Computer Vision based Smart Scarecrow

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***Abstract*—The integration of advanced technologies into agriculture has become imperative to address the challenges faced by farmers in protecting their crops from hazardous animals. In this project, we present an innovative solution that leverages the capabilities of the ESP32 cam and the YOLOv3 pretrained model for the detection of hazardous animals in agriculture. The system, comprising an ESP32-based device, servo motor, buzzer, and lights, effectively identifies potential threats like birds. Upon detection, the system employs the servo motor to initiate scarecrow movement, activates a loud buzzer to deter animals and illuminates lights to enhance visibility. One can monitor whether a bird is in the field or not through a web interface. This project demonstrates a practical and cost-effective approach to enhance crop protection, mitigating the impact of hazardous animals while minimizing human intervention. The successful implementation of this system offers promising prospects for sustainable and efficient agricultural practices.**

***Index Terms*—ESP32 microcontroller, YOLOv3 pretrained model, animal, scarecrow, cost-effective.**

I. Introduction

Agriculture provides a means of subsistence and a means of income for the populace. The majority of people living in rural areas rely on agriculture as their main source of income.Animal attacks in fields have becoming more frequent these days. Crop damage has become a significant issue for farmers as a result of inadequate security and monitoring [1]. Animals can damage crops by eating plant parts or simply trampling over crops across fields. There are so many techniques used to prevent crop damage from animal attacks but some crops like paddy, rice field cannot be always fenced, so there is a possibility for animals like cows, buffaloes, dogs etc. to eat the crop or may damage the field [2]. This results in large amount of crop damage that is developed by farmers for many months. Bird species like resident crows cause extra harm to wheat, while pigeons and doves cause harm to millets and sunflower in search of prey [3]. The existing system mainly focuses on surveillance functionality over the crop and not provide protection from wild animals. And other common methods are used by farmers in order to provide safety over the crops which include physical barriers, electric fences, IOT sensors, manual surveillance [4]. Traditional scarecrows, while a familiar sight in agricultural fields, have significant limitations. Traditional systems also make alert when it detecting human and any other objects that are not hazardous for crops. So it is not that much effective. The objectives of our project are:

- Develop a system utilizing the YOLOv3 pretrained model to accurately identify hazardous animals like birds, in real-time within agricultural environments.
- Integrate the ESP32 microcontroller to control and coordinate the various components of the system, ensuring seamless communication and responsiveness.
- Enable the system to trigger the movement of a scarecrow when a hazardous animal is detected, thereby creating a dynamic and visually intimidating response.
- Implement an audible alarm system through a buzzer to deter animals upon detection, enhancing the protective measures against potential threats.
- Utilize lighting elements to improve visibility and further discourage animals from approaching the protected area.
- Monitor the object detection like bird through a web interface.
- Ensure that the project remains cost-effective and accessible to a wide range of farmers, with a focus on affordability and practicality.

The rest of the paper is structured as follows. Section II describes recent related works. Section III describes the motivation of our project. Section IV provides an in-depth analysis of the methodology and system design. section V shows the result and outcome of the system. Section VI demonstrates the discussion of the paper where we contrast our work with some recent state-of-the-art works. And finally, section VII includes the conclusion of the work.

II. Related Works

Running a real time object detection algorithm involves computational demanding tasks, which involves powerful devices where these algorithms are implemented on. This is essential to achieve good results in less time.There are several platforms available in order to run the object detection algorithms. OpenCV and Tensorflow are considered proven platforms for machine learning purposes [5]. several deep learning approaches, including Region-Based Convolutional Neural Networks (R-CNN), You Only Look Once (YOLO), and Single Shot multibox Detector (SSD) have been applied extensively to agriculture-related applications. Faster R-CNN [6] uses the region proposal network (RPN) method to detect a region of interest (RoI) in the image. He et al. introduced Mask-RCNN [7], which is an extension to Faster R-CNN for instance segmentation. Shifting to animal identification, animal detection has been researched by many researchers for the purposes of estimation, localization among others. The work in

