Enhanced IoT-Based Weed-Detection for Crop Monitoring using Deep Learning

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Abstract: In agriculture, a significant problem is weed infestation which reduces the crop growth by competing for sunlight, water, and nutrients. Widespread herbicide spraying and hand pulling are traditional methods of weed control that consume a lot of labor and time as well as have negative effects on the environment. This project solves the problem of precise and efficient weed detection using IoT technology. The ESP32-CAM captures weeds in real-time and sends it for detection. The pre-processing steps contains removing noise and resizing images are performed to improve accuracy for pictures taken in the field. YOLO not only identifies the regions where weeds are located, but also classifies the type of weed based on the model used. Non-Maximum Suppression (NMS) is one of the detection enhancement methods that is used to improve precision.

Keywords: weed detection, ESP32-CAM, YOLO, smart farming, precision agriculture, image processing, IoT in agriculture, deep learning, realtime detection

I. INTRODUCTION

Farming has always been a tough job, and one of the most annoying issues farmers deal with is weed growth. Weeds pop up everywhere in crop fields and compete with the actual crops for sunlight, water, and nutrients. Over time, they can mess with the growth of plants and reduce how much food the field produces. Usually, farmers either remove weeds by hand or spray herbicides over the entire area. Both methods work to some extent, but they also come with problems. Manual weeding takes a lot of time and labor, while spraying chemicals everywhere isn't good for the soil or the environment.

That's what got us thinking — can we make this process smarter? These days, with how fast tech is moving, especially in areas like AI and IoT, there's a real chance to solve some of these old-school problems in better ways. So, for our project, we decided to build a system that can automatically detect weeds using a camera and a trained AI model. The idea is simple: instead of checking every plant manually, we let the system do the detection part.

To capture images from the field, we used an ESP32-CAM — a small and affordable camera module that can be placed on a moving device or mounted in the field. It takes pictures of the crops and weeds. These images are then sent to a laptop, where we use a deep learning model (YOLO, short for You Only Look Once) to analyze them. YOLO is pretty popular in computer vision tasks because it's fast and can detect multiple objects in a single

image. Our system basically tells the difference between weeds and crop plants. Once it detects weeds, it could, in future versions, be connected to something like a robotic arm or sprayer to take action on the spot. That's not part of the current version, but we see it as a next step.

We wanted to keep the project affordable because many Indian farmers can't invest in expensive machinery. All our components are low-cost and easy to find. We also focused on building something that could actually work in the field, not just in lab conditions. The early results from our testing are promising — the model detects weeds with decent accuracy, and the ESP32-CAM handles image capture well in good lighting.

II. RELATED WORK

Fachinelli and his team [1] explored how different crop histories, like rotating between pasture and annual crops, affected the types and spread of weeds in soybean fields. They found that some weeds tend to come back more often depending on what was grown before. It was pretty eye-opening how past farming choices can actually make future weed problems worse. Their study shows why it's important to watch weed patterns over time, not just season by season.

Fang et al. [2] tried mixing machines with herbicides to deal with weeds in maize fields. Instead of just spraying chemicals or only using tools, they combined both, and it worked better overall. What stood out was how this method helped reduce the need for too many chemicals, which is a big deal when you're trying to farm more sustainably. It also pointed out that weed control doesn't always need fancy AI — sometimes it's about using what you have in a smarter way.

Yang and his co-authors [3] focused on automatic spraying systems for greenhouse-grown vegetables. They weren't necessarily detecting weeds, but they worked on improving how targeted the spraying could be. It's useful for precision farming where accuracy is really important. Their analysis of current tech gave a clear idea of how spraying could become smarter and reduce waste, which is especially important when you're working in limited indoor space.

Su et al. [4] tried using drones to find blackgrass weeds in farms. Instead of just snapping normal pictures, they went with multispectral images, which pick up things the human eye can't see. After collecting the images, they used a machine learning model to figure out where the weeds were showing up. It's a pretty smart way to scan large fields without walking around. Farmers could just fly the drone, run the data, and get a map of where the weeds are. The idea isn't totally new, but the way they combined the tech made it more useful and practical for real farming.

Nik et al. [5] also used UAVs but focused more on classifying different weeds using various kinds of imagery. They looked at hyperspectral and multispectral data to see what gave the best results. Turns out, picking the right wavelengths really makes a difference in how well the system can tell weeds apart. This study basically showed that not all "smart" imaging is created equal — the details matter.

Li et al. [6] used a more old-school machine learning method: SVM. They worked on detecting weeds in cotton fields early on, using PCA to clean up the image data before classification. Even though it wasn't deep learning, the method worked pretty well. It goes to show that simpler models still have value, especially if the data is preprocessed right.

Zhao and Wei [7] looked into how to make weed detection systems work better when field conditions aren't ideal. You know how in real farms, lighting can be weird, plants overlap, and the ground is messy? They dealt with that by mixing

different features — like not just the color of the weed, but its shape, texture, and a few other things. By putting all of that together, their system could recognize weeds more reliably, even when the surroundings weren't super clean or consistent. It's the kind of approach that makes sense in real-world farms, where things rarely go according to plan.

