# Implementation of Multi-feature Image Identification Using Supervised Binary Classification and Maximum Likelihood Estimate in a Robotic Herbicide Spray Machine

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***Abstract- Agriculture sector is adopting new technologies, which seems very promising as it will enable farm productivity and profitability. Weed control is one of Agriculture's few operations that is still not yet fully mechanized, labour-intensive and holds potential for automation. The great demand for labour as a major problem in weed management paved the way for the farmers to look for alternative through the spraying of harmful pesticides. However, this led to several health problems for the farmers and the people who are consuming it. Under natural growing conditions, weeds are generally distributed in small patches, but farmers often uniformly spray herbicide in their fields, which is not in agreement with sustainable agriculture development and increases the cost of crop production. Autonomous robotic weed control systems with multi-feature image identification using Convolution Neural Network (CNN) supervised binary classification and maximum likelihood estimate (MLE) have proven to be a viable alternative, leveraging on the powerful representation learning capabilities of CNNs while incorporating the probabilistic modeling and parameter estimation of logistic regression. The experimental result of the proposed system has achieved an average of 97% classification rate for weed and plants in real time when implemented in small machines. The system hold promise to potentially improve agriculture's sustainability, lessen its negative effects on the environment, and lower the overall cost of production while lowering its current reliance on pesticides.***

***Indexed Terms- Artificial Intelligence, Autonomous Machines, Binary Classification, Convolution Neural Network (CNN), Weed Control***

## I. INTRODUCTION

The Global population explosion and increasing demand for food have presented the world with a threat to food security. The demand for food has outstripped supply in Nigeria, as it does more frequently in most developing nations. This is due to population growth and social mobility, which have led to this massive deficit. The Food and Agricultural Organization (FAO) of the United Nations forecast that global food production will need to increase by 70% if the population reaches 9.1 Billion by 2050 (Doering & Sorensen, 2018).

It is a widely acceptable fact that, the major problems in Agriculture are removing weeds, spraying harmful pesticides which leads to several health problems to the farmers and the people who are consuming it. There have been several methods of weed control (Tu et al., 2001), which include but are not limited to hand weeding and herbicide application. The former is costly and labour-intensive, practically not sustainable in large-scale farming, while the latter is injurious to human health and the environment. There is a great demand for the labour but only few people are interested in the field of agriculture. Under natural growing conditions, weeds are generally distributed in small patches, but farmers often uniformly spray herbicide in their fields, which is not in agreement with sustainable agriculture development and increases the cost of crop production. There have been attempts to address the challenges with the manual indiscriminate and excessive application of herbicides on farmland that leads to wastage of herbicides and subsequently damage of crops.

The agriculture sector is adopting new technologies, which seems promising as it will enable this primary sector to move to the next level of farm productivity and profitability. Precision Agriculture is defined by Wikipedia, as a farming management strategy based on observing, measuring and responding to temporal and spatial variability to improve agricultural production sustainability. One of the major areas of application of precision agriculture is in the area of weed management (Sharma et al., 2021).

Technology has proven to be the game changer in most aspects of human endeavours where it was impossible due to mostly the knowledge and data-driven approaches employed (Saiz-Rubio & Rovira-Más, 2020). These approaches have become the third wave of the modern agriculture revolution nowadays and is being enhanced with an increase of farm knowledge systems due to the availability of larger amounts of data. Autonomous robotic weed control systems hold promise toward the automation of one of agriculture's few remaining tasks not mechanized such as hand weed control (Hasan et al., 2021). Robotic technology may also provide a means of reducing agriculture's current dependency on herbicides, improving its sustainability and reducing its environmental impact.
Farms that decide to be technology-driven in some way, show valuable advantages, such us saving money and work, having an increased production or a reduction of costs with minimal effort, and producing quality food with more environmentally friendly practices. However, taking these advantages to the farm will depend, not only on the willingness of producers for adopting new technologies in their fields, but also on each specific farm potential in terms of scale economies, as profit margin increases with farm size. Further, among these new technologies, detection and identification of weeds under the wide range of conditions common to agricultural fields remains the greatest challenge (Zhang et al., 2023)(Veeragandham & Santhi, 2021).

