*Journal of Harbin Engineering University*
*ISSN: 1006-7043*

Vol 45 No. 4
April 2024

# Artificial Intelligence - Driven Autonomous Robot for Crop Cultivation

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**Abstract:** Agriculture has been considered as the primary occupation by more than 42% of the total population in the world. It can also be seen that agriculture is known as the 'Backbone of India', since more than 70% of the Indian population depends on agriculture. The main goal of Agribot is to apply technologies related to robotics in the field of agriculture. Weeds are plants that take up space in an unproductive area and compete with other crops mainly for light, nutrients, water, and space. The labor-intensive task of weed control frequently makes agricultural challenges like lower yields and higher hardware demands worse. In addition to posing a resource competition with crops, weeds harbor illnesses that have the potential to significantly reduce agricultural output. Our suggested remedy is to incorporate a camera into the farming apparatus. By making use of the live video feed that this camera will offer, weeds among the crops can be identified using image processing techniques. To differentiate between weeds and crops, the Convolutional Neural Network (CNN) algorithm will be used by the system. Through training, the CNN algorithm will extract pertinent information from photos to improve the accuracy of weed detection, opening the door for an effective and automated weed management system.

**Keywords**: Agriculture, CNN Algorithm, Image Processing, Spraying, Weed Detection.

## Introduction

Plants are mainly cultivated for food, fibre, and various products, with over 42% of the entire population engaged in agriculture. Despite this, outdated farming methods persist, leading to increased labour and reduced product accuracy. This project aims to develop an autonomous agricultural robot for tasks like weed disease identification and pesticide recommendations, addressing agricultural challenges and improving end-product accuracy. Agribot is committed to advancing robotic technologies in agriculture. Most nations rely on traditional farming practices involving manual labour, tractors, and animals for ploughing and seed sowing. Historically, weed detection involved manual labour, later transitioning to pesticide use. Despite some automated techniques, poor accuracy hinders widespread adoption. Our research focuses on using image processing to identify weeds in crops accurately. Subsequently, identified weed areas will be targeted by an automatic pesticide sprayer, requiring clear area snapshots for precise detection. Farmers benefit from both human-operated and autonomous robots. The project aims to create a weed identification module that notifies the farmer of the appropriate pesticide based on the weed's form, colour, and spots. This initiative seeks to reduce farmers' workload, enhance productivity, and improve agricultural yield. We address the challenge of weed classification in agricultural research, studying two methods: intensity-based classification and area thresholding classification.

## 1. Objectives

Objectives of our proposed model are as follows:

1. Agribot is designed to navigate the field and is developed to run in two modes: auto mode and manual mode. In manual mode farmer can operate from mobile phone and control functions like disease detection in auto mode robot detects weed and automatically takes action for spraying.
2. Robot receives image information and identifies, classifies, stores and reports from weed prediction
module using Artificial Intelligence and sprinkles weedicide if required.
3. This module employs Machine Learning techniques (CNN) and detects whether the weed is infected or not. It uses image processing modules for detection.
4. To do the performance analysis of the proposed system for validation
module using Artificial Intelligence and sprinkles weedicide if required.

5. This module employs Machine Learning techniques (CNN) and detects whether the weed is infected or not. It uses image processing modules

**Methods**

1.1 Datasets:

The Weed Image Database Consortium (LIDC) and the Image Database Resource Initiative (IDRI) provided the training dataset. The Digital Imaging and Communications in Medicine (DICOM) format stores 1000 weed pictures of large and tiny tumors comprising LIDC and IDRI. The methodology for developing an AI-driven autonomous robot for crop cultivation, incorporating weed detection, involves a comprehensive integration of hardware and software components. Fig 1. shows the initial phase encompasses defining clear objectives and requirements, followed by careful selection and integration of sensors onto the robot platform which is the Arduino Uno board. Autonomous navigation algorithms are developed using inputs from these sensors, ensuring the robot can efficiently traverse the field while avoiding obstacles. The Arduino Uno board is further incorporated with the motor driver which enables the agribot to spray pesticides. To address weed detection, a machine learning model, often based on convolutional neural networks, is trained on labeled datasets.