[8] examined how YOLOv3 was able to locate sheep in drone footage. The work was able to detect sheep as a superclass, with a resolution of 832 × 832 pixels, and a confidence ratio of 0.1 yielding a reliability of 99%. In [9], the authors introduced FLYOLOv3, a deep learning filter layer YOLOv3 to detect the key parts of dairy cows in complex scenes. Wang, Juan, et.al The work in [10] presented a YOLOv3 model to detect the behaviour of egg breeders. In addition, transfer learning was also implemented to expand the DNN model in realizing the behaviour recognition of egg breeders with low stock density. The authors in [11] also followed the same approach by proposing an automated broiler digestive disease detector based on DNN model to classify fine-grained abnormal broiler droppings images as normal and abnormal. The work in [12] provided a holistic approach in using different DNN object detector methods including YOLOv3 to create bird detection models using aerial photographs captured by Unmanned aerial vehicle (UAV). The work presented the model performance, but lacked the implementation of the model on a platform. Reference [13] introduced YOLO Fish, an effective fish detector using YOLO on nordic fish species. Moreover, in [14], the use of animal behavior analysis software was also used to evaluate the behavior of chickens such as Pocket Observer Version 3 (Noldus Information Technology; Wageningen, the Netherlands). In our project we use Yolov3 pretrained model to detect the animals like birds and by detecting them our smart scarecrow is respond through movement, sound and light.

III. Motivation

Birds have long been a significant challenge in the agricultural landscape of Bangladesh, where agriculture serves as a vital pillar of the economy. The impact of birds on crops can be devastating, leading to substantial economic losses and food security concerns. Flocks of birds, including common species like crows and sparrows, can descend upon fields, feeding on valuable crops and significantly reducing yields. Traditional scarecrows, while a familiar sight in these fields, have proven to be of limited effectiveness. These static, non-discriminatory scarecrows are designed to respond to any motion, regardless of its relevance to crop protection. Consequently, they often trigger responses to non-hazardous entities, including humans and other harmless animals. This inefficiency not only fails to deter birds but also leads to unnecessary and ineffective scarecrow activation. The motivation behind our project is to introduce a modern and intelligent approach to crop protection in Bangladesh's agriculture, leveraging advanced technologies like the ESP32 and YOLOv3 object detection to specifically target and deter hazardous animals like birds. By doing so, we aim to significantly mitigate the impact of avian pests and enhance crop yields, aligning with the crucial goal of ensuring food security and sustainable agriculture in the region.

IV. Methodology and System Design

A. Materials and Technology

1) ESP32: The heart of our system, the ESP32, serves as the central control unit, facilitating data processing, communication, and component coordination.

2) ESP32 Cam: An integral part of the project, the ESP32 Cam captures and detect objects for real-time analysis.

3) FTDI USB to TTL Serial Converter Adapter FT232RL: In ESP32 cam we can upload code but the ot fatures of the ESP32 like WiFi, Bluetooth are present here. For this by adding FTDI module we can upload the code into the ESP32 cam. This adapter enables the ESP32's communication with other devices through USB, facilitating data transfer and programming.

4) YOLOV3 Model: The YOLOv3 (You Only Look Once version 3) model is a cutting-edge deep learning algorithm known for its remarkable real-time object detection capabilities. Operating on the principle of single-shot detection, YOLOv3 can identify objects like birds swiftly and accurately. Its network architecture incorporates multiple convolutional layers, dividing the task into different scales to handle objects of varying sizes. The model predicts bounding boxes and class probabilities for detected objects, specifically trained to recognize the "bird" class in your agricultural project. Pretrained models, represented by .pb and .pbtxt files, enable seamless utilization of the YOLOv3 model. Through extensive training on diverse datasets, the model learns to recognize the distinctive features and patterns associated with birds, making it a valuable tool for real-time object detection in your project. YOLOv3's efficiency and speed in processing video frames make it a formidable asset in enhancing crop protection and security in agricultural environments.

5) Servo motor: Crucial for scarecrow movement, the servo motor is controlled by the ESP32 to deter potential threats by creating dynamic scarecrow gestures.

6) Buzzer: A key auditory component, the buzzer emits sound alerts upon detecting hazardous animals, increasing deterrence.

7) LED: These provide enhanced visibility in the protected area and are triggered by the system to further discourage animals.

8) External Power supply: The power source for the system components, ensuring continuous operation and reliability in the field.