This work aims to develop a vision-based autonomous weeding robot with multi-feature image identification using Convolution Neural Network (CNN) supervised binary classification and maximum likelihood estimate. The proposed system will leverage on the powerful representation learning capabilities of CNNs while incorporating the probabilistic modeling and parameter estimation of logistic regression. The developed Robot will be tested by deployment to work in the field to replace manual weeding and indiscriminate or excessive herbicide spray.

## LITERATURE REVIEW

This section reviews the current status of some core technologies (detection, identification and precision) required for the successful development of a robotic system for weed management. Among these technologies, detection and identification of weeds under the wide range of conditions common to agricultural fields remains the greatest challenge (Arif et al., 2021)(Srinivas et al., 2019). A few complete robotic weed control systems have demonstrated the potential of the technology in the field of Agriculture. Additional research and development are needed to fully realize this potential and this review will justify this assertion.

The application of machine vision technology to the field of weeds management in recent times have sensibly been receiving utmost attention by researchers and envisaged to be a useful tool for precision agriculture in the nearest future(Chang & Lin, 2018). However, realizing this potential entails the effective integration of multi-features to the artificial intelligence based robotic machines, whereas inappropriate integration can result in the unstable and inaccurate performance of the robot (Veeragandham & Santhi, 2021). The authors (Du et al., 2022) developed a multi-feature Smart robotic weeding systems which performs plant-specific operations and with the advantage of contribution to the sustainability of agriculture and the environment. This work referred to as under-canopy weeding system has contributed to monumental advances in autonomous robotic technologies for precision weed management in recent years. However, a prerequisite of this system is a reliable detection and classification of weeds to avoid mistakenly spraying in such systems and, thus, damaging the surrounding plants. Therefore, real-time multi-class weed identification enables species-specific treatment of weeds and significantly reduces the amount of herbicide use (Moazzam et al., 2023). Convolutional neural networks (cnns) are similar to “ordinary” neural networks find application in the area of image classification through mapping between raw image pixels and their class scores (Srinivas et al., 2019). since they are made up of hidden layers consisting of neurons with “learnable” parameters they are embedded in a machine vision system. however, a higher precision algorithm such as deep learning(Hasan et al., 2021)(Arif et al., 2021) coupled with parameter estimation algorithm such as maximum likelihood estimation (Sisodia et al., 2014), will provide the desired real-time response in a robotic weed management system. the classification model is evaluated using the following performance measures confusion matrix, accuracy, precision, recall & f1 score (Longtin, 2007).

## MATERIALS AND METHODS

The proposed scheme includes the use of the image processing technique to classify crops and weeds to enable the development of a mobile robot platform for weed detection employing a vision-based detector algorithm that can accurately detect weeds and with the ability of precision herbicide spraying. The system possesses a multi-feature image identification mechanism using Convolution Neural Network (CNN) supervised binary classification and maximum likelihood estimate for image classification. Leveraging on the powerful representation learning capabilities of CNNs and incorporating the probabilistic modelling and parameter estimation of logistic regression, we developed a vision-based autonomous weeding robot with the design details in the subsections below.

### 3.1 Dataset

Datasets are an integral part of the field of machine learning. Major advances in this field can result from advances in learning algorithms such as deep learning. The dataset consists of 1162 images of healthy maize leaves and 1059 images of weeds. These images were gotten from the Kaggle website. Figures 3.1 shows maize leave training set while Figures 3.2 depicts weed training set.

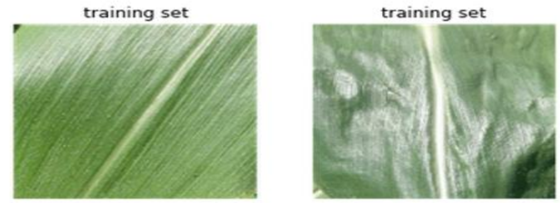


Figure 3.1: Maize leave training set


Figure 3.2: Weed training sets

#### 3.1.1. Weeds Dataset

The dataset was acquired from the Kaggle website with the aim of establishing two main goals to achieve the required variability and generality of the dataset. First, the different weed species of around 1059 images were collected which aid in training at high complexity if CNNs that require large, labelled data sets. Secondly, the dataset was split into equal positive and negative classes of each location. Thus, over-fitting of developed models to scene level image features were avoided by ensuring targets are identified through their native backgrounds. Finally, to ensure expert analysis of the data set, each image is required to labelled as to whether it contains a target weed species or not. The data set consists of images of ten weed species and their respective numbers are shown in Table 1, Figs. 3.2 and 3.3 respectively.

