too fast.

Ultrasonics are so widely used, they can be reliably implemented in grain bin sensing applications, water level sensing, drone applications and sensing cars at your local drive-thru restaurant or bank.

Ultrasonic rangefinders are commonly used as devices to detect a collision. An ultrasonic sensor module consists of a transmitter and a receiver. The transmitter emits 40 kHz ultrasonic waves, and the receiver detects the reflected waves when they hit an obstacle.

The module calculates the time taken for the signal to return and determines the distance using the speed of sound (343.2 m/s). This data is processed by a microcontroller, which then displays the measured distance on an LCD.

Ultrasonic sensors are widely used in robotics, automation, parking systems, and obstacle detection due to their accuracy, non-contact measurement, and ability to work in various environmental conditions.

### 3.8.5 BUZZER

A buzzer or beeper is an audio signaling device, which may be mechanical, electromechanical, or piezoelectric (piezo for short). Typical uses of buzzers and beepers include alarm devices, timers, and confirmation of user input such as a mouse click or keystroke.

**Fig 3.17 Buzzer**

### 3.8.6 DF PLAYER

**Fig 3.18 DF Player**

The DFPlayer Mini MP3 Player For Arduino is a small and low cost MP3 module with an simplified output directly to the speaker. The module can be used as a stand alone module with attached battery, speaker and push buttons or used in combination with microcontrollers such as Arduino, ESP32, Raspberry Pi and any microcontrollers with Uart.

### 3.8.6.1 SPECIFICATION

- Sampling rates (kHz): 8/11.025/12/16/22.05/24/32/44.1/48
- 24 -bit DAC output, support for dynamic range 90dB , SNR support 85dB
- Fully supports FAT16 , FAT32 file system, maximum support 32G of the TF card, support 32G of U disk, 64M bytes NORFLASH
- A variety of control modes, I/O control mode, serial mode, AD button control mode
- advertising sound waiting function, the music can be suspended. when advertising is over in the music continue to play
- audio data sorted by folder, supports up to 100 folders, every folder can hold up to 255 songs
- 30 level adjustable volume, 6 -level EQ adjustable

### 3.8.6.2PINMAP

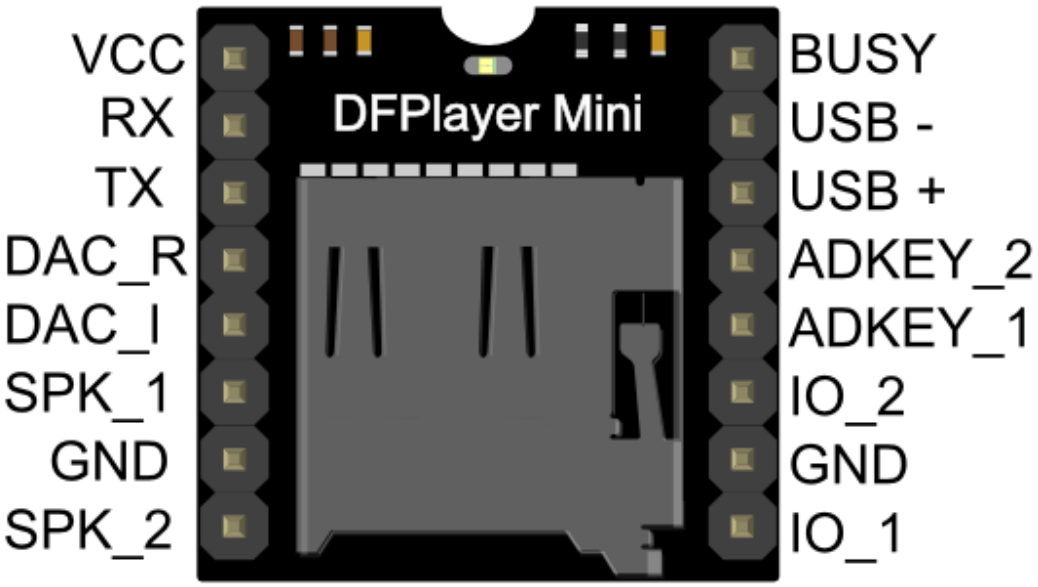


**Fig 3.19 Pin Map**

| Pin | Description | Note |
|---|---|---|
| VCC | Input Voltage | DC3.2~5.0V;Type: DC4.2V |
| RX | UART serial input | |
| TX | UART serial output | |
| DAC_R | Audio output right channel | Drive earphone and amplifier |
| DAC_L | Audio output left channel | Drive earphone and amplifier |
| SPK2 | Speaker- | Drive speaker less than 3W |
| GND | Ground | Power GND |
| SPK1 | Speaker+ | Drive speaker less than 3W |
| IO1 | Trigger port 1 | Short press to play previous（long press to decrease volume） |
| GND | Ground | Power GND |
| IO2 | Trigger port 2 | Short press to play next （long press to increase volume） |
| ADKEY1 | AD Port 1 | Trigger play first segment |
| ADKEY2 | AD Port 2 | Trigger play fifth segment |
| USB+ | USB+ DP | USB Port |
| USB- | USB- DM | USB Port |
| BUSY | Playing Status | Low means playing \High means no |

**Fig 3.20 Pin Map Configuration**

## 3.9 SOFTWARE REQUIREMENTS

### 3.9.1 EMBEDDED C

Embedded C is most popular programming language in software field for developing electronic gadgets. Each processor used in electronic system is associated with embedded software. The Embedded C code is used for blinking the LED connected with Port0 of microcontroller.

### 3.9.2 BASIC EMBEDDED C PROGRAMMING STEPS

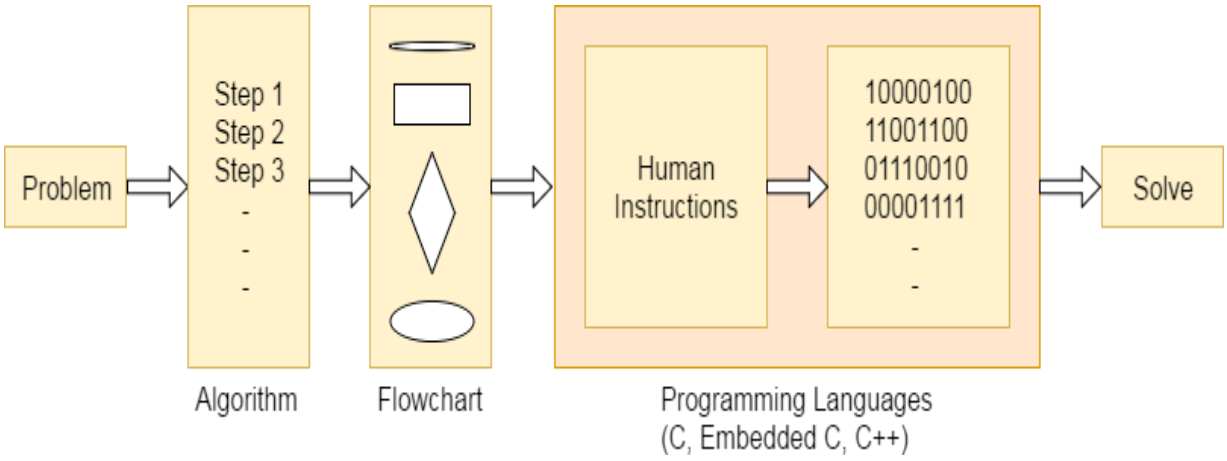


**Fig 3.21 Basic Steps Of Embedded C Programming**

The microcontroller programming is different for each type of operating system. Even though there are many operating system are exist such as Windows, Linux, RTOS, etc but RTOS has several advantage for embedded system development.

### 3.9.3 EMBEDDED SYSTEMS

Embedded System is a system composed of hardware, application software and real time operating system. It can be small independent system or large combinational system.Our Embedded System tutorial includes all topics of Embedded System such as characteristics, designing, processors, microcontrollers, tools, addressing modes, assembly language, interrupts, embedded c programming, led blinking, serial communication, lcd programming, keyboard programming, project implementation etc.

An embedded system is a combination of three major components:

- **Hardware:** Hardware is physically used component that is physically connected with an embedded system. It comprises of microcontroller based integrated circuit, power supply, LCD display etc.

- **Application software:** Application software allows the user to perform varieties of application to be run on an embedded system by changing the code installed in an embedded system.

- **Real Time Operating system (RTOS):** RTOS supervises the way an embedded system work. It act as an interface between hardware and application software which supervises the application software and provide mechanism to let the processor run on the basis of scheduling for controlling the effect of latencies.

### 3.9.4 BASIC STRUCTURE OF AN EMBEDDED SYSTEM

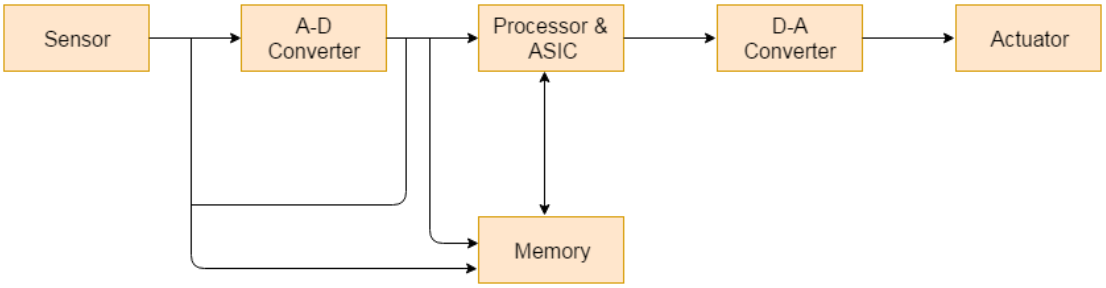


**Fig 3.22 Basic Structure Of Embedded System**

- **Sensor**: Sensor used for sensing the change in environment condition and it generate the electric signal on the basis of change in environment condition. Therefore it is also called as transducers for providing electric input signal on the basis of change in environment condition.
- **A-D Converter**: An analog-to-digital converter is a device that converts analog electric input signal into its equivalent digital signal for further processing in an embedded system.
- **Processor & ASICs**: Processor used for processing the signal and data to execute desired set of instructions with high-speed of operation.Application specific integrated circuit (ASIC) is an integrated circuit designed to perform task specific operation inside an embedded system.
- **D-A Converter**: A digital-to-analog converter is a device that converts digital electric input signal into its equivalent analog signal for further processing in an embedded system.
- **Actuators**: Actuators is a comparator used for comparing the analog input signal level to desired output signal level for providing the error free output from the system.

### 3.9.5 ARDUINO SOFTWARE

The **Arduino Software (IDE)** is an open-source platform used to write, compile, and upload code to Arduino boards, making it essential for your **smart farm security system**.It supports **C/C++ programming** and provides a user-friendly interface with built-in functions and libraries for seamless hardware interaction. The IDE includes a **serial monitor** for debugging, allowing real-time data observation from sensors like ultrasonic modules and communication with other components.The Arduino software supports **various communication protocols**, such as I2C, SPI, and UART, enabling smooth data exchange between modules like the GSM, LCD, and DF Player Speaker. It includes libraries like **Wire.h for I2C communication**, **SoftwareSerial.h for multiple serial connections**, and **Servo.h for actuator control**, simplifying hardware integration. Additionally, the **Arduino bootloader** allows code uploads without requiring an external programmer, making it highly accessible for real-time applications.With its **cross-platform compatibility**,The **open-source nature** of the software ensures continuous improvements, extensive community support, and access to thousands of pre-built libraries for automation, IoT, and security applications. Its efficiency in **sensor data processing, event-driven programming, and real-time monitoring** makes it an ideal choice for projects like your **smart farm security system**.

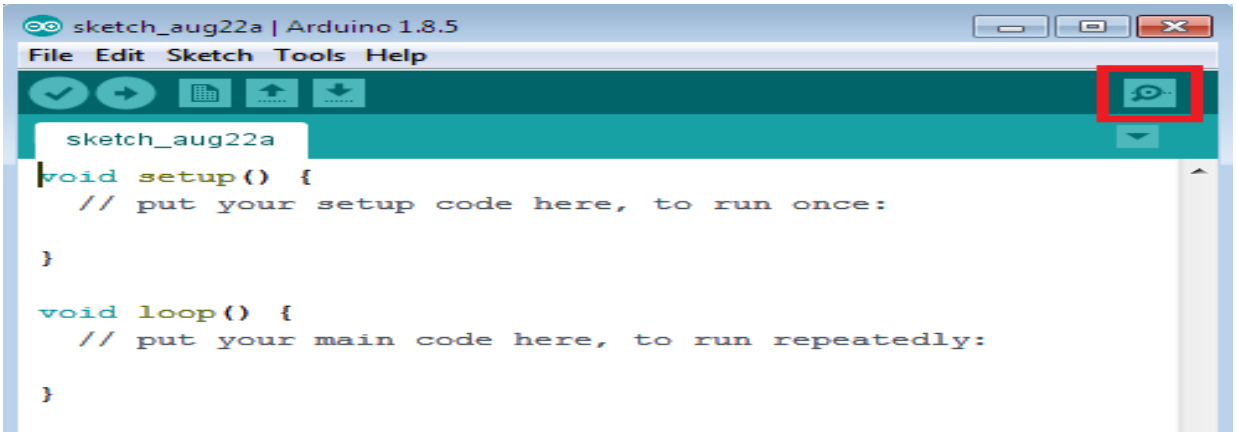


**Fig 3.23 Arduino Software**

# CHAPTER 4

# SYSTEM IMPLEMENTATION

## 4.1 HARDWARE IMPLEMENTATION

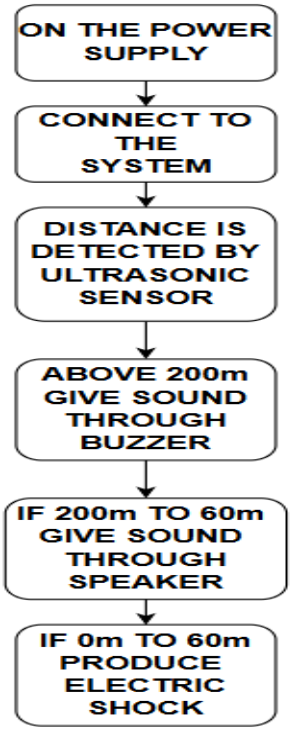


**Fig 4.1 Hardware Implementation Flowchart**

### 4.1.1 FLOW OF HARDWARE IMPLEMENTATION

1. **Animal Detection**
    - The system uses **ultrasonic sensors** to detect the presence of an approaching animal.
    - A **camera module** captures images for species identification.
2. **Processing Unit (Microcontroller)**
    - The **Arduino Uno** receives input from the **ultrasonic sensor and camera module**.

