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Weed Detection In Crops Using Convolutional Neural Networks

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Abstract: Agriculture was one of the first methods used by humans to survive on our planet. Today, in order to fulfil demand, we need agriculture to be more productive. This is due to the expanding population. In the past, humans increased output naturally by utilising things like cow dung as a fertiliser for the fields. This led to an increase in output sufficient to meet the population's needs. But with time, people started to think about boosting profits by having more success. Consequently, the "Green Revolution"—a revolution—began. Herbicides and other deadly poisons were then used far more frequently. While doing so, we increased productivity but neglected to take into account the environmental damage that was incurred, raising concerns about our ability to exist on this beautiful world. To reduce the usage of herbicides by only using them where weeds are present, we have implemented many solutions in this research. With this research, we use MATLAB to develop image processing to identify weed regions in an image we captured in the fields. Precision agriculture is gaining more and more attention from experts Since the global population has increased recently and the amount of available land and natural resources has reduced techniques for image processing could be used to address this issue.

***Index Terms* - CNN, colour segmentation, agriculture, and image processing.**

I. INTRODUCTION:

As living standards improve, green vegetables become increasingly important in our diets and have significant economic value. However, Vegetables compete with weeds for nutrients, sunlight, and water. they become more vulnerable to infestation by insects and diseases. Studies have shown that vegetable output can decrease by up to 95% when weeds and vegetables are in competition. Additionally, Chemical pesticide misuse can result in overapplication in places where there are no weed infestations, which can harm the ecosystem by causing soil and ground water pollution.. Therefore, organic food production requires weed management without chemicals. Hand weeding is currently the main approach for controlling weeds in vegetable crops. Developing a visual technique to distinguish Creating a barrier between weeds and plants is essential because sustainable management of weed, considering the large labor costs associated with this process.

Vegetable cultivation lacks uniform row and plant spacing, making weed identification a challenge compared to crop plantations. Vegetables and weeds flourish irregularly and can be mixed up during mechanised harvesting, resulting in increased labour costs. Despite the variety of weed species, research on weed identification in vegetable plantations is still at an early stage. Previous weed identification methods focused primarily on directly identifying weeds. We presented a deep learning-based approach to address this., specifically Convolutional Neural Networks, to first identify and segment the vegetable. This approach reduces the size increasing the precision and efficiency of weed recognition. of the training picture dataset and the complexity of weed detection.

Research has extensively examined machine vision techniques for weed detection. Deep learning is a powerful tool for automatically extracting complex information from images and is often used for picture classification and object recognition. Deep learning incorporates two categories of approaches for image detection: categorisation of objects and semantic segmentation (or pixel-level object classification). Several models based on convolutional neural networks are currently available.
The only method for performing image detection, classification, and recognition is the convolutional neural network. For classification, there are four main layers. The convolutional layer in CNN is fed both the test image and the training picture as input. Here, the kernel matrix is used to extract the image features. To find edge detection and blur an image, many filters are utilised. An image's pixels are the filter matrix multiplied by the specified value. This input matrix shifted many times using the stride. The non-linearity of a picture is then introduced using a ReLU function. In order to lessen the over-fitting issue, it utilised to make the negative number equal zero. The matrix's dimensions are then decreased using a pooling layer. Here, the largest element in the matrix is taken using max-pooling to correct the feature map. To provide a probability value for an image, a layer that is fully linked and has an activation function like the sigmoid or soft-max is utilised. The classification is completed on the basis of that likelihood. To extract the features from a picture in this study, a convolutional layer with the ReLU function is utilised with CNN. To avoid an over-fitting issue, the matrix size is decreased via max pooling. Finally, the classification's sigmoid function's input matrix is multiplied using the fully connected layer.

II.LITERATURE SURVEY:

Camilo Andres Pulido-Rojas(2017) In order to minimise illumination and sharpness issues during the acquisition process, this work provides a machine vision system for weed detection in vegetable fields utilising outside photos. This product will serve as a module for a mobile robot for weed eradication using a camera obscura (Latin for "dark room") for controlled illumination conditions. The goal of this study is to create a practical algorithm for weed discrimination. Image filtering is used to extract colour and area characteristics, after which a method to name each object in the picture is performed. Finally, a classification based on area is suggested, with sensitivity and specificity considerations,positive and to assess the effectiveness of the algorithm, forecasted values are used. To remove soil from images and minimise picture information, a green plant recognition algorithm is first constructed.Only vegetation is the subject of the algorithm's subsequent steps, after which median filtering, which has the advantage of maintaining edges, eliminates noise as "salt and pepper"[1].