Table 1: Summary of the types of weeds and their representation

| S/No. | Weed Types | Representation |
|---|---|---|
| 1. | Speargrass (Imperata cylindrica) | W1 |
| 2. | Siam weed (Chromolaena odorata) | W2 |
| 3. | Nutgrass (Cyperus rotundus) | W3 |
| 4. | Milkweed (Euphorbia heterophylla) | W4 |
| 5. | Nuke-Noh (Tridax procumbens) | W5 |

| | | |
|---|---|---|
| 6. | Witchweed (Striga genus) | W6 |
| 7. | Couchgrass (Digitaria abyssinica) | W7 |
| 8. | Dayflower (Commelina benghalensis) | W8 |
| 9. | Bahama grass (Cynodon dactylon) | W9 |
| 10. | Elephant grass (Pennisetum purpureum) | W10 |

The data augmentation method employed to reduce overfitting during the training and validation process, was (Sharma et al., 2021). This is a scheme that can produce extra training and validating data from the present dataset. Thus, new weeds images for the training set were produced through the data augmentation process such as zooming, rotating, colour, flipping, horizontal and vertical shift, varying the brightness level and cropping.

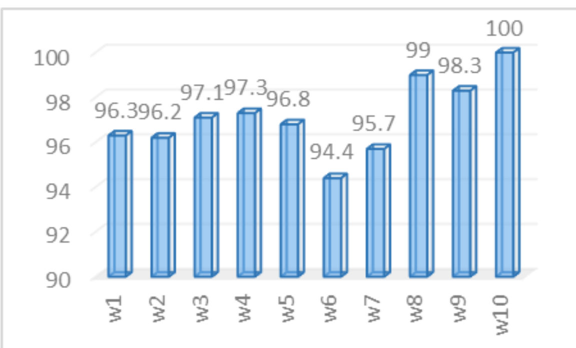


Fig. 3.3: A Distribution of the weed species

3.2.0 Binary image classification using maximum likelihood estimate (MLE)

To generate a model equation for image binary classification using maximum likelihood estimate (MLE), the following general steps were followed.

*Step 1: Deep learning*

Deep learning is a type of machine learning that trains a computer to perform human-like tasks, such as recognizing speech, identifying images or making predictions. Instead of organizing data to run through predefined equations, deep learning sets up basic parameters about the data and trains the computer to learn on its own by recognizing patterns using many layers of processing.

*Step 2: Image Pre-processing*

Data pre-processing can refer to manipulation or dropping of data before it is used in order to ensure or enhance performance, and is an important step in the data mining process. We Prepared our dataset obtained in section 3.1 by pre-processing the images. This may include resizing, normalizing, and any other necessary steps to ensure consistency and quality of the data as depicted in Figure 3.4.

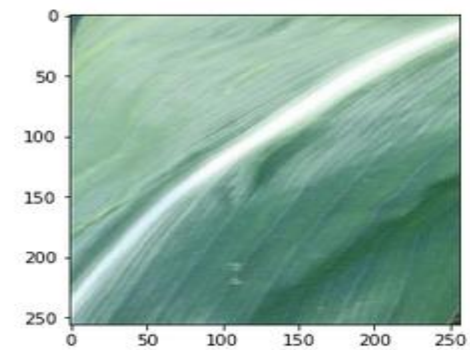


Figure 3.4: scaled sample of maize training set

*Step 3: Data Augmentation*

Large dataset is crucial for the performance of both ML and Deep Learning (DL) models.

Data Augmentation is a technique that can be used to artificially expand the size of a training set by creating modified data from the existing one. It is a good practice to use DA if you want to prevent overfitting, or the initial dataset is too small to train on, or even if you want to squeeze better performance from your model. It means that Data Augmentation is also good for enhancing the model's performance.