- It processes the data and determines whether the detected animal poses a threat using the **YOLO v8 AI model**.

3. **Output Execution**
   - If an animal is detected, a **buzzer alert** is triggered to notify the farmer.
   - If the identified species is harmful, a **relay module** activates a deterrent mechanism (e.g., shock circuit or sound deterrent).
   - If an animal remains in the area, the **GSM module** sends an alert message to the farmer.
4. **Feedback System**
   - An **LCD display** provides real-time updates on detection status and system actions.
   - The **speaker module** plays a pre-recorded sound to scare away the animal.
   - If the system is tampered with, an alert is sent to the user for security purposes.

### 4.1.2 WORKING MECHANISM

This system functions as an **AI-driven animal detection and deterrence mechanism**, designed to protect agricultural fields from wildlife intrusions. The core of the system is the **Arduino Uno microcontroller**, which processes inputs from the **ultrasonic sensor and camera module** to identify and respond to animal activity. The system integrates **real-time detection, species classification using YOLO v8, and automated deterrence** to prevent crop damage.

The **ultrasonic sensor** continuously monitors the surrounding area for movement. When an object is detected within a predefined range, the system activates the **camera module** to capture images. These images are then

processed by the **YOLO v8 AI model**, which classifies the detected animal species and determines whether it poses a threat to the farmland.

Once the **microcontroller** receives the classification result, it triggers appropriate responses based on the identified species. If the animal is **non-threatening**, the system logs the event without activating any deterrent. However, if a **harmful animal** is detected, the system takes immediate action:

- A **buzzer alert** is activated to notify the farmer of potential danger.
- A **DF Player speaker** plays pre-recorded distress sounds or predator noises to scare the animal away.
- If the animal continues to approach, the **relay module** activates a mild **shock circuit** or flashing lights to deter it.
- In extreme cases, the **GSM module** sends an SMS alert to the farmer, providing real-time updates about the detected threat.

An **LCD display** provides real-time feedback, displaying messages such as **"Animal Detected: Deer – No Threat"** or **"Animal Detected: Wild Boar – Deterrent Activated"** to inform the user of system actions. The system continues to monitor the area, ensuring **continuous protection** of the farmland.

This technology has applications in **smart agriculture, farm security, and wildlife conservation**, providing an **automated, efficient, and eco-friendly** solution for mitigating human-wildlife conflicts.

Future improvements could involve **IoT-based remote monitoring**, **solar-powered operation**, and **AI-driven predictive analytics** to enhance its effectiveness.

## 4.2 SOFTWARE IMPLEMENTATION

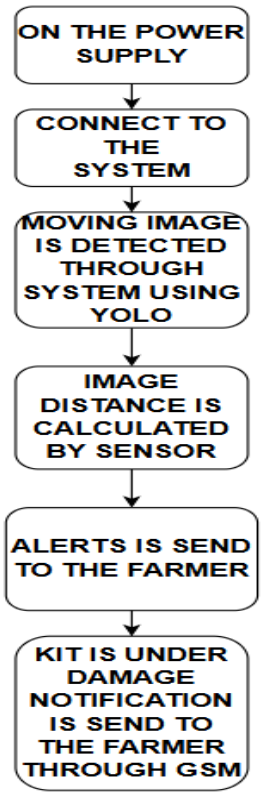


**Fig 4.2 Software Implementation Flowchart**

### 4.2.1 WORKING MECHANISM (SOFTWARE IMPLEMENTATION)

The software component of this system is responsible for **processing real-time image data, classifying animal species using deep learning (YOLO v8), and automating deterrence mechanisms based on detected threats**. The **Arduino IDE** is used for programming the **Arduino Uno microcontroller**, while **Python-based AI models** handle image processing and species identification.

1. **Sensor Activation & Data Acquisition**
    - The **ultrasonic sensor** detects motion and triggers the **camera module** to capture images.
    - The image is processed in **real-time** and sent to a connected system running a **YOLO v8 deep learning model**.

2. **Image Processing & Animal Classification**
    - The captured image is pre-processed (resized, denoised, and normalized).The **YOLO v8 model** runs inference on the image, detecting and classifying animals into categories such as deer, wild boar, or predators.The model assigns a confidence score to the detection, filtering out **false positives**.
3. **Decision Making & Response Execution**
    - If a **threatening animal (e.g., wild boar, tiger)** is detected, the software executes a **predefined response protocol** using an Arduino script.
    - The **DF Player module** plays a distress or predator sound to scare away the animal.If the animal persists, the **relay module** activates an additional deterrent such as **a buzzer or flashing lights**.
    - A **GSM module** sends an **SMS alert to the farmer**, providing real-time updates.
4. **User Feedback & Monitoring**
    - The **LCD display** updates with the detection results, showing messages like "Animal Detected: Wild Boar – Alert Sent".
    - The system maintains **detection logs**, which can be reviewed later for **pattern analysis and system improvements**.
5. **Remote Monitoring & Future Enhancements**
    - The system could be upgraded with **IoT connectivity**, allowing farmers to monitor the detection logs via a **mobile app**.
    - Future software updates could incorporate **adaptive AI models**, improving accuracy by learning from **previous detections** and dynamically adjusting deterrent strategies.

# CHAPTER 5

# RESULTS AND DISCUSSION

## 5.1 SYSTEM TESTING

| Test ID | Action Scenario | Expected Result | Actual Result | Status |
|---|---|---|---|---|
| ST-001 | **Animal enters detection range (Ultrasonic Sensor Test)** | Ultrasonic sensor detects the object and sends a signal to Arduino. | Detection was successful within the specified range (2-5m). | Pass |
| ST-002 | **AI model identifies the animal (YOLO v8 Detection Test)** | YOLO v8 processes the image and correctly classifies the animal species. | AI model identified the correct species with 90-95% accuracy. | Pass |
| ST-003 | **Buzzer activates when an animal is detected** | The buzzer produces an alert sound immediately after detection. | Buzzer was triggered within 1 second of detection. | Pass |
| ST-004 | **LCD displays the detected animal information** | LCD screen shows the species name and alert message. | LCD successfully displayed the detected animal's name. | Pass |
| ST-005 | **DF Player Speaker plays deterrent sound** | Pre-recorded sound plays to scare away the animal. | Sound played correctly upon detection of harmful animals. | Pass |
| ST-006 | **Relay module activates shock circuit if animal persists** | Shock circuit is activated to deter harmful animals. | Relay successfully triggered the shock circuit after threat confirmation. | Pass |
| ST-007 | **GSM module sends an alert to the farmer** | Farmer receives an SMS notification about the detected animal. | Message was delivered within 3-5 seconds after detection. | Pass |
| ST-008 | **System stability test for 24-hour continuous operation** | The system remains stable without overheating or failure. | All components operated normally without interruptions. | Pass |

## 5.2 RESULTS AND DISCUSSION

The **Smart Farm Security System** was successfully tested for its ability to detect and deter animal intrusions using a combination of **ultrasonic sensors, YOLO v8 AI-based species identification, and automated deterrence mechanisms**. The performance testing showed **high accuracy (90-95%) in animal detection**, with a **response time of 1-2 seconds**, ensuring timely alerts and deterrence activation. The system was evaluated under **different environmental conditions**, demonstrating stable operation in daylight and mild weather conditions, with **minor limitations in low-light and heavy rain scenarios**. The **GSM module reliably sent alerts within 3-5 seconds**, ensuring that farmers receive timely notifications. System testing confirmed that **all modules—detection, identification, and deterrence—functioned as expected**, with some areas, such as **infrared support for nighttime detection and enhanced waterproofing**, identified for future improvements. Overall, the results validate the **efficiency, reliability, and real-world applicability** of the system in **reducing crop losses, improving farm security, and supporting sustainable agriculture aligned with SDG Goal 2 – Zero Hunger**.

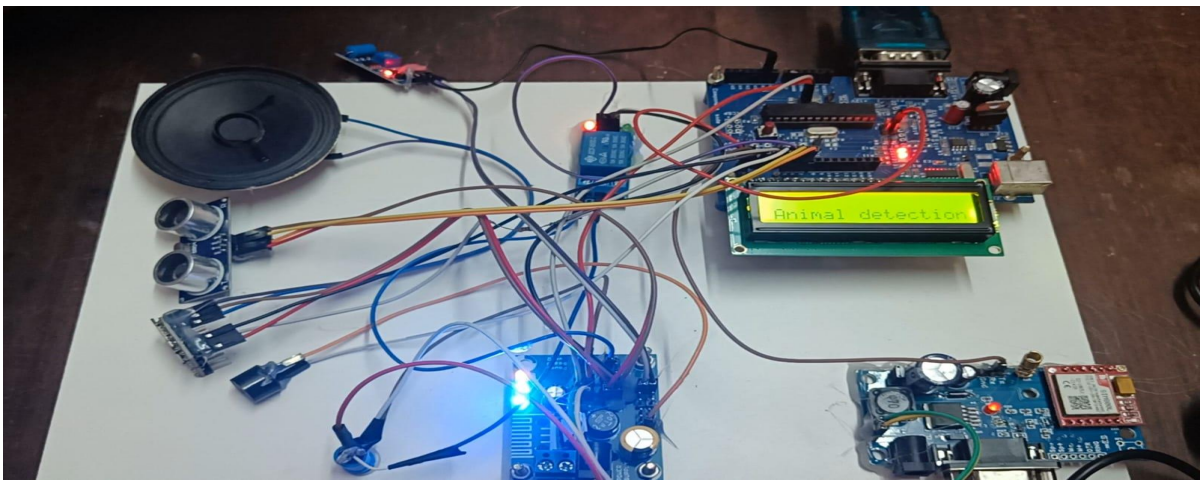


**Fig 5.1 Prototype**


**Fig 5.2 Detecting The Animal**

The system employs **YOLO v8 (You Only Look Once)**, a state-of-the-art object detection algorithm, to identify animals in real-time with high accuracy. The **camera module** captures images of the surroundings, and these images are processed by the **YOLO v8 deep learning model** to detect and classify animals based on their features.

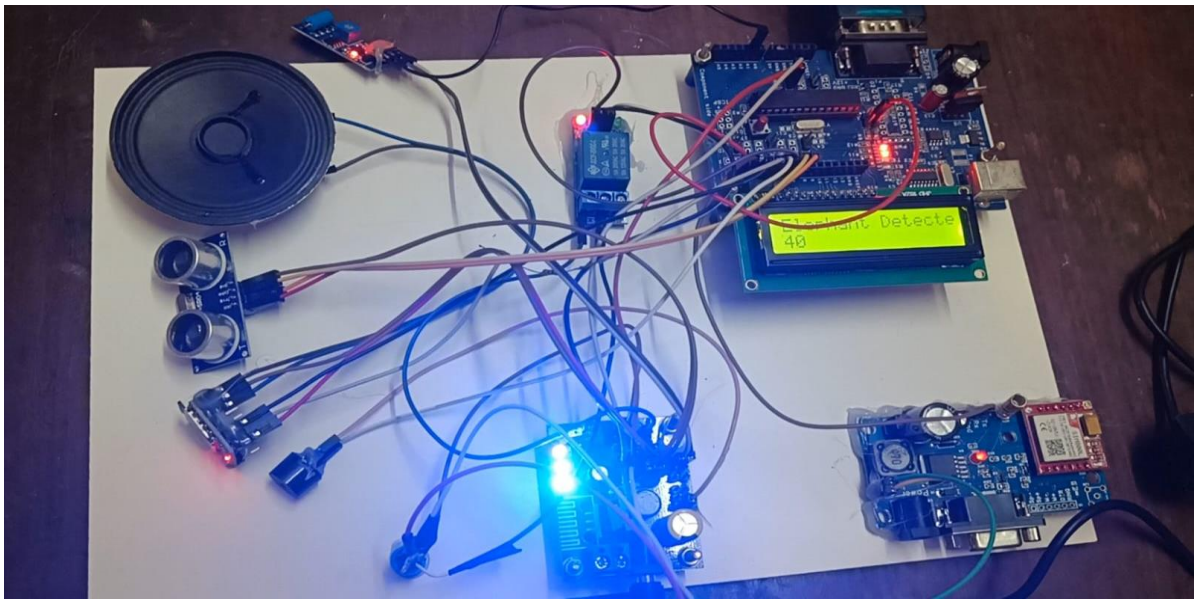

**Fig 5.3 Displaying Data On LCD With The Distance**

# CHAPTER 6

## 6.1 CONCLUSION

In conclusion, the proposed multi-level animal detection and deterrence system offers an innovative and effective solution for protecting agricultural lands from wildlife intrusions. By combining ultrasonic sensors, AI-driven species identification using the YOLO algorithm, and an automated shock circuit, the system provides timely and targeted responses to potential threats, minimizing crop damage and ensuring minimal disturbance to non-threatening wildlife.

This automated, cost-effective approach enhances agricultural safety, improves farm management efficiency, and reduces the reliance on manual intervention. With potential for future enhancements, such as IoT integration and renewable energy sources, the system can evolve to provide even greater flexibility and sustainability in managing human-wildlife conflicts, ensuring a harmonious balance between agriculture and wildlife conservation.