III. METHODOLOGY

In this project, we mainly worked with the ESP32CAM module. It's a small and budget-friendly board that has a camera and Wi-Fi built in, which is perfect for what we needed. We used it to take pictures from the field, basically trying to capture weeds in their natural setting — sunlight, soil, shadows, and all that. Once the image is taken, it gets sent to the laptop. That's where the actual detection part happens. The laptop is running a YOLO model, which we trained earlier using a bunch of weed images. But before sending the image to the model, we do a couple of preprocessing steps. Mostly just resizing and a bit of noise cleaning. Sometimes the images from the field are a little messy — maybe too bright or blurry — so we try to fix that before detection.
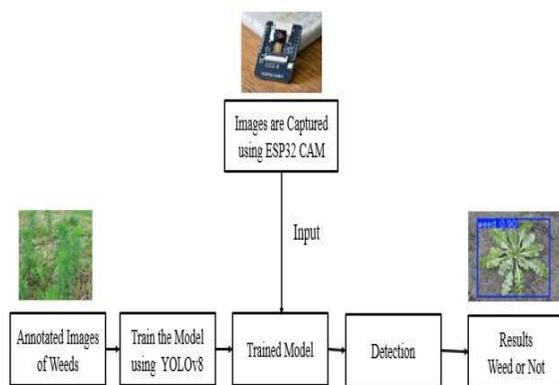
Fig 1: System Architecture

The YOLO model (we used a lighter version because it's faster) then goes through the image and draws boxes around anything it thinks is a weed. Sometimes it detects too many boxes in

the same place, so to clean that up we used something called Non-Maximum Suppression, or NMS. It just helps avoid marking the same weed more than once. That made a big difference in accuracy. One challenge was handling real-time performance. Since ESP32CAM doesn't have the power to run YOLO on its own, we had to offload the model to the laptop. But we made sure the images could be transmitted easily and without delay. If the Wi-Fi drops or slows down, we set it up to retry or store the image temporarily.

A. Dataset Description

We used a dataset with around 2,000 images in total, which had a mix of weed plants and tomato plants. The main idea behind using this dataset was to help the model learn how to correctly spot weeds and tell them apart from healthy tomato crops.Once we had the images ready, we went through and labeled them manually. For each weed image, we drew bounding boxes around the weed areas. It took a bit of time, but it's a crucial step because the model (YOLOv8) needs those markings to understand what to look for when it's trying to detect weeds later on.

The images were grouped into two main categories—weed and tomato. The numbers weren't exactly equal, but we made sure there was enough of each type to keep things balanced during training. Also, since the images came with different lighting and angles, it gave the model a chance to learn from more real-world-like situations.

B. Pre-processing

Before jumping into weed detection, we had to make sure the images we were feeding into the model were clean and consistent. The ESP32CAM, while great for its price, captures raw images in all sorts of conditions — sometimes in bright sunlight, sometimes in low light, and often with a bit of motion blur. So, the first step was to tidy them up. We resized each image to 416x416 pixels, which is what our YOLO model expects. After that, we converted the images into NumPy arrays so they

could be processed efficiently. But more than just resizing, we also cleaned up the images by reducing noise and enhancing contrast a little — things that help the model see the difference between crops and weeds more clearly. Once we had a neat set of images, we split them into two groups: one for training the model and another for testing how well it performs.

C. Hardware Integration

We chose the ESP32-CAM due to its affordability and ability to capture and send images over Wi-Fi. It's a lightweight module but powerful enough for basic IoT applications. The captured images are either sent directly to a local laptop or a cloudbased inference server, where the YOLO model is hosted. This avoids the need for expensive edge computing hardware like a Jetson Nano or Raspberry Pi.

D. Image Processing Pipeline

The process starts with the ESP32-CAM capturing images of the field, either automatically at set intervals or manually when needed. Since outdoor conditions can be unpredictable—like changing light or dust— some basic noise reduction filters are applied to clean up the images. After that, each image is resized to 416x416 pixels so it fits properly into the YOLOv4 model's input format. Once the image is cleaned and resized, it's fed into the YOLO model, which scans for any weeds present. To make sure the model isn't drawing too many overlapping boxes around the same weed, a technique called Non-Maximum Suppression (NMS) is used. This helps clean up the results by keeping only the most accurate bounding box for each detected object.