*Step 4: Data splitting*

One of the first decisions to make when starting a modelling project is how to utilize the existing data. One common technique is to split the data into two groups typically referred to as the *training* and *testing* sets. The training set is used to develop models and feature sets; they are the substrate for estimating parameters, comparing models, and all of the other activities required to reach a final model. The test set is used only at the conclusion of these activities for estimating a final, unbiased assessment of the model's performance. It is critical that the test set not be used prior to this point. After the division of dataset into training and testing sets in 2:1 ratio, sliding windows of various sizes are scanned over each training image to slice them into sub-images. If $w \times w$ is the sliding window size that is scanned over each image of size $m \times n$ with no padding and stride '$w$', then the number of sub-images($N$) formed for an image for that window size would be

$N = (m*n) / (w*w)$

*Step 5: Feature Extraction using Convolutional Neural Network*

Extract relevant features from your images that can help distinguish between the two classes. There are various techniques available for feature extraction, such as using pre-trained convolutional neural networks (CNNs) or handcrafted features like color histograms or texture descriptors.

Neural Networks are complex structures made of artificial neurons that can take in multiple inputs to produce a single output. This is the primary job of a Neural Network is to transform input into a meaningful output. Usually, a Neural Network consists of an input and output layer with one or multiple hidden layers within. In a Neural Network, all the neurons influence each other, and hence, they are all connected. The network can acknowledge and observe every aspect of the dataset at hand and how the different parts of data may or may not relate to each other. This is how Neural Networks can find extremely complex patterns in vast volumes of data. In this work, 10 layers were used in the data filtering.

*Step 6: Model Selection*

The appropriate model for binary classification adopted in this work is Logistic Regression and is suitable for this task. It is deployed to model the probability of an image belonging to a particular class.

*Step 7: Model Parameterization*

In the case of logistic regression, the model equation is typically represented as follows:

$$P(y=1|x) = 1 / (1 + \exp(-z)) \quad (1)$$

Where $P(y=1|x)$ is the probability of the positive class, x represents the input features, and z is a linear combination of the features weighted by the corresponding coefficients:

$$z = \beta0 + \beta1*x1 + \beta2*x2 + ... + \beta n*xn \quad (2)$$

Here, β0, β1, β2, ..., βn are the coefficients (parameters) to be estimated.

*Step 8: Maximum Likelihood Estimation*

The goal of MLE is to estimate the values of the coefficients that maximize the likelihood of the observed data. In binary classification, you can define the likelihood function based on the assumption that the labels follow a Bernoulli distribution. The likelihood function can be written as:

$$L(\beta) = \prod(P(y=1|x))^{\wedge}(y) * (1 - P(y=1|x))^{\wedge}(1-y) \quad (3)$$

Where y represents the true labels (0 or 1).

Maximizing the likelihood is equivalent to minimizing the negative log-likelihood (NLL) loss:

$$NLL(\beta) = -\sum(y*\log(P(y=1|x)) + (1-y)*\log(1 - P(y=1|x)) \quad (4)$$

The goal is to find the optimal values for the coefficients (β) that minimize the NLL loss.

*Step 9: Optimization*

The CNN was used to minimize the NLL loss and estimate the values of the coefficients. These techniques iteratively update the coefficients until convergence is reached.

3.2.2 Performance Evaluation Indicators

The performance evaluation for the binary classification will be employed using the commonly used evaluation indicators in the field of target detection: confusion matrix, precision (P), recall rate (R), and average precision (AP). The formulae for their computation are as follows.

(i) Confusion Matrix: In this work, we employed a matrix of size 2×2 for binary classification with actual values on one axis and predicted on another as depicted in Figure 3.5

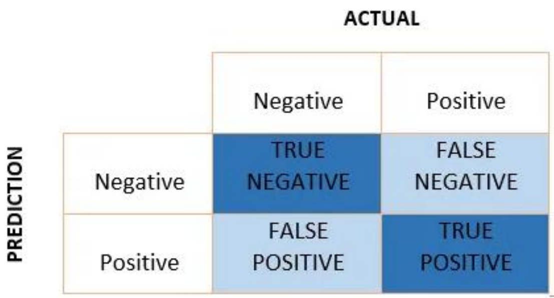


Figure 3.5: A 2 x 2 Confusion Matrix for Binary Classification

True Positive (TP) — model correctly predicts the positive class (prediction and actual both are positive). True Negative (TN) — model correctly predicts the negative class (prediction and actual both are negative). False Positive (FP) — model gives the wrong prediction of the negative class (predicted-positive, actual-negative). FP is also called a TYPE I error. False Negative (FN) — model wrongly predicts the positive class (predicted-negative, actual-positive). FN is also called a TYPE II error.