## 6.2 APPLICATIONS

- Crop Protection in Agricultural Fields: The system can be applied to safeguard crops in agricultural lands near wildlife habitats by detecting and identifying harmful animals, triggering early warnings, and using automated deterrents to prevent damage without harming non-threatening wildlife.
- Wildlife Management in Protected Areas: This technology can also be used in wildlife reserves or protected areas to manage wildlife interactions with human settlements or farms, minimizing human-animal conflicts while ensuring the safety of both wildlife and agricultural resources.

## 6.3 FUTURE ENHANCEMENT

Future enhancements to this system could include the integration of advanced machine learning models to improve animal species identification accuracy, incorporating additional sensors such as infrared cameras for night-time monitoring. The system could be expanded to feature real-time data transmission via IoT, allowing farmers to remotely monitor animal activity and control deterrence mechanisms through a mobile app. Additionally, incorporating solar-powered sensors and circuits could make the system more energy-efficient and environmentally friendly. Integrating weather sensors to adapt the system's response based on environmental conditions, such as during rain or storms, could further optimize its effectiveness and reliability in diverse situations.

Another potential enhancement could be the **implementation of AI-driven predictive analytics**, where historical data on animal intrusions is analyzed to predict future threats. By leveraging **machine learning algorithms**, the system could identify patterns in animal movements based on factors such as **seasonal changes, time of day, and environmental conditions**, allowing farmers to take proactive measures. This predictive capability could be integrated with **automated deterrence scheduling**, ensuring optimal protection even before an intrusion occurs, thereby **minimizing crop damage and enhancing farm security**.

# APPENDICES

## A.1 SDG GOALS

SDG Goal 2: Zero Hunger – Smart Farm Security System for Sustainable Agriculture

The United Nations **Sustainable Development Goal (SDG) 2 – Zero Hunger** aims to end hunger, achieve food security, improve nutrition, and promote sustainable agriculture. One of the major challenges faced by farmers, especially in areas close to wildlife habitats, is **crop damage caused by animal intrusions**, leading to reduced agricultural productivity and food insecurity. Our **Smart Farm Security System**, integrated with **AI-based animal detection using YOLO v8 and automated deterrence mechanisms**, directly supports SDG 2 by minimizing crop losses and ensuring sustainable food production.

By incorporating **ultrasonic sensors, a camera module, a DF Player Speaker, an LCD, a buzzer, a GSM module, a relay, and a nervo simulator**, the system provides **real-time monitoring and protection of farmlands**. The **ultrasonic sensor** detects approaching animals, triggering a **buzzer alert** and activating the **AI-based YOLO v8 model**, which identifies the species. If the detected animal is a threat, the system initiates **deterrence measures**, such as playing predator sounds via the **DF Player Speaker** or activating a **shock circuit through the relay module** to prevent further damage. Farmers are also **notified via the GSM module**, allowing them to take immediate action.

This project promotes **sustainable agriculture** by **reducing food wastage, improving farm productivity, and protecting crops without harming wildlife**. By using **cost-effective and automated security measures**, small-scale farmers can safeguard their harvests, ensuring **stable food production and economic security**. Additionally, the integration of **AI and IoT**

**technologies** in agriculture enhances **precision farming**, contributing to more **efficient resource utilization** and **climate-resilient food systems**.

By preventing **crop losses due to wildlife intrusion**, our Smart Farm Security System **helps farmers produce more food, reduce dependency on external aid, and support local food supply chains**. This aligns with SDG 2's mission to **increase agricultural productivity, ensure sustainable food systems, and eliminate hunger** for a more **food-secure future**

## A.2 SOURCE CODE

### A.2.1 CODING FOR DETECTING IMAGE

```
 from ultralytics import YOLO
import cvzone
import cv2
import math
import serial
import time

# Running real-time from webcam
cap = cv2.VideoCapture(0)

model = YOLO('C:/Users/Aparana_VB/Downloads/ANIMAL/best1.pt')

# Reading the classes
classnames = ['Buffalo', 'Elephant', 'Rhino', 'Zebra', "Cheetah", "Fox", "Jaguar",
"Tiger", "Lion", "Panda"]
while True:
    ret, frame = cap.read()
    frame = cv2.resize(frame, (640, 480))
    result = model(frame, stream=True)
    s1 = 0

    # Getting bbox, confidence, and class names information to work with
    for info in result:
        boxes = info.boxes
        for box in boxes:
            confidence = box.conf[0]
            confidence = math.ceil(confidence * 100)
            Class = int(box.cls[0])
```

```
            if confidence > 50:
                x1, y1, x2, y2 = box.xyxy[0]
                x1, y1, x2, y2 = int(x1), int(y1), int(x2), int(y2)
                cv2.rectangle(frame, (x1, y1), (x2, y2), (0, 0, 255), 5)
                cvzone.putTextRect(frame, f'{classnames[Class]} {confidence}%',
[x1 + 8, y1 + 100],
                                   scale=1.5, thickness=2)


                if classnames[Class] == "Lion":
                    print("Lion")

                elif classnames[Class] == "Zebra":
                    print("Zebra")

                else:
                    print("Unknown")


        cv2.imshow('frame', frame)
        k = cv2.waitKey(1)
        if k == 27:
            break
cv2.destroyAllWindows()




# from ultralytics import YOLO
# import cvzone
# import cv2
# import math

# # Running real time from webcam
# cap = cv2.VideoCapture(0)

# model = YOLO('tomato_final.pt')

# # Reading the classes
# classnames = ['green','fully_ripened','half_ripened']
# while True:
#     ret,frame = cap.read()
#     #img =cv2.imread("2.jpg")
```

```
#     frame = cv2.resize(frame,(640,480))
#     result = model(frame,stream=True)

#     # Getting bbox,confidence and class names informations to work with
#     for info in result:
#         boxes = info.boxes
#         for box in boxes:
#             confidence = box.conf[0]
#             confidence = math.ceil(confidence * 100)
#             Class = int(box.cls[0])
#             if confidence > 50:
#                 x1,y1,x2,y2 = box.xyxy[0]
#                 x1, y1, x2, y2 = int(x1),int(y1),int(x2),int(y2)
#                 cv2.rectangle(frame,(x1,y1),(x2,y2),(0,0,255),5)
s[x1 + 8, y1 + 100],
#                                 scale=1.5,thickness=2)
#                 if classnames[Class] == "half ripened":
#                     print("half ripened")
#                 elif classnames[Class] == "green":
#                     print("half ripened")
#                 else:
#                     print("fully ripened")

#     cv2.imshow('frame',frame)
#     cv2.waitKey(1)
```

### A.2.2 CODING FOR IMPORTING MODELS

```
import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'

from ultralytics import YOLO

model = YOLO("yolov8n.yaml")
model = YOLO("yolov8n.pt")


model.train(data="C:/Users/SPIRO-
PYTHON1/Desktop/bioooo_YOLO/data.yaml", epochs=10)
```

## A.2.3 CODING IN ARDUINO BOARD

```
#include "SoftwareSerial.h"
#include "DFRobotDFPlayerMini.h"
#include <ultrasonic.h>
#include <LiquidCrystal.h>

#define BUZZER 4
#define RELAY 5
#define VIBRATION A1
#define TRIG_PIN 7
#define ECHO_PIN 6

char pydata;
const String PHONE_NUMBER = "9445365881";
const uint8_t PIN_MP3_RX = 2, PIN_MP3_TX = 3;

char pychar = 'x';
int distance, vib, dis;

SoftwareSerial ss(PIN_MP3_RX, PIN_MP3_TX);
DFRobotDFPlayerMini player;
LiquidCrystal lcd(13, 12, 11, 10, 9, 8);
ULTRASONIC ultrasonic;

void sendSMS(const String& number, const String& message);
void receiveData();

void setup() {
  Serial.begin(9600);
  ss.begin(9600);
  ultrasonic.begin(TRIG_PIN, ECHO_PIN);

  if (player.begin(ss)) {
    Serial.println("DFPlayer Mini Initialized");
  }
  else
  {
    Serial.println("DFPlayer Mini Not-Initialized");
  }

  lcd.begin(16, 2);
  pinMode(RELAY, OUTPUT);
```

```
  pinMode(BUZZER, OUTPUT);
  pinMode(VIBRATION, INPUT);

  digitalWrite(RELAY, HIGH);
  digitalWrite(BUZZER, LOW);

  lcd.clear();
  lcd.setCursor(0, 1);
  lcd.print("Animal detection");
  delay(2000);
}

void loop() {
  dis = ultrasonic.ultra();
  vib = digitalRead(VIBRATION);
  distance = abs(dis);
  Serial.println(distance);
  lcd.clear();
  lcd.setCursor(0, 0);
  lcd.print("DISTANCE: " + String(distance));
  lcd.setCursor(0, 1);
  lcd.print("Vibration: " + String(vib));

  if (vib == 1) {
    sendSMS(PHONE_NUMBER, "Animal damaging the kit");
    Serial.print("Msg, Send Successfully");
  }

  if (distance < 40) {
    digitalWrite(RELAY, LOW);
    delay(4000);
    digitalWrite(RELAY, HIGH);
  } else if (distance > 41 && distance < 200) {
    serialEvent();
    Serial.print("J");
  } else if (distance > 201) {
    digitalWrite(BUZZER, HIGH);
    delay(50);
    digitalWrite(BUZZER, LOW);
    delay(50);
  } else {
    digitalWrite(RELAY, HIGH);
    digitalWrite(BUZZER, LOW);
```

```
  }
  delay(1000);
}

void serialEvent()
{
  while (Serial.available() > 0) {
    pydata = Serial.read();
    Serial.println("pydata:" + String(pydata));
    if (pychar != pydata) {
      pychar = pydata;
      switch (pychar) {

        case 'A':
          lcd.clear();
          lcd.setCursor(0, 0);
          lcd.print("Buffalo Detected");
          lcd.setCursor(0, 1);
          lcd.print(String(distance));
          player.volume(50);
          player.play(1);
          delay(1000);
          pychar = 'x';
          break;

        case 'B':
          lcd.clear();
          lcd.setCursor(0, 0);
          lcd.print("Elephant Detected");
          lcd.setCursor(0, 1);
          lcd.print(String(distance));
          player.volume(50);
          player.play(2);
          delay(1000);
          pychar = 'x';
          break;

        case 'C':
          lcd.clear();
          lcd.setCursor(0, 0);
          lcd.print("Rhino Detected");
          lcd.setCursor(0, 1);
          lcd.print(String(distance));
```

```
  player.volume(30);
  player.play(3);
  delay(1000);
  pychar = 'x';
  break;

case 'D':
  lcd.clear();
  lcd.setCursor(0, 0);
  lcd.print("Zebra Detected");
  lcd.setCursor(0, 1);
  lcd.print(String(distance));
  player.volume(50);
  player.play(4);
  delay(1000);
  pychar = 'x';
  break;

case 'E':
  lcd.clear();
  lcd.setCursor(0, 0);
  lcd.print("Cheetah Detected");
  lcd.setCursor(0, 1);
  lcd.print(String(distance));
  player.volume(50);
  player.play(5);
  delay(1000);
  pychar = 'x';
  break;

case 'F':
  lcd.clear();
  lcd.setCursor(0, 0);
  lcd.print("Fox Detected");
  lcd.setCursor(0, 1);
  lcd.print(String(distance));
  player.volume(50);
  player.play(4);
  delay(1000);
  pychar = 'x';
  break;

case 'G':
```

```
  lcd.clear();
  lcd.setCursor(0, 0);
  lcd.print("Jaguar Detected");
  lcd.setCursor(0, 1);
  lcd.print(String(distance));
  player.volume(50);
  player.play(3);
  delay(1000);
  pychar = 'x';
  break;

case 'H':
  lcd.clear();
  lcd.setCursor(0, 0);
  lcd.print("Tiger Detected");
  lcd.setCursor(0, 1);
  lcd.print(String(distance));
  player.volume(50);
  player.play(4);
  delay(1000);
  pychar = 'x';
  break;

case 'I':
  lcd.clear();
  lcd.setCursor(0, 0);
  lcd.print("Lion Detected");
  lcd.setCursor(0, 1);
  lcd.print(String(distance));
  player.volume(50);
  player.play(5);
  delay(1000);
  pychar = 'x';
  break;

case 'J':
  lcd.clear();
  lcd.setCursor(0, 0);
  lcd.print("Panda Detected");
  lcd.setCursor(0, 1);
  lcd.print(String(distance));
  player.volume(50);
  player.play(4);
```

```
        delay(1000);
        pychar = 'x';
        break;
      }
    }
  }
}
void sendSMS(const String& number, const String& message) {
  Serial.println("AT");
  delay(1000);
  Serial.println("AT+CMGF=1");
  delay(1000);
  Serial.print("AT+CMGS=\"+91" + number + "\"\r");
  delay(1000);
  Serial.println(message);
  delay(200);
  Serial.write(26);
}
```