Rani Meshram, Ajinkya Vrushali, and V.B. Raskar (2017) In this system, the author has created a technique for employing image processing to find marijuana. We can identify and distinguish weed-affected areas from agricultural plants thanks to the use of our method. To identify and reuse weed-affected areas for additional seeding, such a system was developed. Additional weed management efforts should be considered for this area to increase productivity [2].

The classification of sugar beetroot and weeds is the main topic of Miloto, et al., 2017. The training on the semantic segmentation-based CNN was completed in 48 hours with a 94.74% accuracy rate using about 10,000 images. The most recent study, Chavan et al. (2018), is the only one to attempt classifying various crops. They did this by combining AlexNet and VGGNET to create AgroAVNET, a CNN with five layers and a precision of 93.64% that was trained with 5544 photos.
Both McCool et al. (2017) and Knoll et al. (2018) investigate the application of image-based CNN for the detection of weeds and carrot crops. In the first study, three categories—weed, carrots, and background—are classified using an eleven-layered network. 500 RGB photos taken using a camera are used to train the network. The second paper creates a deep CNN using GoogleNet that has been compressed and pretrained on ImageNet using an online dataset. The initial paper showed an accuracy of 93%, whereas this method reported an accuracy of 90.5% [4].

R. Castro Castro and A. J. Iras Tejeda, 2019 The invention of an image-processing algorithm to identify the presence of weeds at a particular crop site is the main goal of the research as proposed by the authors. In order to remove all of the dirt from the image and reduce unnecessary information, the first stage in image processing is the detection of green vegetation. The vegetation was therefore the main focus after segmentation and the removal of irrelevant data using morphological and medium filters [5].
Xinhua, Aichen Wang, Wen Zhang, 2019 This review has been suggested by the author as a way to advances of weed detection using ground-based machine vision and image processing techniques.

Concretely, the four procedures, i.e., pre-processing, segmentation, feature extraction and classification, for weed detection were presented in detail. To separate vegetation from background,different color indices and classification approaches like color index-based, threshold- based and learning-based ones, were developed [6].

Fawakherji, et al., (2019), this study focuses on the classification of sunflower crops and weeds using pixel-wise segmentation with a CNN. With a training dataset of 500 images, the first step taken is the pixel-wise classification of soil and vegetation, using UNet semantic segmentation network. The second step is background removal and extraction of Regions of Interests (ROI) for their later classification in the third and final step as a crop or weed using a thirteen-layer CNN model. The accuracy obtained with this method is of a 90% [7].
Ryan Bruch and Bo Liu, 2020 This article summarises the trends in this field over the past few years and offers a mini-review of all the many developing and well-liked weed identification approaches for selective spraying. Weed identification also contributes to the reduction or elimination of pesticide use, minimising the negative effects of agriculture on the environment and human health, and enhancing sustainability. recent discoveries With the development of new models and growing computer capacity, deep learning-based techniques are replacing conventional machine learning techniques to detect weeds in real time [8].

III. PROPOSED METHODOLOGY

After examining all the fit falls of other approaches, the proposed methodology—deep convolutional neural network—is elaborated in this session. Convolutional neural network (CNN), auto-encoders, and other supervised learning techniques were examined in order to determine the methodologies used by other authors. The most appropriate methodology was found to be Inception V3, even though it shares some similarities with the CNN model in terms of efficiency.

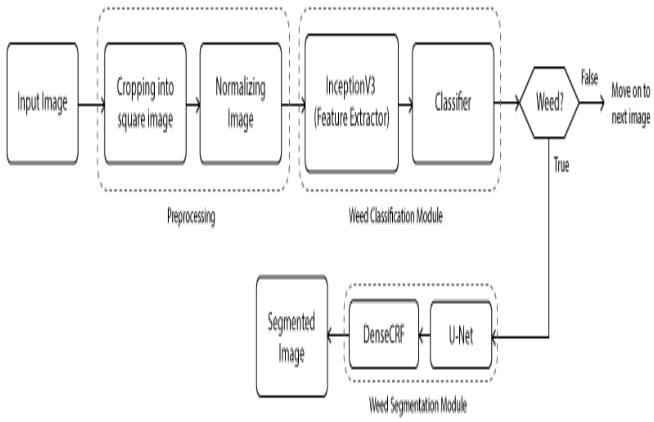


Figure 1: Flow chart of weed detection using Inception V3 algorithm

Figure 1 depicts the flow chart of the implementation of the weed detection using inception V3 algorithm.