(ii) Precision: This metric gives, what percentage is truly positive Out of all the positive predicted.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

(iii) Recall: This gives out of the total positive what percentage are predicted positive.

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

(iv) Average Precision: This represents the area composed of the PR curve and the coordinate axis. The higher the AP value, the better the performance of the target detection algorithm.

$$AP = \int_0^1 P(R)\mathrm{d}(R) \tag{7}$$

where, TP represents the number of correctly detected corn and weeds; FP represents the number of misclassified corn and weeds; FN represents the number of missed corn and weeds.

## RESULTS AND DISCUSSION

This section presents and discusses the results of the experiments conducted. For the training during the experiment, the HP computer used has the following as its specifications: 32GB install memory (RAM), Intel(R) Core™ i7-4790 CPU @ 3.60GHz Processor and Window 64-bit operating system. storage SSD is 2TB, display card is Nvidia TITAN RTX, display memory is 24GB. For model training, Python version 3.7 and PyTorch version 1 were also used.

### 4.1 Model Evaluation and Summary

The trained model will be evaluated using the accuracy and loss metrics. You may also apply the model on a separate validation or test set to assess its performance. Figure 4.1 shows the summary of the model evaluation, and the layers are explained below:

➢ The first layer is a convolution, which takes an input shape (16,3).

- The first convolution has an output with shape (None, 180, 180, 16), where: None is the batch size , 180 and 180 are the size of the resulting image , 16 are the number of filters of this convolution and also the number of channels in its output
- The max-pooling layer takes the output of the convolution as input. The output of the pooling has shape (None, 90, 90, 16), it divided the size of the image by two, leaving the rest as it was.
- The Next convolution layer takes the output of the max-pooling as input. Now the output shape of this new convolution is (None, 90, 90, 32). The process continues repeatedly for max-pooling layers and next convolution layers as seen vividly in the summary table.
- The Flatten layer, which takes the images and transform them into a single vector, output shape is (None, 30976), where None is still the batch size untouched, the 30976 are all elements in the input tensor, now in a single vector, one vector per sample in the batch.
- Dense layers: The first has 128 units, the second has 2 units.
- Each layer has several parameters (which are generally the weights). The parameters that are trainable will be updated with backpropagation. The parameters that are not trainable will remain static or will be updated with a different method

(only a few layers such as Batch-Normalization has parameters that are updated with different methods)

- Therefore, the model has a total of 3,988,898 weights, all trainable.

```
[16] model.summary()

Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling_1 (Rescaling)      (None, 180, 180, 3)       0
_________________________________________________________________
conv2d (Conv2D)              (None, 180, 180, 16)      448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 90, 90, 16)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 90, 90, 32)        4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 45, 45, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 45, 45, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 22, 22, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 30976)             0
_________________________________________________________________
dense (Dense)                (None, 128)               3965056
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 258
=================================================================
Total params: 3,988,898
Trainable params: 3,988,898
Non-trainable params: 0
_________________________________________________________________
```

Figure 4.1: Model summary showing the convolutional layers.

4.2 Weed Classification Accuracy

The ensemble CNN and MLE methods were applied in this work to classify the weeds as depicted in Table 1. The results of the proposed CNN + MLE shown in Table 2 explains and Figure 4.2 depicts the classification accuracy of each weed. The achieved results are promising, as their average classification accuracy of CNN + MLE is 97.11% while CNN-MLE is above 94% which shows that the use of MLE estimation is responsible for the 4% performance increase. In the case of Elephant grass (Pennisetum purpureum) weed, the CNN + MLE achieved 100% of accuracy. It shows that the proposed method is much capable to classify the most prevalent weeds accurately. This was made possible because the MLE aids in estimating the description from image data sets, whereas CNN provides features from the data sets. Further, MLE interprets, and this ensemble approach ultimately quite helpful to classify the weed data sets. Hence, we get the impression that all the weeds are necessary to classify for better agriculture production. Application of deep learning methods on agriculture data set will help in farm management systems with real artificial intelligence systems, providing strong recommendations and insights for the increase of agricultural crops and their production, and also save them from the unwanted crops as they can decline the productivity of crops.