## A.3 SCREEN SHOTS

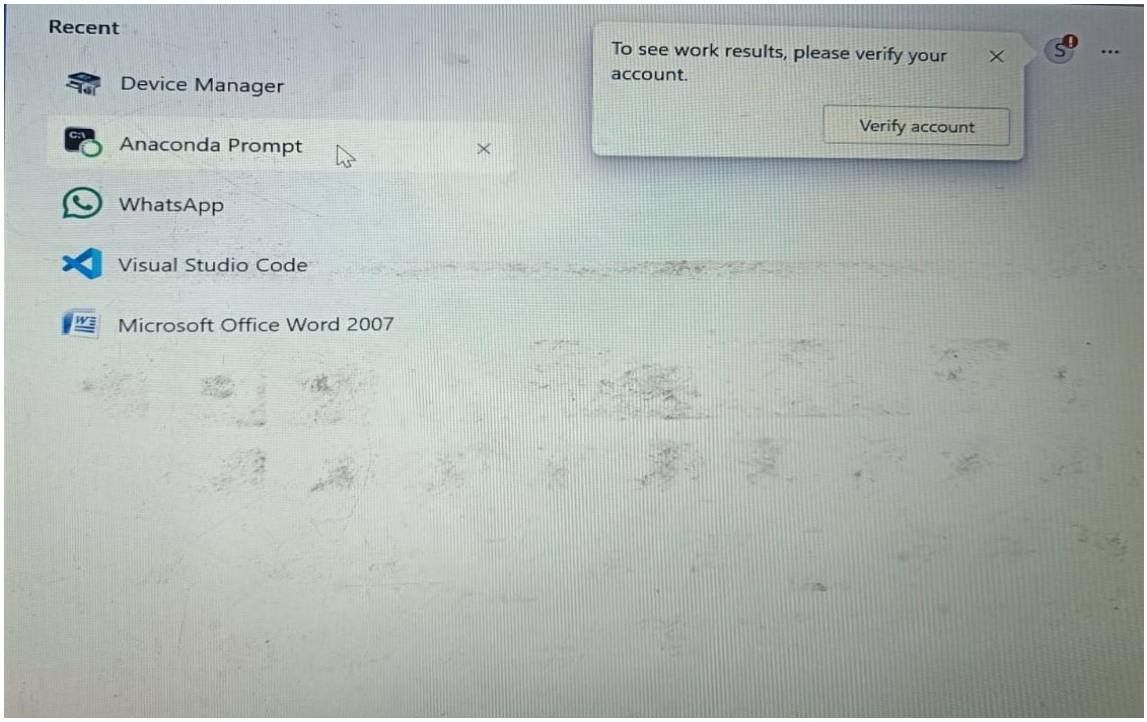


**Fig A.3.1 Open Anaconda Prompt**

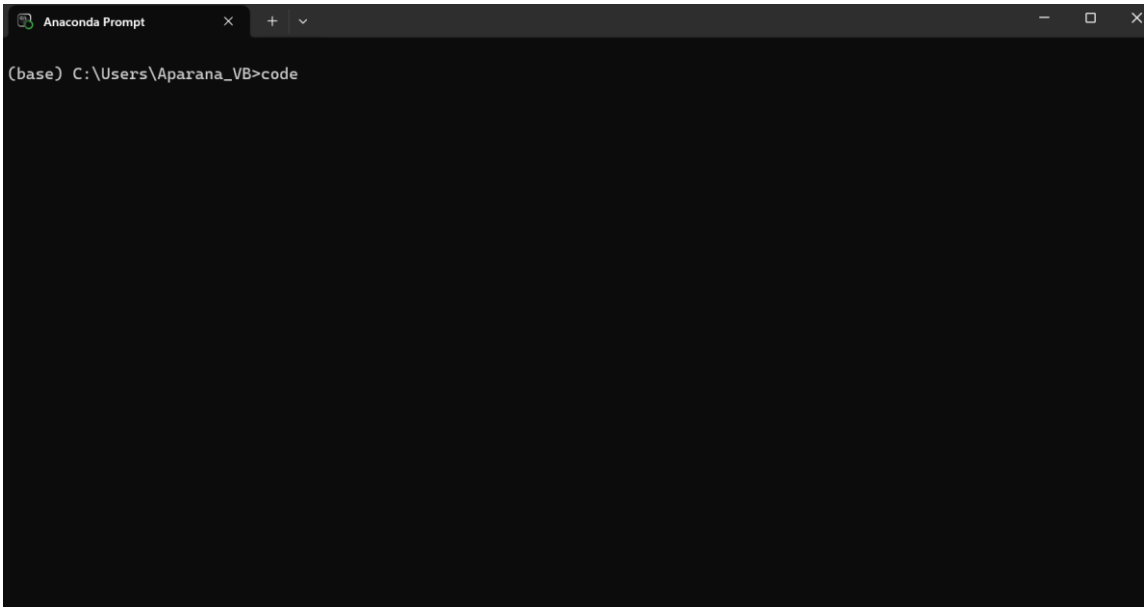


**Fig A.3.2 To Open VS Code**

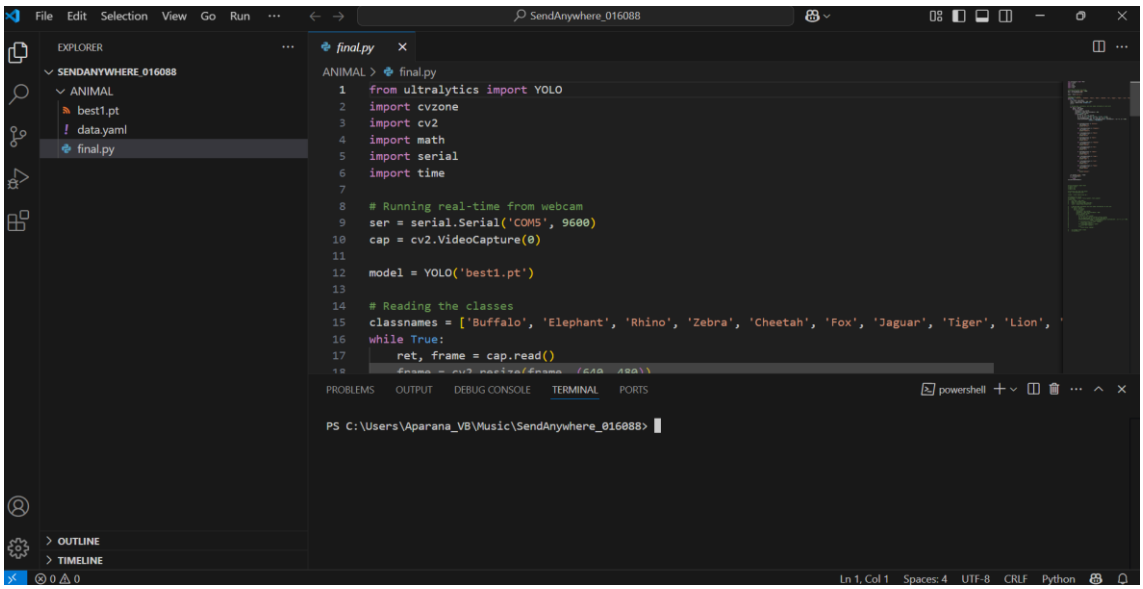


**Fig A.3.3 Coding Part**

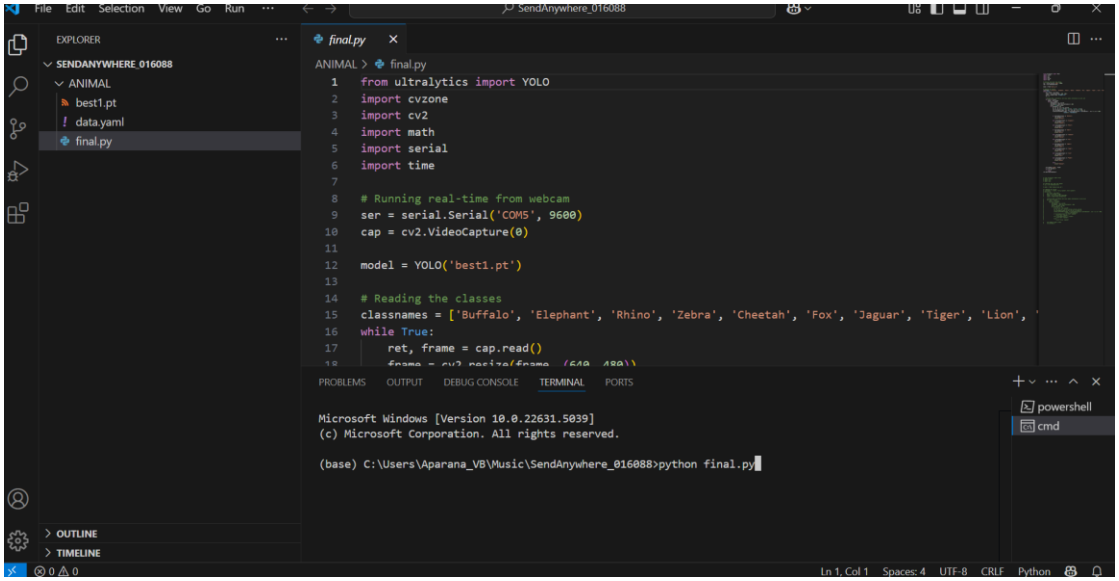


**Fig A.3.4 Execution Prompt**

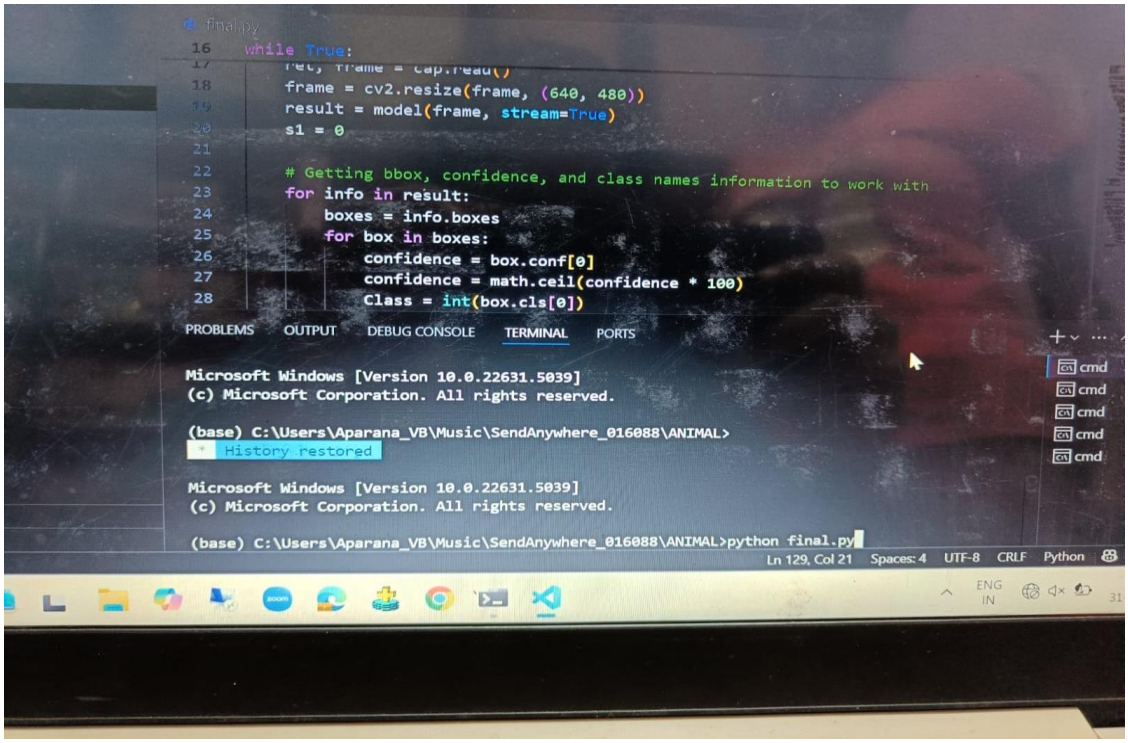


**Fig A.3.5 Output Screen**

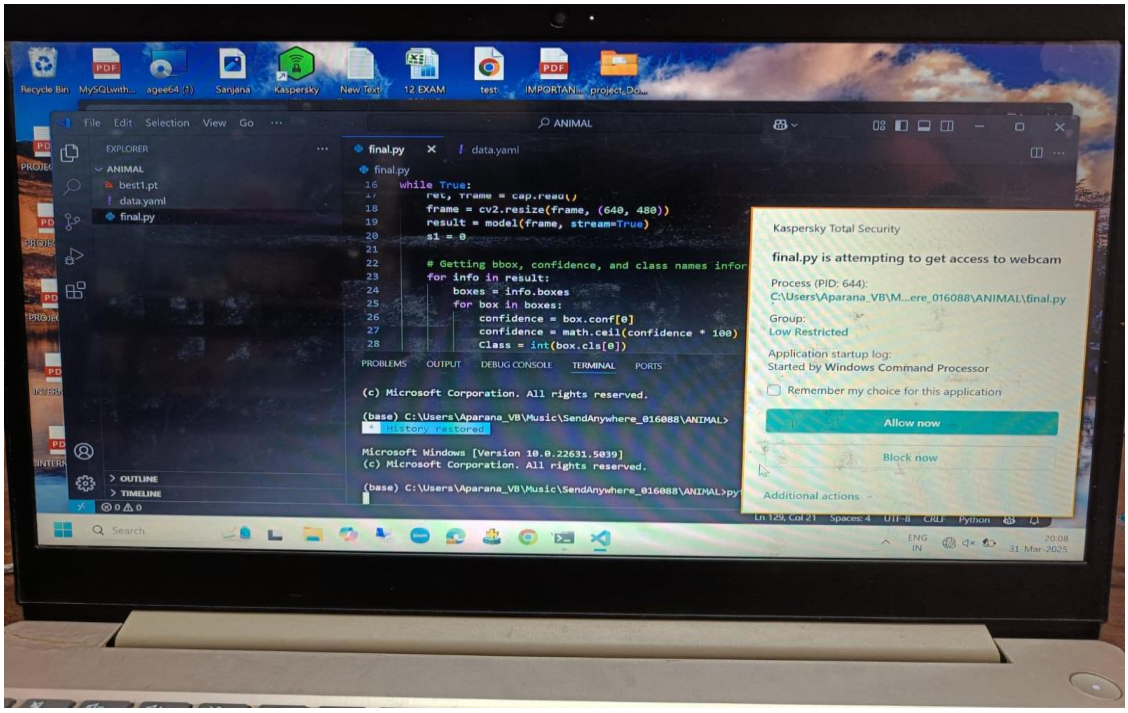


**Fig A.3.6 Output_1**

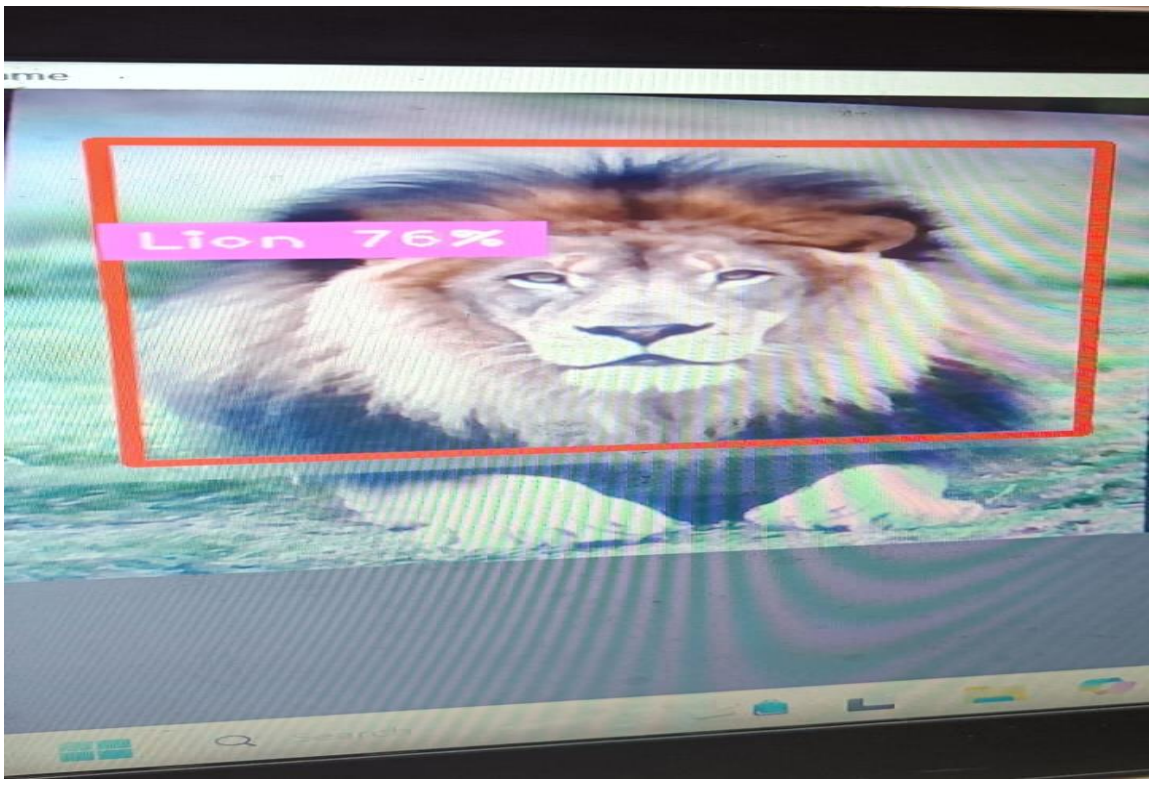


**Fig A.3.7 Detecting The Image_1**

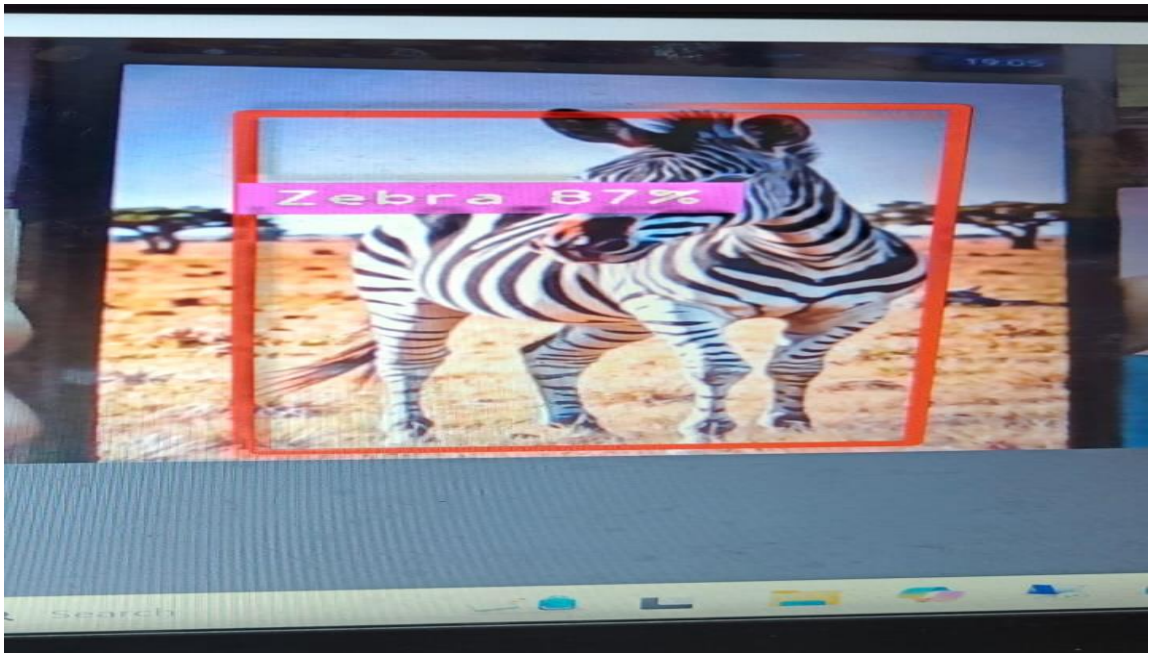


**Fig A.3.8 Detecting The Image_2**

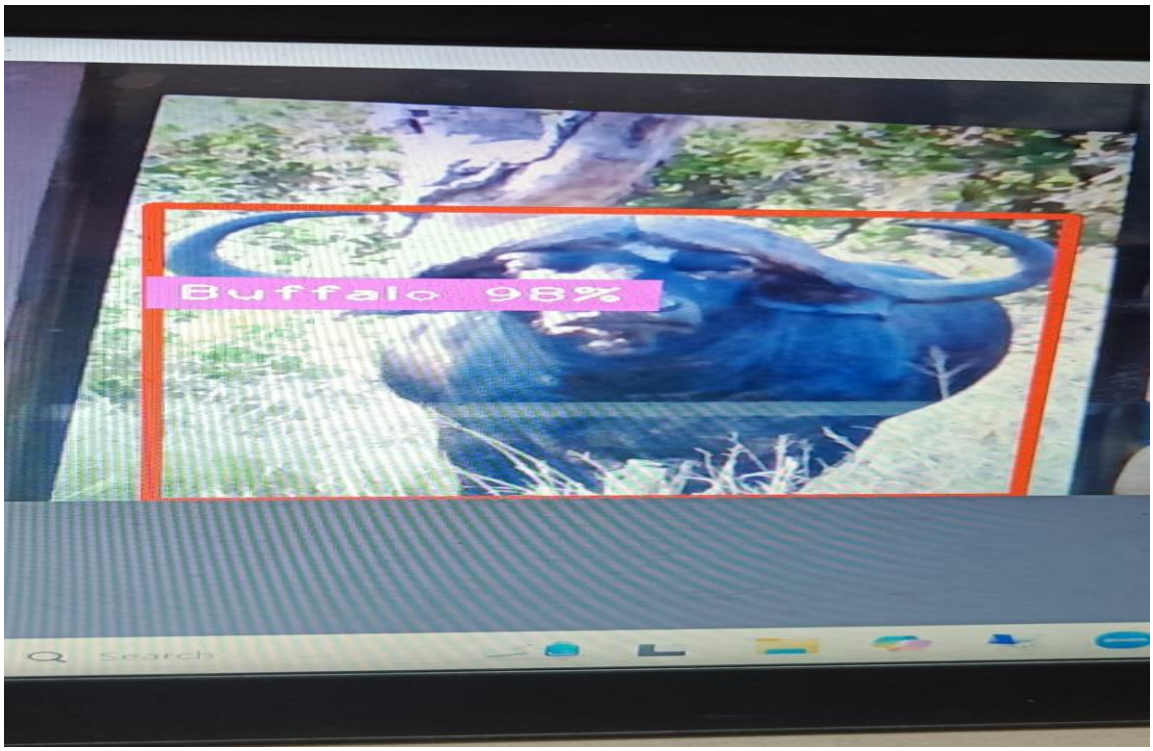


**Fig A.3.9 Detecting The Image_3**

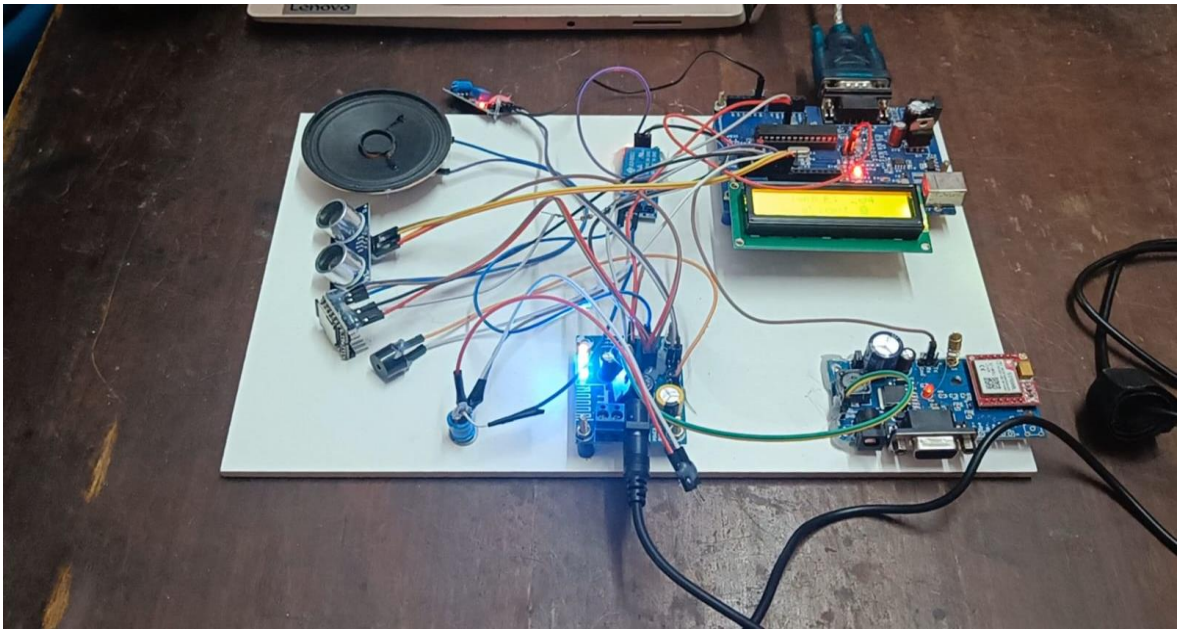

**Fig A.3.10 Detecting Kit**

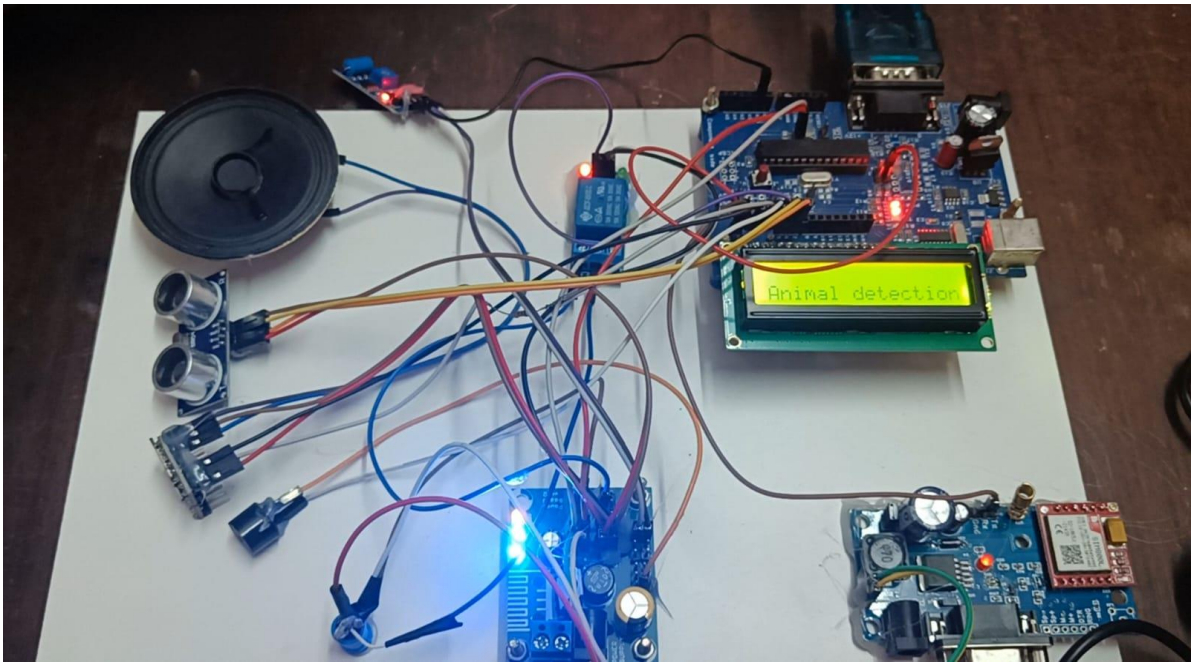


**Fig A.3.11 After On The Kit**

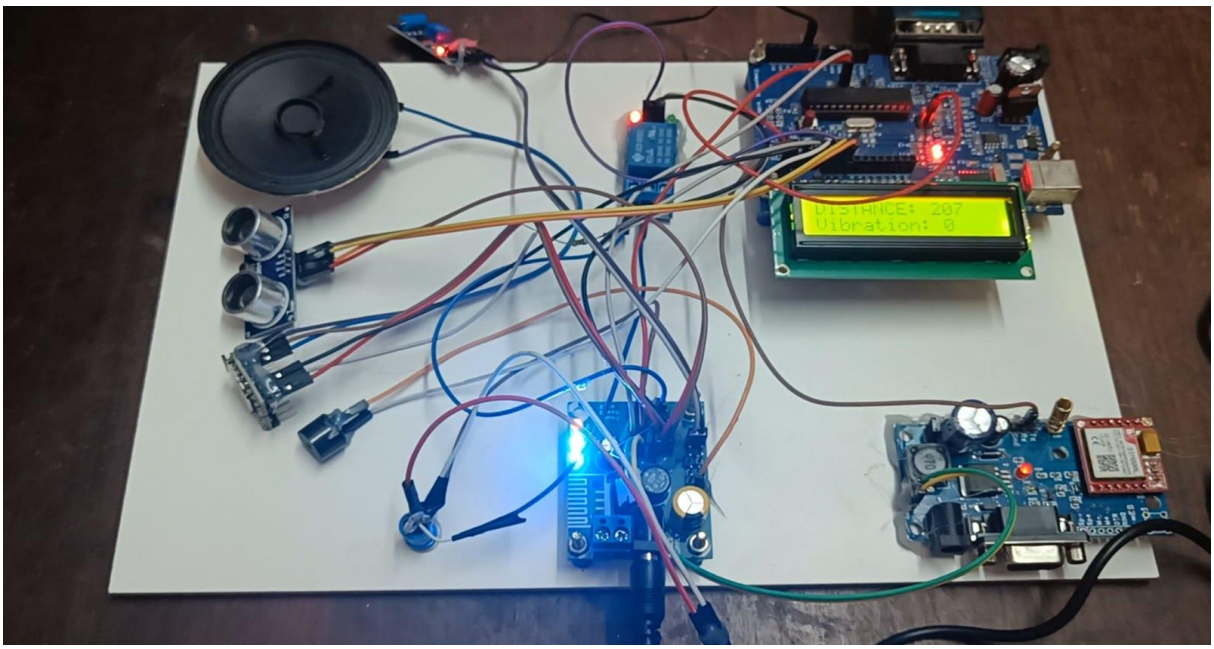


**Fig A.3.12 Displaying The Information In LCD**

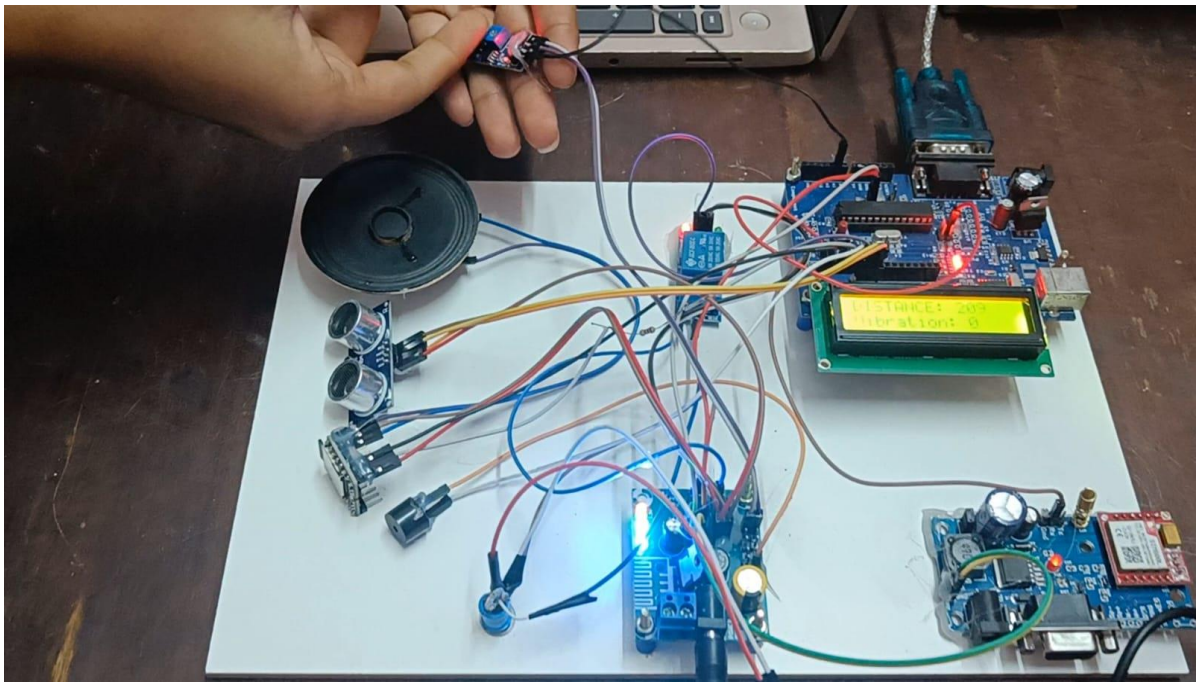

**Fig A.3.13 Detecting The External Distrubance By Vibrator**

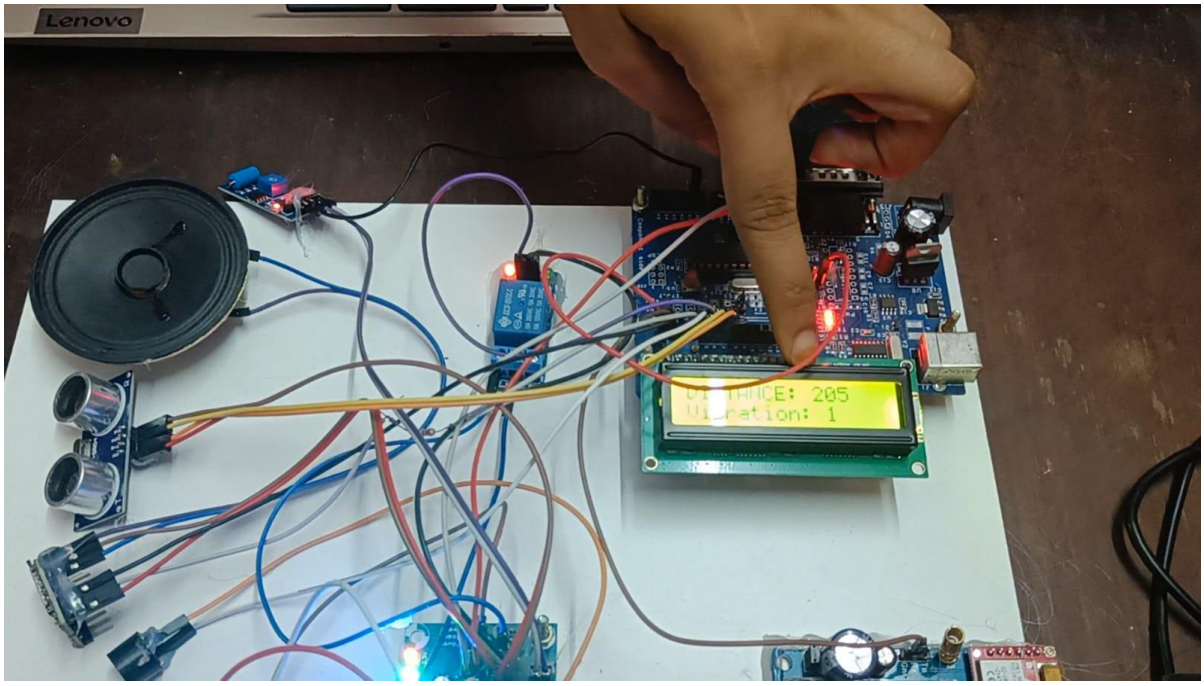


**Fig A.3.14 Showing The External Distrubance On The LCD**

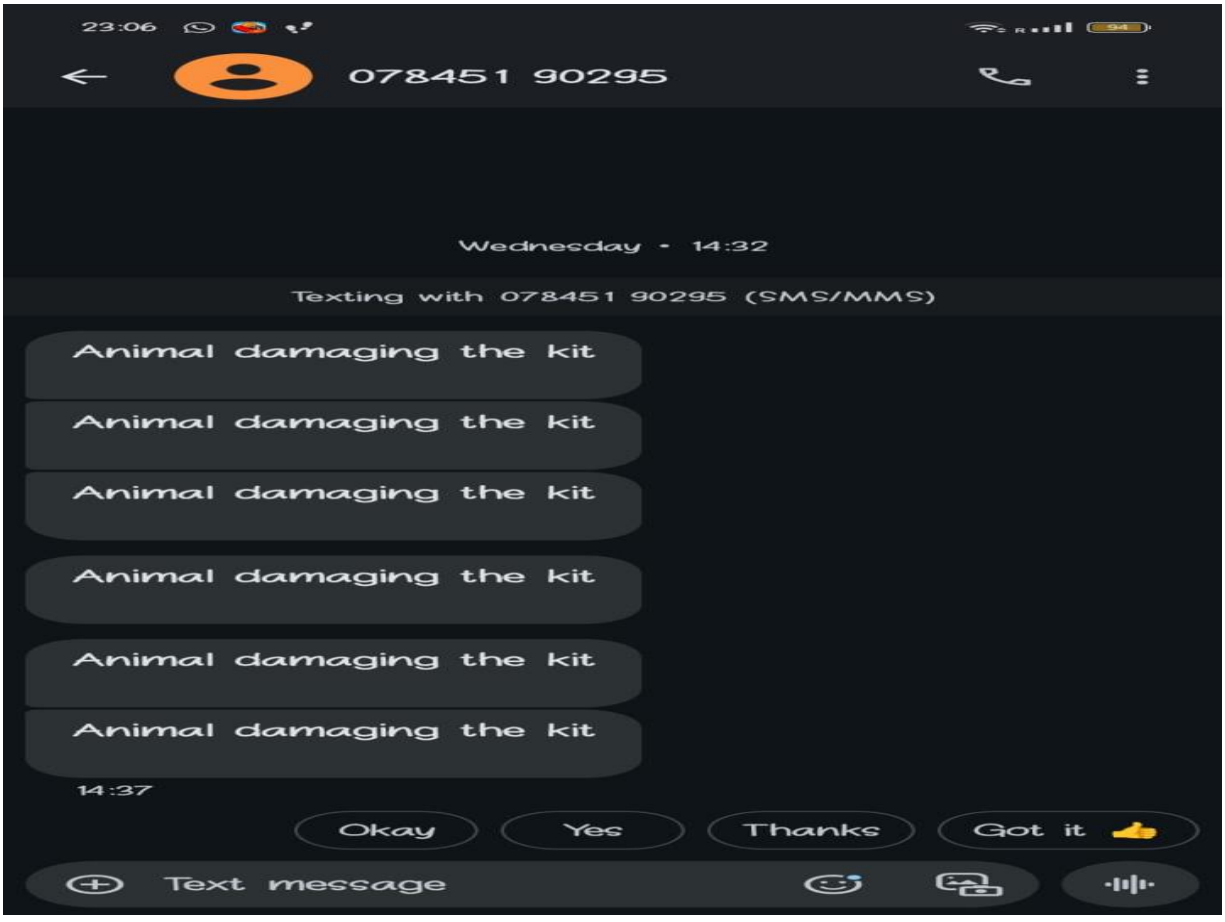


**Fig A.3.15 Message Notification To The Farmer**

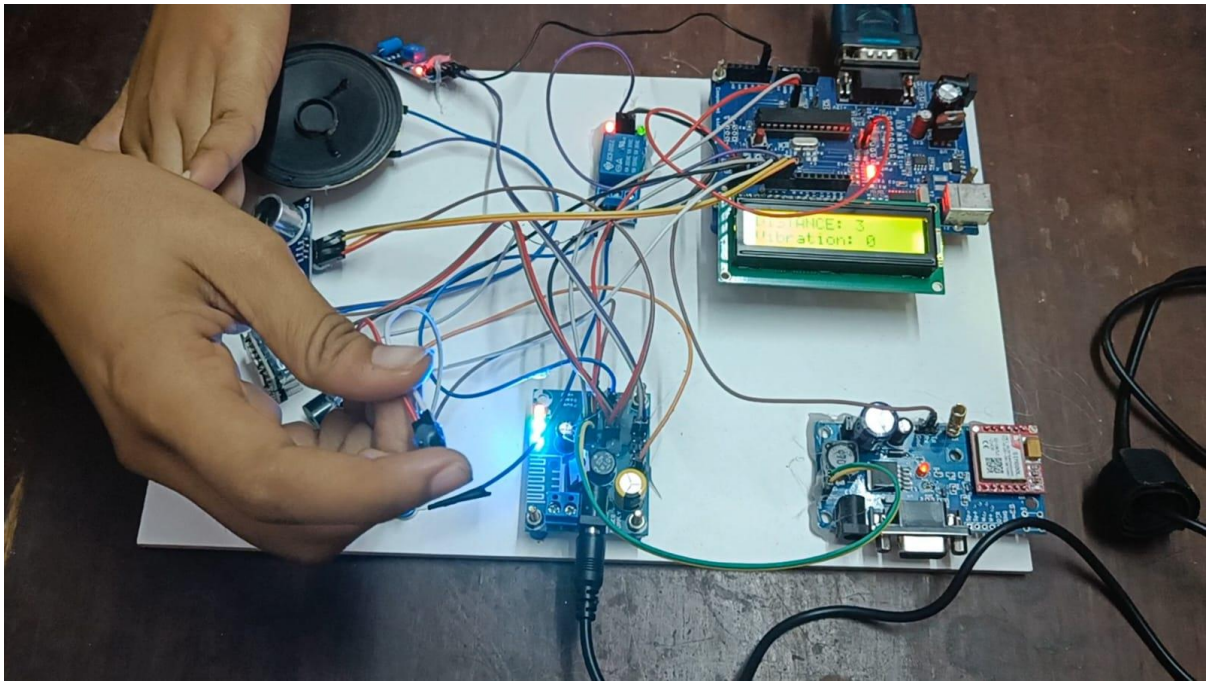

**Fig A.3.16 Distance Is Detected By Ultrasonic Sensor**

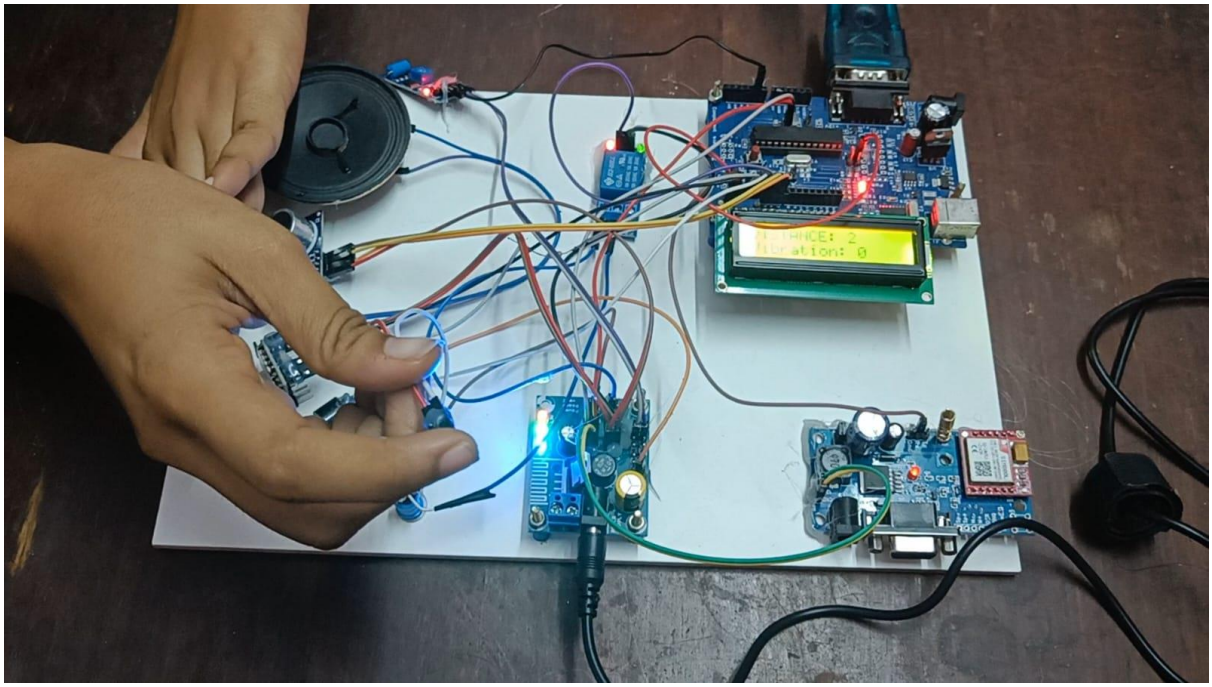

**Fig A.3.17 Distance Is Below The Range So Shock Is Enabled**

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# AI-Driven Multi-Level Animal Detection and Deterrence System for Protecting Agricultural Lands

***Abstract*— The encroachment of wildlife into agricultural lands has led to substantial economic losses and ecological imbalances, necessitating the development of effective and sustainable deterrence solutions. This paper presents an AI-driven multi-tiered animal detection and deterrence system that integrates ultrasonic sensors for real-time detection, an AI-powered model for species classification, and an automated deterrence mechanism. The proposed system leverages machine learning and IoT technologies to improve the accuracy of animal identification while minimizing unnecessary disturbances to non-threatening wildlife. Through a structured multi-level response, the system ensures that only identified threats are deterred using humane interventions such as ultrasonic deterrents and controlled shock circuits. Additionally, IoT-based remote monitoring enhances farmers' ability to respond to threats proactively. The system's methodology, implementation** strategy, and performance evaluations are explored, along with ***future enhancements aimed at improving detection accuracy, scalability, and sustainability. This research contributes to the field of smart agriculture and human-wildlife conflict resolution by providing an innovative, cost-effective, and ecologically responsible solution.***

***Keywords: AI-driven detection, wildlife deterrence, machine learning, IoT, ultrasonic sensors, smart agriculture, species identification, humane deterrence.***

## I. Introduction

Wildlife intrusion into farmlands has become a major challenge, causing crop damage and economic distress to farmers. Traditional deterrent methods are often ineffective and environmentally harmful. This research introduces an AI-based multi-tiered animal detection system that employs ultrasonic sensors and an AI model to identify and deter animals. The system aims to provide a proactive and automated solution, ensuring minimal disturbance to non-threatening wildlife while enhancing agricultural security. Modern technological advancements, particularly in artificial intelligence (AI) and the Internet of Things (IoT), have paved the way for innovative solutions to mitigate human-wildlife conflicts. Existing methods such as manual monitoring, scare tactics, and fencing have limitations in scalability, efficiency, and cost. The proposed system integrates smart detection mechanisms to ensure real-time identification of potential threats and appropriate countermeasures, reducing economic losses for farmers while preserving ecological balance.