B. Working Procedure

In our project ESP32 Cam capturing video from the agricultural field. This camera acts as the project's "eyes," continuously recording the surroundings. On the PC,the localhost read the video frames from the server and the YOLOV3 model is employed to process. It analyzes the video frames, identifying objects within them like birds.The YOLO V3 model sends the object detection results to an IoT device. This device serves as the project's "brain" and control center. It receives real-time information about the objects detected by the model. The YOLO V3 model sends the object detection results to an IoT device. Based on the received object detection results, the IoT device takes action. If it detects bird, it instructs the servos to move, creating movement in the system. It also controls the LEDs, adjusting their state to enhance visibility in the field.

When the IoT device detects bird, it activates the buzzer to sound an alert. The working procedure is shown in the figure 1

C. Methodology

1) Object Detection: In our project, the ESP32 Cam captures video in the agricultural field, which continuously generates video frames. These video frames are transmitted to a server, which acts as a data intermediary in the project. The PC, functioning as a localhost server, reads the individual frames of the video through a URL. No storage of these frames is maintained, as each new frame replaces the previous one. This real-time frame retrieval ensures that only the latest frame is available for processing.The frames retrieved by the PC server are provided as input to the YOLOv3 model. This deep learning model processes each frame independently, analyzing them for object detection.YOLOv3, equipped with the necessary pretrained files like .pb and .pbtxt, takes the image frames as input and predicts objects within each frame. If the model detects a bird or any other object of interest, it makes a prediction. When the YOLOv3 model detects a bird, it writes a value of 1 to a file called "data.txt." This serves as a binary indicator of bird presence in the frame. Conversely, if the model does not detect a bird, it writes a value of 0 to the "data.txt" file. The circuit diagram, that is needed for object detection is given in the figure 5a.

2) Actuation: The ESP32 is continuously monitoring the "data.txt" file, which is periodically updated by the YOLOv3 model. This file contains binary values (1 or 0) that indicate the presence of a bird (1) or its absence (0) in the most recent frame.The ESP32 is continuously monitoring the "data.txt" file, which is periodically updated by the YOLOv3 model. This file contains binary values (1 or 0) that indicate the presence of a bird (1) or its absence (0) in the most recent frame. When the ESP32 reads the "data.txt" file, it interprets the binary value. If it reads a "1," indicating that a bird has been detected in the latest frame, it proceeds to take specific actions.The ESP32 initiates an immediate response when it detects a "1" value in the "data.txt" file. It triggers the servo motor to move, which causes the scarecrow to make dynamic movements.Simultaneously, the ESP32 activates the LEDs to provide enhanced visibility in the field. These lights remain illuminated for 3 seconds, enhancing the deterrence effect.A buzzer is also activated, producing a sound for 3 seconds. The audible alert serves as an additional deterrent to scare away birds or other detected objects. Following these actions, the ESP32 implements a 3-second delay during which it does not read the "data.txt" file. This delay is intended to allow the deterrence measures to take effect before resuming monitoring.After the 3-second delay, the ESP32 resumes monitoring the "data.txt" file for any further updates. This ensures that it can respond promptly to the next object detection result.When the ESP32 reads a "0" value in the "data.txt" file, indicating the absence of any birds or detected objects, it simply continues monitoring without initiating any delay or further actions. The circuit diagram related to the actuation section is given in the figure 5b

D. Deployment in web interface

The project's web interface serves as a crucial tool for monitoring and interacting with the system's bird detection and scarecrow activation processes. Developed using HTML and CSS, the interface provides a user-friendly platform for real-time status updates. Supported by a PHP backend, it seamlessly connects with the "data.txt" file, which continuously updates with binary values (1 or 0) indicating bird presence. In response to these updates, the interface dynamically generates alerts, displaying "Bird detected" and "Scarecrow active" when a bird is detected (value = 1), providing users with immediate insight into the system's activity. Conversely, when no bird is detected (value = 0), the interface displays "No bird detected" and "Scarecrow not active," reassuring users that the scarecrow remains idle. This dynamic and informative web interface enhances user engagement and facilitates effective monitoring of the agricultural protection system's performance. The web interface is shown in the figure 3.

V. Results and Outcomes

The project successfully demonstrated the capability to detect and deter hazardous animals, particularly birds, in agricultural fields 4. This led to a tangible reduction in crop damage, resulting in higher crop yields and increased agricultural productivity. By incorporating the ESP32 microcontroller and YOLOv3 object detection, the project significantly reduced the need for human intervention in crop protection. The system's automated responses to bird detections streamlined the protection process, making it more efficient and cost-effective for farmers.