E. YOLOv8 Algorithm

In this project, we used the YOLOv8 algorithm to detect weeds in agricultural field images. YOLOv8 (You Only Look Once, version 8) is a real-time object detection model that processes the entire image in one go, making it both fast and accurate. Once the ESP32-CAM captures an image, it's passed to YOLOv8, which identifies and locates weeds by drawing bounding boxes around them. Unlike older models, YOLOv8 is more efficient and better at handling real-world conditions like poor lighting, blurry images, or cluttered backgrounds. It also uses a technique called Non-Maximum Suppression (NMS) to remove overlapping boxes and highlight only the most accurate detections. Overall, YOLOv8 acts as a smart, reliable eye in the field, helping detect weeds precisely and quickly.
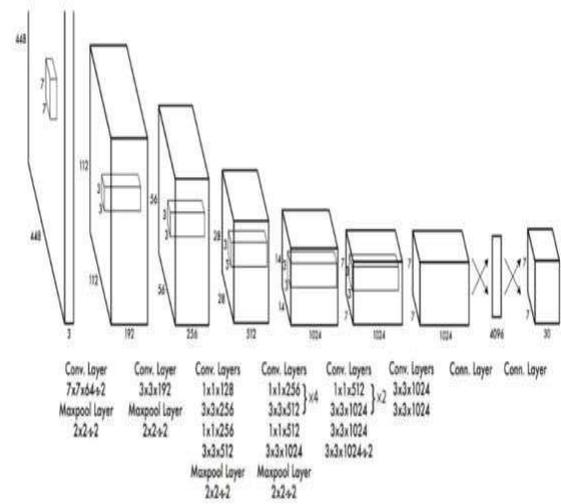
Fig 2: YOLO Architecture
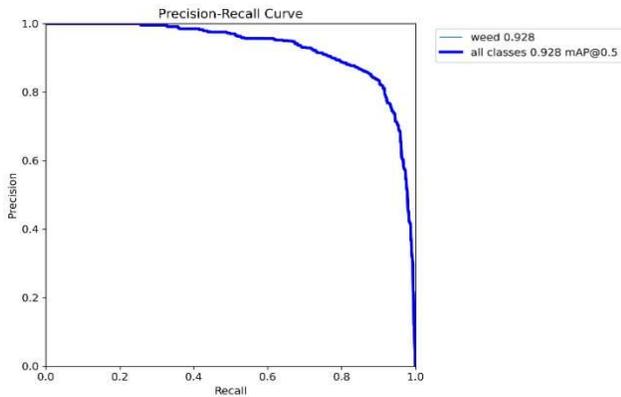
IV. RESULT
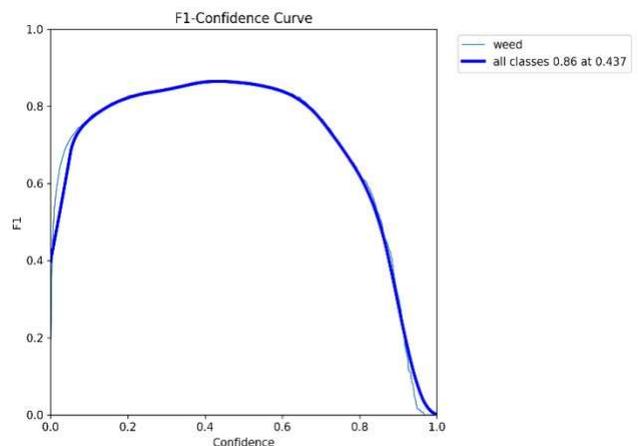
Fig.3: F1-Confidence Curve
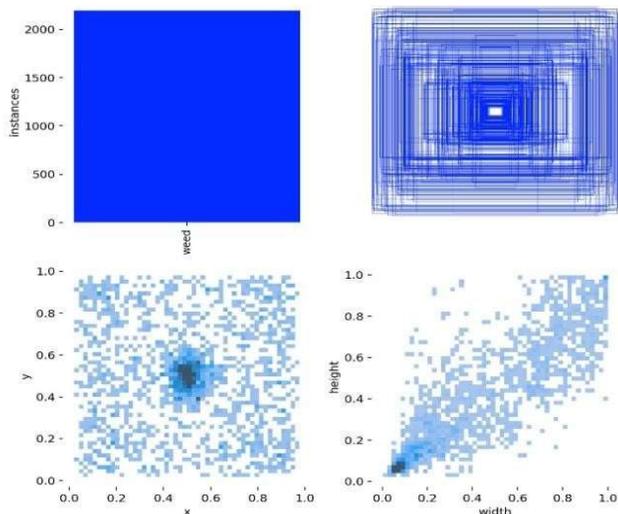
Fig 4: Precision-Recall Curve

Figure 5: Labels Matrix

Fig 6: Detects the Weed

V. CONCLUSION

This whole thing started because we wanted to tackle a common problem farmers face — weeds messing up crops. We didn't want to go with expensive stuff like drones or heavy setups, so we picked the ESP32-CAM. It's small, cheap, and to be honest, pretty easy to work with once you figure it out. We trained a YOLO model and tested it with the images the camera sent. The accuracy wasn't perfect every time, but most of the time it caught the weeds. To make things smoother, we also did some resizing and cleaned up extra detections using something called NMS, which basically helps avoid repeating boxes on the same weed.

VI. FUTURE WORK

Honestly, there were challenges. Sometimes the Wi-Fi dropped or the images were blurry because of the sunlight. Also, since the ESP32-CAM can't run heavy models, we had to use a laptop, which isn't very portable. In the future, we're thinking of trying it out with something like Raspberry Pi, or maybe train a lighter version of the model to work directly on the board. We're also interested in adding a spraying feature. Right now it only detects weeds, but if we can make it spray at the same time, that would save a lot of effort for farmers. A simple mobile app might also help — maybe something that shows the images and alerts them when weeds are spotted.

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