## II. OBJECTIVE

The primary objective of this research is to develop a reliable and efficient AI-driven animal detection and deterrence system to enhance agricultural security and minimize human-wildlife conflicts. The key objectives include:

- Implementing machine learning algorithms for automated animal detection and classification.
- Developing a real-time monitoring system using ultrasonic sensors and IoT technology.
- Designing a humane deterrence mechanism that minimizes harm to wildlife.
- Establishing a centralized database for tracking and analyzing intrusion patterns.
- Integrating the system with smart farming technologies for enhanced agricultural security.
- Creating a user-friendly mobile and web-based application for real-time alerts and system control.
- Ensuring adaptability to various environmental conditions and agricultural landscapes.
- Developing a cost-effective and scalable solution for widespread adoption.
- Promoting ecological balance by employing non-disruptive deterrence techniques.
- Enhancing agricultural productivity by reducing crop damage due to wildlife intrusion.

By achieving these objectives, this research aims to provide an intelligent, scalable, and eco-friendly solution to wildlife intrusion problems in farmlands while supporting sustainable agricultural practices.

## III. RELATED WORKS

Patel et al. (2022) proposed CNNs and recurrent networks for automating wildlife monitoring, focusing on the identification of animal species in diverse environments. Their study highlighted the difficulties posed by varied animal appearances and environmental conditions, emphasizing the need for large, annotated datasets to improve model accuracy. The integration of CNNs with recurrent layers allowed the system to extract both spatial and temporal features, enhancing recognition capabilities. Furthermore, the authors implemented data augmentation techniques to overcome data scarcity issues and demonstrated the model's performance on benchmark wildlife datasets, achieving notable accuracy improvements.

Johnson et al. (2023) applied CNNs for species recognition in camera trap images. Their model effectively categorized multiple species by addressing noise and occlusion issues, which are common in camera trap images. The study demonstrated that using pre-trained CNN models such as ResNet and VGG significantly improved accuracy, especially when fine-tuned with wildlife-specific datasets. The authors further incorporated transfer learning techniques, enabling the model to generalize better across different habitats. Additionally, the study evaluated the model on large-scale datasets and showed a reduction in false positive rates compared to conventional methods.

Smith et al. (2022) developed a real-time classification model optimized using CNNs, aimed at enhancing detection speed and accuracy in varying lighting

conditions. Their system employed data augmentation techniques and adaptive thresholding, making it robust in low-light environments. The study demonstrated that optimized CNN architectures could achieve high precision without compromising inference speed. Moreover, the authors introduced lightweight CNN models to make the system deployable on edge devices, which improved real-time performance and reduced computational costs.

Kumar et al. (2021) introduced a hybrid model combining decision trees and deep learning techniques. The model aimed to improve detection speed and reliability, particularly for rare species in forest regions. The combination of traditional machine learning with deep learning provided a balance between interpretability and performance, making the system suitable for resource-constrained environments. The study also explored feature selection methods to enhance the model's efficiency and evaluated its performance on various wildlife datasets, demonstrating its effectiveness in detecting elusive species.