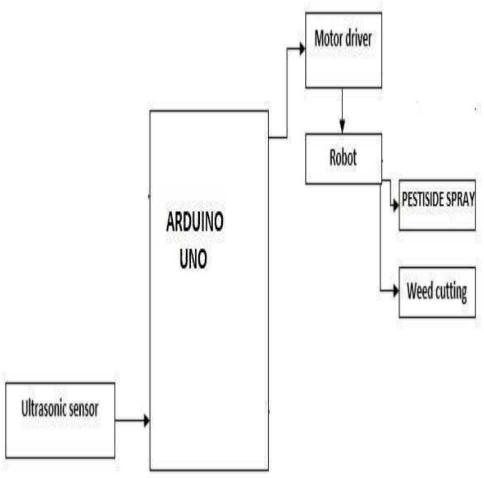



**Fig 1: Block diagram of Agribot**

6. for detection.To do the performance analysis of the proposed system for validation

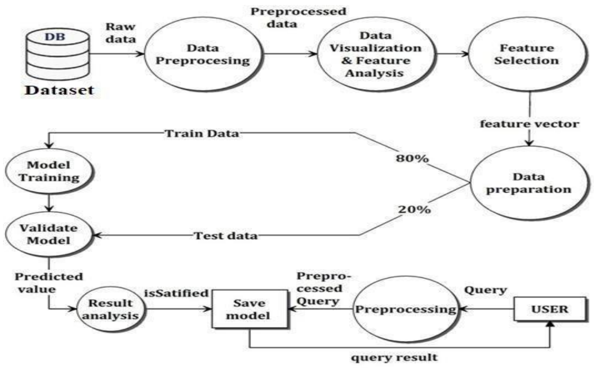



**Fig 2: Block diagram of system design**

A dataflow overview can be used to describe how knowledge evolves from one module to the next, as seen in Fig. 2. The module yield and information are shown in the graph. To help the user comprehend the accuracy as a whole, it offers an overview of the training and testing data used along with an analysis of the anticipated value and result.

1.2 Image acquisition process

The process of processing an image begins with image acquisition. In image processing, this stage is often referred to as pretreatment. The process entails obtaining the image from a source, typically one that is hardware-based. Fig 3. shows that the images are obtained using the digital camera that is connected to the laptop. The images captured are subjected to further pre-processing.

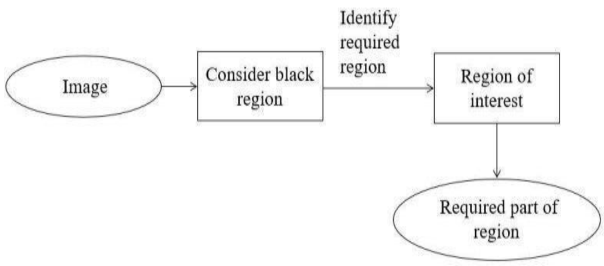



**Fig 3: Image Acquisition Process**

1.3 Image pre-processing process

The process of image enhancement helps to carry out the image analysis process for a more appropriate display by improving the input image.

Fig 4. shows how image data reduces unwanted distortions and enhances some image features for further image processing. Image pre-processing involves three main things a) Grayscale conversion b) Noise removal c) Image enhancement

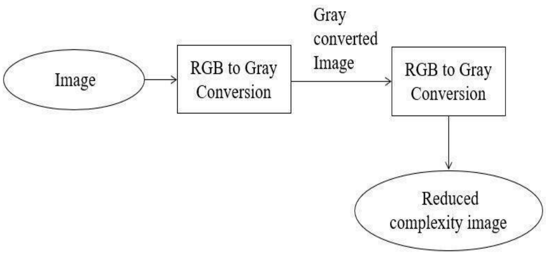



**Fig 4: Image Pre-processing Technique**

1.4 Image Segmentation process

Images that have been divided into smaller segments, a collection of pixels, or sub-pictures remain after the segmentation process. Fig 5. illustrates the three stages of segmentation that the input image goes through in order to extract the item. The clustering algorithm used in this implementation for picture segmentation iscalled mean shift clustering.

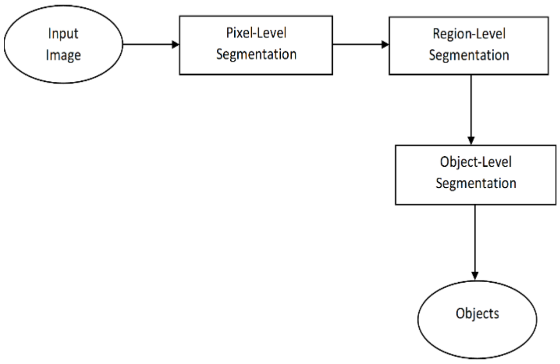



**Fig 5: Image Segmentation**

1.5 Feature Extraction Process

The process of extracting features from the segmented image comes next. The feature extraction procedure, which primarily concentrates on the feature of interest and eliminates extraneous characteristics, is depicted in Fig. 6. This technique helps to decrease the image data. This is accomplished by taking measurements of specific characteristics including the weed's entropy, energy, mean, texture, and so forth.