A. Experimental prototype

The project prototype is shown in the figure 5.

VI. Discussion

A. Limitations

- Latency: One of the limitations of the project is latency, particularly in the real-time response to bird detections. While the YOLOv3 model is efficient, there may be some delay between bird detection and the activation of scarecrow, lights, and buzzer. Reducing this latency is an area for improvement.
- ESP32 Cam's Vision Range: The ESP32 Cam's vision range is restricted, and its ability to capture objects at a distance is limited. This range can be influenced by factors like lighting conditions and the camera's placement. Expanding the vision range is an important consideration for comprehensive crop protection.
- Environmental Conditions: Adverse weather conditions, such as heavy rain, fog, or extreme heat, can impact the effectiveness of the ESP32 Cam and object detection.

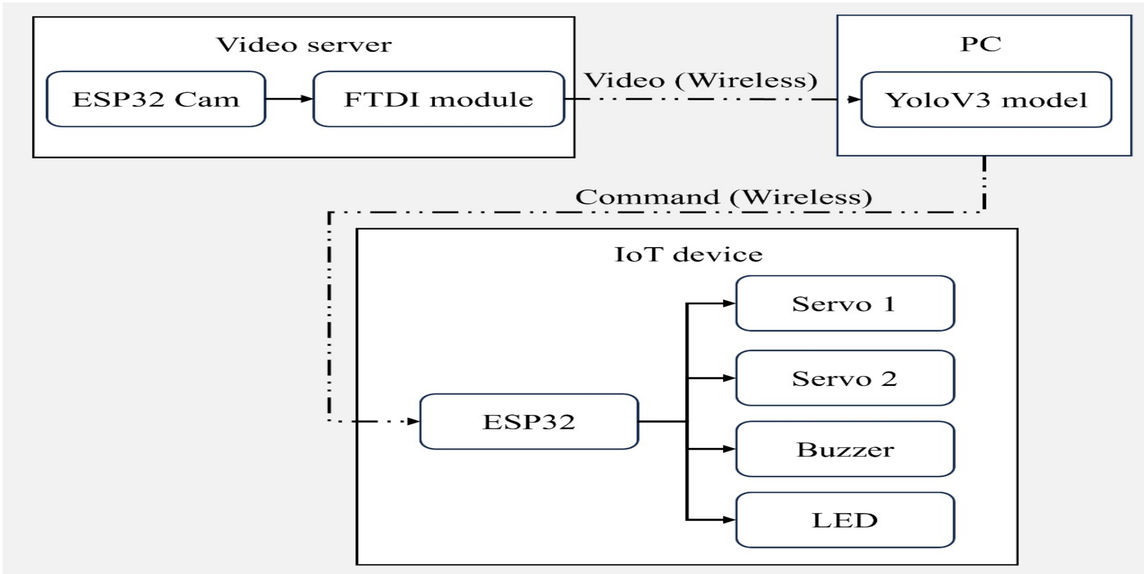
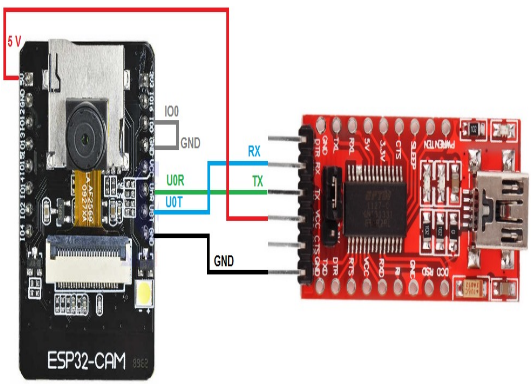
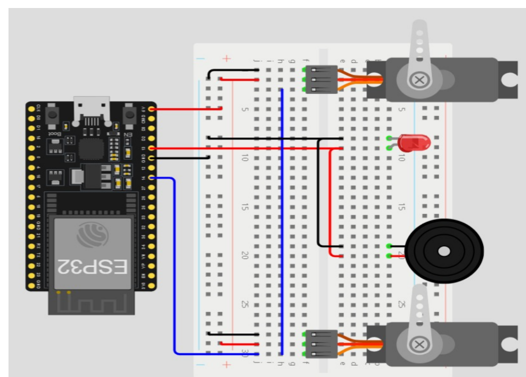


Fig. 1: Basic Workflow of the Project



(a) Circuit diagram for object detection



(b) Circuit diagram for actuation.