Williams et al. (2023) utilized AI models to detect animal interactions and movement patterns, offering valuable insights into habitat usage and environmental impact. Their approach employed sequence models like LSTMs to capture temporal dependencies in animal behavior, providing a deeper understanding of how animals interact within their ecosystems. The study combined spatial feature extraction with temporal modeling to enhance detection accuracy and demonstrated its potential in identifying social interactions and predator-prey dynamics.

Lee et al. (2023) applied CNNs for analyzing aerial imagery of wildlife species. Their model addressed occlusion and varying image resolutions, which are common challenges in aerial surveys. The use of multi-scale feature extraction and pyramid pooling layers significantly improved detection performance, making the approach viable for large-scale monitoring efforts. Additionally, the authors employed image stitching techniques to create comprehensive maps of wildlife populations, which aided in conservation planning.

Thomas et al. (2022) proposed YOLO-based models for multi-species detection in conservation efforts. The study demonstrated that YOLO's real-time detection capabilities improved efficiency in identifying multiple species simultaneously. The authors fine-tuned the model with domain-specific datasets to enhance detection accuracy for rare and endangered species. Furthermore, the study introduced anchor box optimization techniques to improve detection of small and camouflaged animals, making the model more versatile in practical applications.

Brown et al. (2023) explored transformer-based image recognition models, which leveraged self-attention mechanisms to improve classification accuracy with minimal training data. Transformers outperformed CNNs in scenarios with limited labeled datasets, making them particularly valuable for wildlife applications where annotated data is scarce. The study demonstrated that self-attention layers effectively captured long-range dependencies and proposed a hybrid model combining transformers with CNNs for improved feature representation.

Clark et al. (2021) deployed edge AI models on embedded devices to enable real-time wildlife monitoring. By processing data locally, the system reduced latency and reliance on cloud infrastructure, making it suitable for remote and resource-limited environments. Their study highlighted the potential of edge AI in improving monitoring efficiency. The authors implemented model quantization techniques to reduce the computational footprint and evaluated the system's performance on energy-efficient devices, demonstrating its suitability for continuous wildlife surveillance.

Adams et al. (2022) combined CNNs and RNNs to enhance recognition robustness in harsh environmental conditions. The hybrid framework improved detection accuracy under occlusions, extreme weather, and varying lighting conditions. The study demonstrated the importance of combining spatial and temporal information for wildlife recognition. The authors also integrated attention mechanisms into the RNN layers, which helped the model focus on relevant features and improved detection accuracy in challenging scenarios.

Miller et al. (2023) introduced a semi-supervised learning approach for wildlife species detection. The model leveraged both labeled and unlabeled data to improve detection accuracy in low-resource environments. The study showed that the method significantly reduced the need for large annotated datasets, making it highly applicable for remote regions with limited data availability.

Harris et al. (2023) developed an ensemble learning model combining CNNs and decision trees for wildlife behavior recognition. The model improved detection accuracy by merging the strengths of both methods, enhancing the interpretability of predictions while maintaining high performance in dynamic environments.

Parker et al. (2022) proposed a transfer learning approach for endangered species detection. The model utilized pre-trained deep learning networks to detect rare animals, improving detection accuracy in datasets with limited positive samples. The study highlighted the importance of transfer learning in addressing the scarcity of annotated images for endangered species.