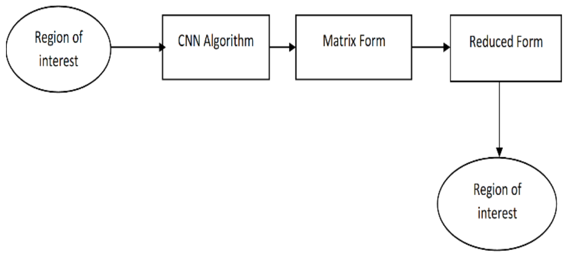



**Fig 6: Feature Extraction Process**

1.6 Classification Process

In the classification process, the input data is often represented as a feature matrix. Each sample or data point is a row in this matrix, and the features are the columns. Fig 7. shows the extracted features from the weed images are used as input to a classifier, which classifies weed images based on the type of disease and magnitude of disease. Convolution neural networks (CNN) are used in binary classifiers that employ the hyper-plane, often known as the decision boundary between two classes. The boundary is maximized between the hyperplane and two classes. The samples that are nearest to the margin will be selected in determining the hyperplane is called support vectors.

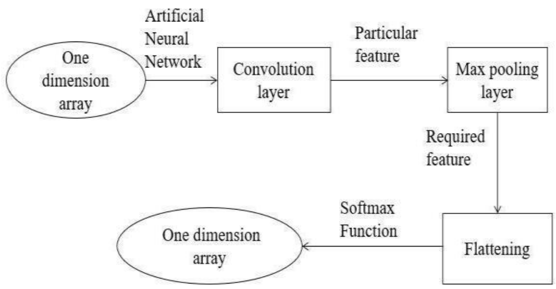
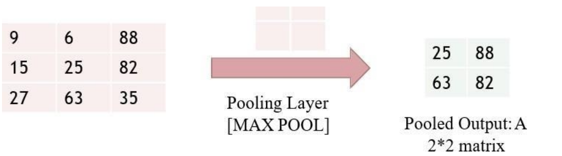


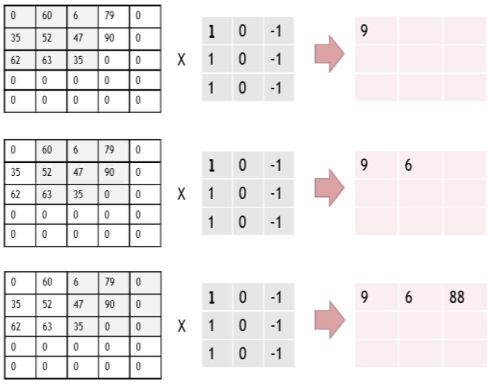

**Fig 7: Classification process**

1.6.1 Convolutional Layer

Following the computer's reading of an image in the form of pixels, we use convolution layers to extract a small portion of the pictures. The terms "features" and "filters" refer to these pictures or patches. As shown in Fig 8, when the convolutional layer receives these approximate feature matches, it becomes much more adept at identifying similarities than when it receives whole picture matching situations. When these filters and the newly input photos match, the image is correctly categorized. In this case, align the features and the image, multiply each pixel in the image by its corresponding pixel in the feature, add up the pixels, and divide the total number of pixels in the feature.




The filter values are placed at the appropriate locations on the map that we produce. Similarly, we'll transfer the feature to each other point in the image and check to see if it matches there. Ultimately, the output will be a matrix. In




conclusion, this layer scans the whole image for patterns and formulates it in the form of a matrix of 3x3 dimensions. This convolved feature matrix of the image is known as Kernel. Each value in the kernel is known as a weight vector.

**Fig 8: Output Matrix for convolutional layer**

### 1.6.2 Relu Layer

The filtered images with any negative values eliminated and replaced with zero make up the rectified linear unit (ReLU) layer. This is done to keep the values from adding up to zero. With the help of this transform function, all negative values are eliminated from the matrix, and nodes are only activated when the input value exceeds a predetermined threshold. If the input value is less than zero, the output will be zero.

### 1.6.3 Pooling Layer

Followed by the ReLu layer is the pooling layer. The main advantage of the pooling layer is that it increases computer performance and decreases overfitting chances. As shown in Fig 9. the output matrix obtained is minimized and the image matrix is broken down into sets of 4 rectangular segments which are non-overlapping. Max pooling and Average pooling are the two different forms of pooling. Using max pooling, the maximum value inthe taken relative matrix region is obtained. The average value in the related matrix region is obtained using average pooling. The pooling layer's primary benefit is that it improves computer efficiency while lowering the likelihood of overfitting.

**Fig 9: Output Matrix for pooling layer**

## 2. Results

PERFORMANCE ANALYSIS: For the performance analysis of this model, we haveused tensorboard

visualizations and their functions.TensorFlow is an open-source library that was developed by Google initially for deep learning applications. It also supports traditional Lachine Learning. Primarily, TensorFlow was developed for large numerical computations. However, later it proved to be extremely useful for deep learning development as well.