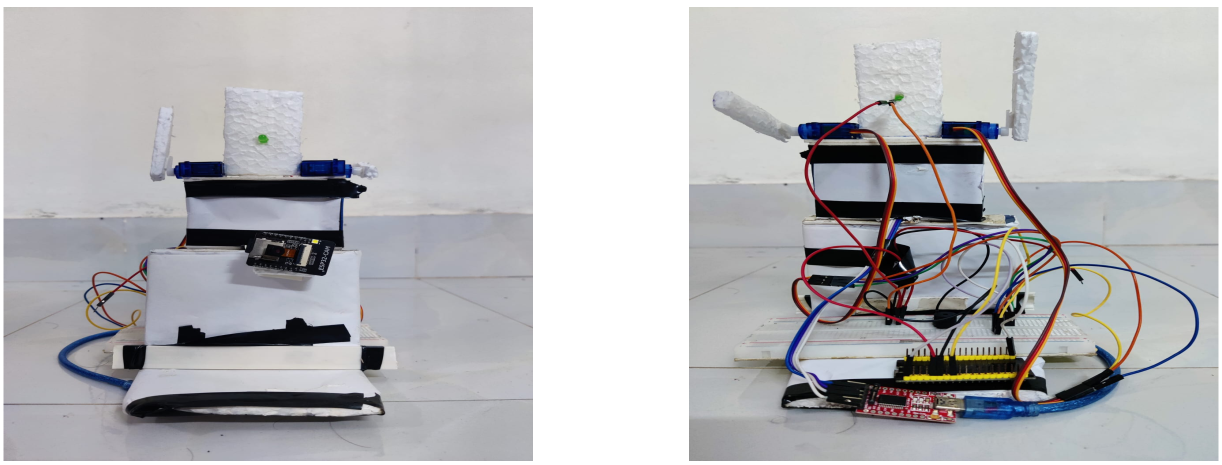
Fig. 2: Circuit Diagram

(a) Interface for detecting bird.

(b) Interface for not detecting bird.

Fig. 3: Web Interface

Fig. 4: Object Detection(Bird)



(a) Front Side.

(b) Back Side.

Fig. 5: Prototype of the Project.

B. Future Scope

There are several avenues for future research and development that can build upon the work presented in this project. Some potential directions for future work include:

- Improved Latency: To enhance the system's real-time response, future plans involve optimizing the processing pipeline to minimize latency. This might include optimizing code and leveraging hardware acceleration where applicable.
- Extended Vision Range: Expanding the ESP32 Cam's vision range is a key focus for future development. This could involve incorporating additional cameras or utilizing cameras with enhanced zoom capabilities to capture objects at greater distances.
- Custom Object Detection: Training the model to recognize specific bird species or other relevant objects in addition to generic bird detection. This customization can lead to more precise responses and insights.
- Multi-Object Detection Model: Develop or adapt a multi-object detection model capable of identifying various hazardous animals commonly found in agricultural environments, such as birds, rodents, insects, and larger mammals.

VII. Conclusion

In conclusion, the project represents a significant advancement in the realm of agricultural protection by integrating cutting-edge technology and machine learning to address the longstanding challenge of crop damage caused by hazardous animals. The implementation of the ESP32 microcontroller, YOLOv3 object detection, and a responsive web interface has enabled real-time monitoring and dynamic responses to bird detections in the agricultural field. Through the innovative use of the ESP32 Cam, the system has improved crop protection by effectively deterring hazardous animals. The work can help in mitigating crop losses, enhancing agricultural productivity, and contributing to food security in the region. Its user-friendly web interface provides a valuable platform for farmers to monitor and interact with the system, fostering accessibility and engagement. By amalgamating modern technology, machine learning, and a comprehensive approach to agricultural protection, the project exemplifies a sustainable and efficient solution for addressing the challenges faced by farmers in Bangladesh and similar agricultural regions. It not only offers immediate benefits but also paves the way for further advancements in precision agriculture and environmental sustainability.

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