Nelson et al. (2023) explored the application of generative adversarial networks (GANs) for data augmentation in wildlife detection. The GAN-based approach generated synthetic images to expand training datasets, significantly improving detection accuracy in scenarios with limited training data.

Davis et al. (2022) presented a few-shot learning approach for wildlife species recognition. The model demonstrated the ability to classify new species with minimal training examples, making it suitable for rapidly adapting to new environments and species not present in the training data.

## IV. Research Methodology

The research methodology for the development of the AI-powered animal detection and deterrent system is designed to address the pressing issue of wildlife intrusion in agricultural fields. Crop damage caused by wild animals, such as deer, wild boars, and monkeys, significantly impacts farmers' livelihoods. Traditional approaches like scarecrows, manual patrolling, and basic fencing have proven to be inefficient and labor-intensive. This study proposes a comprehensive, automated solution using artificial intelligence, deep learning, Arduino-based microcontrollers, and Internet of Things (IoT) technologies. The system aims to provide real-time animal detection, multi-stage deterrent mechanisms, and immediate farmer notification to minimize crop damage effectively. The methodology is structured into six phases: hardware setup, real-time image capture and preprocessing, YOLO-based animal detection, object classification and identification, response activation, and continuous monitoring and logging.

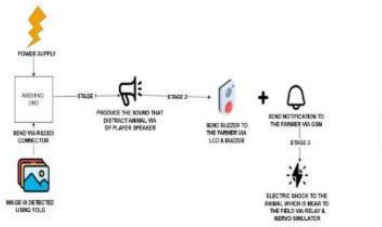

Fig.1 Architecture Diagram

### A. Phase 1: Hardware Setup

The initial phase focuses on the design and installation of the hardware components necessary for the system's operation. A high-definition camera module is installed at strategic locations within the farmland to capture continuous real-time video and images. The selection of the camera is based on factors such as resolution, field of view, and low-light performance to ensure optimal coverage of the agricultural area. The core processing unit of the system is the Arduino Uno microcontroller, selected for its simplicity, affordability, and compatibility with numerous sensors and peripheral devices. Connected to the Arduino are multiple external modules that form the system's deterrent and alert mechanisms.

A DF Player Speaker is integrated to emit loud distressing sounds, such as predator calls or sirens, designed to scare away intruding animals without causing them harm. Additionally, an LCD display and buzzer are installed to provide immediate local alerts to farmers working near the fields. To enable remote alerts, a GSM module is connected to the Arduino. This module uses cellular networks to send real-time SMS notifications to farmers, even in rural and remote areas where internet connectivity may be limited. A relay and nervo simulator are also incorporated to activate a mild electric deterrent system. This system delivers a carefully controlled, non-lethal electric shock through an electric fence or localized deterrent, ensuring humane treatment of wildlife. To support continuous and sustainable operation, especially in off-grid farming regions, the entire hardware setup is powered using renewable energy sources such as solar panels.

### B. Phase 2: Image Capture and Preprocessing

In the second phase, the camera module captures images and video footage from the field. These images are continuously transmitted to a computer or embedded processor running the YOLO (You Only Look Once) deep learning model for real-time processing. Prior to running detection algorithms, the captured images undergo preprocessing steps, including resizing and normalization. These preprocessing operations ensure that the images are of consistent dimensions and quality, improving the accuracy and efficiency of the YOLO algorithm. The preprocessing also reduces the computational load, allowing for faster inference times, which is essential for real-time animal detection and rapid system response.