**Fig 10: Accuracy Vs Training steps**

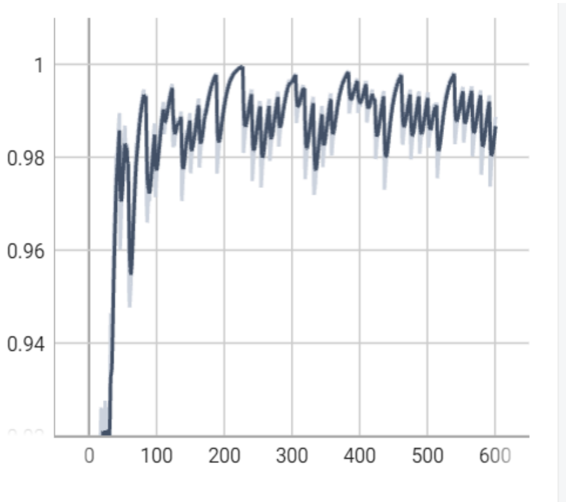
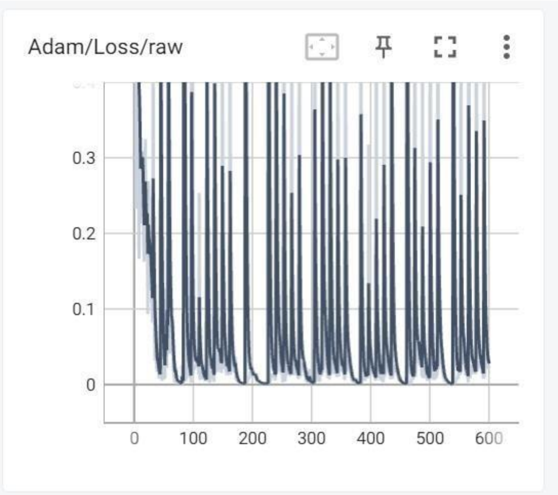



Fig 10. shows the accuracy of the dataset that has been utilized. In the initial stages of training, accuracy tends to be low as the model is exposed to the dataset and begins to learn relevant patterns. The ReLU activation function, known for introducing

**Fig 11: Loss Vs Training steps**




non-linearity to the model, plays a crucial role in enabling the network to capture complex relationships in the data. As training progresses, the accuracy typically improves,
reflecting the network's ability to generalize from the training data to unseen examples. The ReLU activation function facilitates the model's capacity to learn and model intricate features within the images, contributing to the overall effectiveness of weed detection.
The accuracy-versus-training steps curve may exhibit variations such as plateaus or fluctuations. Plateaus might suggest that the model has reached a saturation point in learning from the current data, and further training may not yield substantial improvements. Fluctuations could be indicative of the model encountering diverse patterns and adjusting its weights accordingly. The accuracy we are expecting is 98 percent, it varies from 99 to 98 depending on the OS (Operating System).

As shown in Fig13. in the above image, Adam optimizer in Tensorflow is an algorithm used in deep learning models. All the graphs displayed are the final output which was received after ignoring outliers. There were also two lost cards during the analysis process.

Comparative Analysis:
Table.1. as shown below gives an overall comparative analysis of all the referenced papers which was taken into consideration for review purposes.

| Training Steps | Accuracy (%) |
|---|---|
| 100 | 98.3 |
| 200 | 99 |
| 300 | 99.8 |
| 400 | 98.7 |
| 500 | 98.5 |
| 600 | 98.3 |

Table 1: Comparative Analysis of training steps

| Model | Accuracy (%) |
|---|---|
| Rahul D S. et al., [2] (IOT) | 92 |
| Xinyu Gao. et al., [6] (CNN) | 96.7 |
| Kailiang Zhang et al., [9] (CNN) | 65.3 |
| Guanjun Bao et al., [10] (CNN) | 97 |
| Min Hyuc Ko et al., [11] (CNN) | 98 |
| Proposed model (CNN) | 99.8 |

**Table 2: Comparative Analysis of different models**

## 3. Discussion

Given agriculture's central role as a primary occupation, the development of an agribot with weed disease detection capabilities offers an alternative approach to streamline agricultural tasks. This robot is designed to handle various agricultural activities, including pesticide spraying, while also leveraging a database for identifying diseases in weeds by distinguishing between healthy and unhealthy specimens. The primary goal of this project is to create a comprehensive agricultural robot capable of performing essential tasks and simultaneously identifying potential threats posed by weed diseases, thereby preventing harm to the plants. In conclusion, recent advancements in deep learning-based weed detection have yielded promising results. The implementation of sophisticated deep learning techniques has led to the creation of more accurate and efficient weed detection models. These models not only assist farmers in minimizing herbicide usage, with potential environmental benefits, but also have the capacity to significantly reduce the labor and costs associated with manual weed management in agriculture.

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