Table 2: Comparison of classification accuracy (%) of the weed plants

| S/No. | Weed Types | Weed Rep | CNN + MLE | CNN – MLE |
|---|---|---|---|---|
| 1. | Speargrass (Imperata cylindrica) | W1 | 96.3 | 94.3 |
| 2. | Siam weed (Chromolaena odorata) | W2 | 96.2 | 92.5 |
| 3. | Nutgrass (Cyperus rotundus) | W3 | 97.1 | 94.7 |
| 4. | Milkweed (Euphorbia heterophylla) | W4 | 97.3 | 94.2 |
| 5. | Nuke-Noh (Tridax procumbens) | W5 | 96.8 | 95.1 |
| 6. | Witchweed (Striga genus) | W6 | 94.4 | 91.7 |
| 7. | Couchgrass (Digitaria abyssinica) | W7 | 95.7 | 90.4 |
| 8. | Dayflower (Commelina benghalensis) | W8 | 99.0 | 95.2 |
| 9. | Bahama grass (Cynodon dactylon) | W9 | 98.3 | 94.9 |
| 10. | Elephant grass (Pennisetum purpureum) | W10 | 100 | 95.8 |

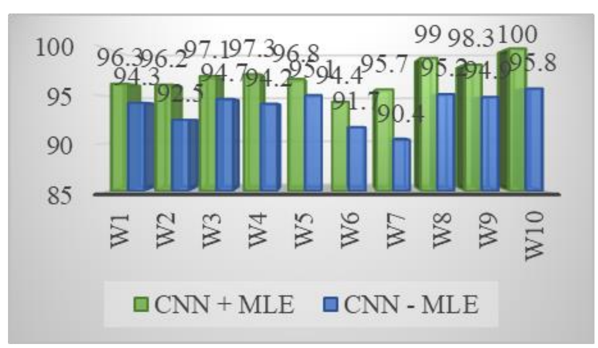


Figure 4.2: Classification Accuracy of the Weeds

4.4 Working Principle

The solar panel is placed on top of the Robot and is connected to the battery for charging the battery. Thus, the maximum efficiency is utilized from the sun by the solar panel and to the battery. The whole Robot requires the 12V battery to operate the system. The Robot is moving with the help of the gear motors. Some amount of power is driven by the H-Bridge IC to rotate the motors in clockwise direction. The images of weeds are captured by the camera and forwarded to the Raspberry pi which compares the captured images with the original images using Image Processing. The other devices are activated by the Arduino micro controller chip. (ATMEGA 328)

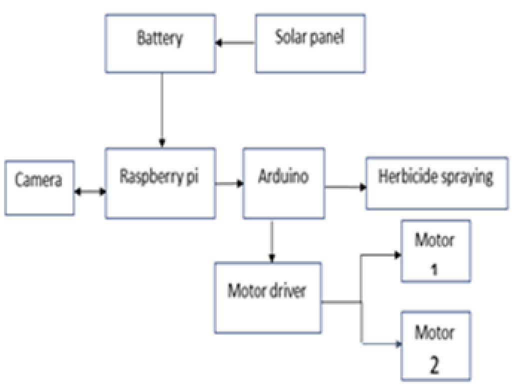


Figure 4.1: Assembled Robotic Herbicide Sprayer and its Block Diagram

## CONCLUSION

In this research work, a new approach has been proposed based on the convolutional CNN and MLE for the classification of the weed plants. The algorithms have been validated doing the different experiments, and the experimental results show that the proposed schemes are noticeably a better technique for the classification. There are many methods are proposed based on computer vision for the plant classification, but still, this research field needs the advance and automatic classifiers. The proposed method has a significantly high capability to detect and classify weed plants. Furthermore, commercial solutions are required for the identification of weed plants.

Future work, robotic based commercial solutions will be developed for identifying weeds and spraying pesticides. The limitations of the proposed work are that due to heavy data sets, it requires high-end computation time on both methods either by augmentation and without augmentation with MLE. To overcome, we suggest the future researcher before training the data set, split them into epoch and execute each epoch as a training data set to validate the classification accuracy. Where each epoch will generate a different predictive model.

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