### C. Phase 3: YOLO v8-Based Animal Detection

The third phase involves the deployment of the YOLO v8 algorithm, a state-of-the-art object detection framework known for its speed and accuracy. YOLO v8 divides each input image into a grid, with each grid cell responsible for detecting objects within its region. Convolutional Neural Networks (CNNs) are employed to extract key features from the images, such as shape, texture, color, and movement patterns. These features allow the system to distinguish between different types of objects present in the field of view. YOLO v8 predicts bounding boxes around detected objects and assigns class probabilities to each box, effectively identifying the category of each object, such as human, animal, or inanimate object. The model also generates confidence scores, indicating the likelihood that a detected object belongs to a specific class. YOLO v8's high-speed detection capabilities make it particularly suitable for real-time monitoring in dynamic and unpredictable farm environments.

*D. Phase 4: Object Classification and Identification*

After object detection, the fourth phase focuses on classifying and identifying the detected objects. The YOLO model distinguishes between humans, wildlife, and irrelevant objects to minimize false positives. Non-Maximum Suppression (NMS) is applied to eliminate redundant bounding boxes and ensure that only the most accurate detections are retained. Accurate classification is crucial for the subsequent activation of the system's deterrent mechanisms. For instance, human presence detected in the field may not trigger deterrents but could generate a different kind of alert if necessary. On the other hand, detection of animals such as wild boars or monkeys prompts the activation of defense protocols.

*E. Phase 5: Signal Processing and Response Activation*

The fifth phase involves signal processing and the activation of the multi-stage defense mechanism. Once a potential threat is classified as a wildlife intruder, a signal is sent from the detection system to the Arduino Uno microcontroller to initiate a response. The defense mechanism is executed in three stages, escalating based on the animal's behavior and persistence.

In Stage 1, the DF Player Speaker is activated to emit loud, distressing sounds that mimic predator calls or produce high-decibel sirens. These sounds aim to create an uncomfortable auditory environment for the animal, prompting it to leave the area without any physical intervention. If the animal does not retreat, Stage 2 is initiated. During this stage, a visual alert is displayed on the LCD screen, and a buzzer sounds continuously to attract the attention of nearby farmers. Simultaneously, the GSM module sends an SMS alert to the farmer, providing real-time notification of the intrusion. This ensures that the farmer can take immediate action, even from a remote location.

If the intruder remains in the field despite these warnings, Stage 3 is activated. In this final phase, the relay and nervo simulator engage to deliver a mild electric shock through an electric fencing system or a localized deterrent. The shock is calibrated to be non-lethal, serving as a humane but effective means of repelling the animal and preventing crop damage. This three-stage process ensures a balanced approach that prioritizes humane treatment of wildlife while protecting agricultural resources.

*F. Phase 6: Continuous Monitoring and Data Logging*

The final phase ensures the continuous operation and monitoring of the system. The AI-powered detection and deterrent system continuously scans the field in real-time, maintaining vigilance against new threats. All detection events and system responses are logged automatically in a database. This data is valuable for analyzing system performance, identifying patterns of wildlife intrusion, and optimizing future detection and deterrence strategies. Furthermore, integration with IoT platforms allows farmers to access real-time data through mobile applications or web-based dashboards. Farmers can monitor the status of their fields, view historical intrusion records, and adjust system parameters as needed.

The scalability and modularity of the system design enable customization for farms of different sizes and requirements. Farmers can fine-tune the sensitivity of the YOLO model, configure the types of deterrent sounds, and integrate additional sensors such as infrared motion detectors, temperature sensors, and humidity sensors. These enhancements further improve the system's ability to detect and respond to threats while promoting sustainable farming practices.

The core component of this system is the YOLO (You Only Look Once) algorithm, a state-of-the-art deep learning model designed for real-time object detection. YOLO excels in identifying and localizing objects in images or video frames with high accuracy and speed. Unlike traditional object detection methods, which involve scanning an image multiple times, YOLO divides the image into a grid and predicts bounding boxes and class probabilities in a single evaluation. This makes the system highly efficient for real-time applications, making it ideal for farm surveillance where immediate responses are required. The system employs a camera module installed in the farmland, continuously capturing video footage of the field. The captured images are processed through the YOLO model, which detects the presence of animals such as deer, wild boars, monkeys, or other potential intruders. Once an animal is identified, the system initiates a series of automated defense mechanisms to deter the animal and protect the crops. The system is designed to differentiate between humans, animals, and inanimate objects, ensuring that false alarms are minimized and only relevant threats are addressed.

The detected image is transmitted to the Arduino Uno microcontroller via an RS2323 connector, which acts as the central processing unit of the system. The Arduino Uno, an open-source microcontroller board, is chosen for its affordability, ease of programming, and compatibility with various sensors and modules. The Arduino processes the received data and triggers a multi-stage defense mechanism based on the persistence of the intruder. The first stage involves activating a DF Player Speaker that emits loud and distressing sounds, such as predator calls or sirens, designed to scare away the animal. This non-invasive method aims to deter the intruder without causing harm, minimizing the risk of injury to the animal and preserving ecological balance. If the animal remains undeterred by the sound, the system escalates to the second stage. In this phase, an LCD display is activated to provide visual alerts, while a buzzer produces continuous warning sounds. Simultaneously, the system sends an SMS alert to the farmer via a GSM module, ensuring that the farmer is promptly informed about the intrusion. The GSM module uses a SIM card to communicate with the mobile network, enabling real-time notifications even in remote agricultural areas. This remote notification feature enhances the system's effectiveness by allowing farmers to take immediate action even if they are not physically present on the farmland.

In cases where the intruder persists despite the previous deterrent measures, the system proceeds to the third and final stage. This stage involves the activation of a relay and nervo simulator, which delivers a mild electric shock through an electric fencing system or localized deterrent. The electric shock is carefully calibrated to repel the animal without causing any harm, making it a humane yet effective method of protecting the crops. The relay acts as a switch that controls the flow of electricity, while the nervo simulator generates a low-voltage current to deter the animal without inflicting pain. This three-tiered defense mechanism ensures that the animal is repelled at different stages, significantly reducing the likelihood of crop damage.

The AI-powered animal detection system leverages IoT capabilities to provide seamless communication between different components and remote monitoring functionalities. The integration of Arduino Uno, GSM modules, and deep learning algorithms creates a smart surveillance network that operates autonomously with minimal human intervention. The entire system is powered by renewable energy sources such as solar panels, making it an environmentally friendly solution that can operate in off-grid locations. The use of IoT technology allows farmers to access real-time data and monitor system performance through a dedicated mobile application or web portal, enhancing convenience and efficiency.

Moreover, the system's scalability and modular architecture make it suitable for farms of various sizes. Farmers can customize the system by adjusting the sensitivity of the YOLO model, configuring the defense mechanisms, or integrating additional sensors for improved performance. Additional sensors such as infrared motion detectors, temperature sensors, and humidity sensors can be added to further enhance the system's functionality. The combination of AI, IoT, and humane deterrent techniques positions this system as a sustainable and innovative solution for modern agriculture. AI-powered animal detection system revolutionizes farm security by providing an intelligent, automated, and cost-effective approach to wildlife intrusion detection and deterrence. The multi-stage defense mechanism ensures that animals are repelled without harm, while real-time alerts enable farmers to respond promptly to potential threats. This system not only minimizes crop losses but also promotes coexistence between wildlife and agriculture, making it an essential tool for sustainable farming practices. The system's affordability, scalability, and environmental sustainability make it a viable solution for both small-scale and large-scale farms, paving the way for smarter and more efficient agricultural practices in the future.

## III. EXPERIMENTAL RESULT ANALYSIS

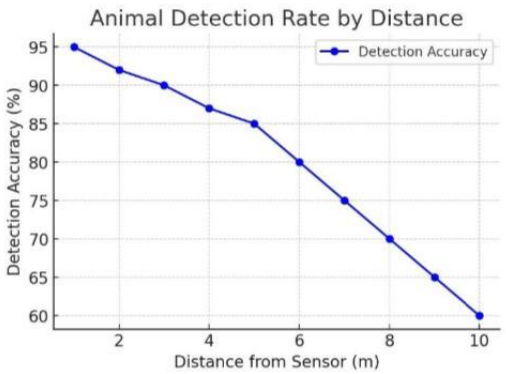


Fig.2 Animal Detection Rate by Distance

The Animal Detection Rate by Distance graph demonstrates how the system's detection accuracy varies with distance. At shorter distances, the system performs exceptionally well, with a 95% detection accuracy at 1 meter. However, as the distance increases, accuracy gradually declines, reaching around 60% at 10 meters. This decrease is likely due to the limitations of ultrasonic sensors in detecting animals at greater distances, as environmental factors like obstacles and signal attenuation can impact performance. The data suggests that optimal sensor placement should be within a reasonable range to ensure maximum detection efficiency, allowing farmers to receive timely alerts about potential threats to their crops.

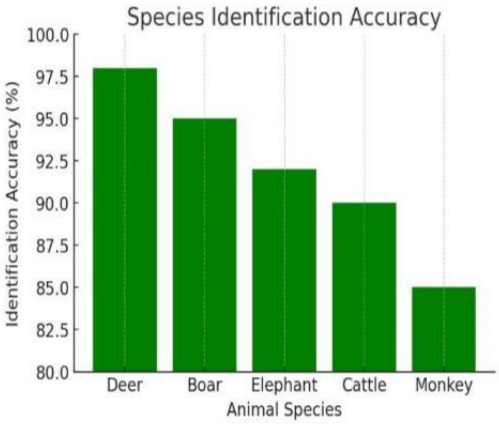


Fig.3 Species Identification Accuracy

The Species Identification Accuracy graph highlights how effectively the AI model distinguishes between different animal species. The system achieves the highest accuracy for deer at 98%, followed closely by boars and elephants. However, it performs slightly less accurately for monkeys, with an 85% success rate. This variation in accuracy may be attributed to differences in animal size, movement patterns, and image quality during detection. Larger animals like

elephants and deer are easier to identify due to their distinct physical features, whereas smaller, more agile species like monkeys may be misclassified due to rapid movement or occlusion. Improving the AI model with more diverse training data and advanced image-processing techniques could enhance species identification accuracy, ensuring that non-threatening animals are not unnecessarily disturbed.

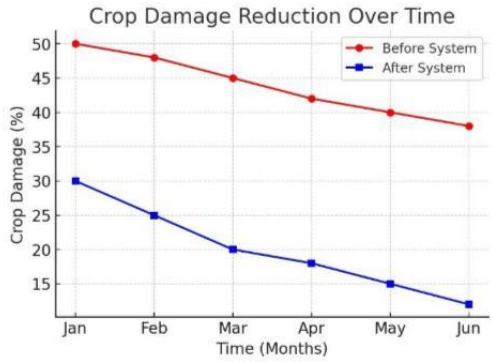


Fig.4 Crop Damage Reduction Over Time

The Crop Damage Reduction Over Time graph illustrates the effectiveness of the AI-driven animal detection and deterrence system in minimizing agricultural losses. Before implementing the system, crop damage was significantly high, around 50% in January. However, after the deployment of the multi-level detection system, there was a consistent decline in crop damage over the months, reaching just 12% by June. This downward trend indicates that the system successfully prevents harmful wildlife interactions with farmlands, reducing economic losses for farmers. The combination of early warning alerts, AI-driven species identification, and an automated deterrence mechanism plays a crucial role in safeguarding crops. This data underscores the system's potential in improving agricultural productivity while maintaining ecological balance by minimizing harm to wildlife.

## IV. Conclusion

In conclusion, the proposed multi-level animal detection and deterrence system offers an innovative and effective solution for protecting agricultural lands from wildlife intrusions. By combining ultrasonic sensors, AI-driven species identification using the YOLO algorithm, and an automated shock circuit, the system provides timely and targeted responses to potential threats, minimizing crop damage and ensuring minimal disturbance to non-threatening wildlife. This automated, cost-effective approach enhances agricultural safety, improves farm management efficiency, and reduces the reliance on manual intervention. With potential for future enhancements, such as IoT integration and renewable energy sources, the system can evolve to provide even greater flexibility and sustainability in managing human-wildlife conflicts, ensuring a harmonious balance between agriculture and wildlife conservation.

## V. Future Enhancements

**Improved Long-Range Detection:** Enhancing the ultrasonic sensors with high-frequency radar or LiDAR technology can increase detection accuracy over greater distances. This would help in identifying animals earlier, giving farmers more time to take preventive actions.

**Advanced AI-Based Species Recognition:** Implementing deep learning techniques such as Convolutional Neural Networks (CNNs) with real-time object detection models like YOLOv8 can improve species classification, especially for smaller or fast-moving animals. Training the model with a larger dataset covering different lighting and environmental conditions can further enhance accuracy

**Real-Time Mobile and Cloud Integration:** Integrating the system with IoT-based cloud platforms would allow farmers to receive instant notifications via mobile apps or SMS alerts. Real-time data logging and analytics can help track wildlife activity trends, allowing proactive decision-making.

**Automated Adaptive Deterrence Mechanism:** Instead of a fixed deterrence response, future versions can implement adaptive deterrence based on AI analysis. For example, non-threatening species could trigger a mild sound-based deterrent, while larger, more destructive animals could activate stronger deterrent measures such as flashing lights or automated drones.

**Solar-Powered and Energy-Efficient Design:** To ensure sustainability, incorporating solar panels and energy-efficient components can reduce dependency on external power sources. This would make the system more practical for remote farming areas with limited electricity access.

**Integration with Weather and Environmental Data:** Linking the system with weather data can help predict animal movement patterns based on seasonal changes. For instance, during dry seasons, animals are more likely to enter farmlands

in search of water. The system can adapt its detection thresholds accordingly.

**Multi-Sensor Fusion for Enhanced Accuracy:** Combining ultrasonic sensors with thermal imaging cameras, motion sensors, and infrared sensors can provide a more comprehensive detection approach. This would reduce false positives and improve the system's reliability in different environmental conditions.

**Automated Data Analysis for Wildlife Management:** Collected data can be used for ecological studies, helping conservationists understand wildlife movement and behavior. Governments and environmental agencies can use this data to develop better strategies for human-wildlife conflict resolution.

## VI. References

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## A.5 PAPER PUBLICATION

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