The output from the preceding layer serves as the input for the subsequent layer in either a regular neural network layer or a convolutional neural network layer, and this process continues until the prediction. The inception block is the fundamental component of the inception network. It separates the layers into their component parts and, rather than sending it through just one layer, sends the input from the previous layer through four parallel operations before concatenating the outputs from each of these operations. Convolutional neural networks are used by the Inception v3 method, a deep learning model, to identify images. Several fields, including object identification and image classification, have effectively used it. We will go over how the Inception v3 algorithm may be used to find weeds in crops in this session. It has been demonstrated that Inception v3 achieves greater than 78.1% accuracy on the ImageNet dataset. The model is a culmination of different ideas that have been developed over the years by numerous researchers. Convolutions, average pooling, maximum pooling, concatenations, dropouts, and completely linked layers are a few of the symmetric and asymmetric building blocks that make up the model itself. Batch normalisation, which is also used to normalise the inputs for activation, is heavily utilised in the model.

Soft-max is utilised to calculate loss. The implementation of Inception v3 as it stands is almost input-bound. Images are retrieved from the file system following decoding and pre-processing. From mild to sophisticated, there are different pre-processing stages. Pre-processing will be restricted for the training pipeline Using a reasonably sophisticated pre-processing stage that maintains the model TPU-bound, you can achieve accuracy greater than 78.1%.

Gathering photos of crops and weeds is the initial stage in using the Inception v3 algorithm for weed detection. Then, noise is removed from these photos during pre-processing in order to improve the image quality. To help distinguish between crops and weeds, feature extraction is done to find the image's distinctive properties.The Inception v3 algorithm then receives the pre-processed images and categorises them as either containing weeds or not. The algorithm's output can be used to create a field map that highlights the locations of weeds. Then, this knowledge can be applied to target certain locations for weed control.

IV.IMPLEMENTATION:

The suggested method entails three fundamental steps in order to produce the best model for fake review identification. The following provides an explanation of these phases:

A. Image Acquisition: High resolution cameras are used to capture images of weed in crop fields or from online datasets for greater accuracy. Each acquired image is saved in its appropriate size and as a jpg file.

B. Pre-processing: Several elements, including noise, varying lighting, low image quality, and undesirable backdrop, have an impact on the final photographs. The conversion of RGB to grayscale, the conversion of grayscale images into binary images, and the employment of filtering techniques to eliminate background noise are all examples of pre-processing tools.

C. Feature Extraction: In order to identify the weed, features are extracted following pre-processing. Feature extraction is the process of defining a set of characteristics to effectively describe the data for analysis and categorization. Size, shape, and color-based features as well as texture-related elements like entropy, energy, contrast, etc. are used to extract the properties.

D. Classification: The weed is classed using categorization techniques. Feature vectors serve as the input for the classifiers. The training, validation, and testing of classifiers in classification use images of diverse weeds. A few types of classifiers include edge-based classifiers, genetic algorithms, probabilistic neural networks, and artificial neural networks.

V. RESULTS AND DISCUSSION

As the training dataset, we chose 780 photos, and as the validation dataset, 100 images. The Jupyter notebook is the platform used to put this approach into practise. The implementation in this handbook is accomplished by importing all the necessary libraries, including keras, which is used to create a deep learning model, tensorflow, computer vision, for processing and analysing the provided images, OS module from Python numpy, for organising the matrices to comprehend the images, and pandas, for working with the imported datasets. Unlike other platforms, this one is fairly open source and has a web application that is very flexible to use when computing deep learning models and producing outputs that have been mathematically examined.

To traverse the deep convolutional neural network, various stages are taken. Data generation, data pre-processing, dividing the training and validation datasets, running the epoch for a variable amount of time, displaying the output, and contrasting the actual values with the rendered or anticipated results are all steps in the data analysis process. The ensuing demonstration includes the matching photos together with the generated outputs. The training dataset is designed to span various deep learning model layers, as seen in figure 2. These layers assist in computing the picture dataset and convolving it, which increases the model's intelligence over time. Then, when the model is being validated, some characteristics of the crops and weeds it acquired are discovered.

Table 2 : Layers of Inception V3 model

Model: "functional_1"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 224, 224, 3)	0	
conv2d (Conv2D)	(None, 111, 111, 32)	864	input_1[0][0]
batch_normalization (BatchNorma	(None, 111, 111, 32)	96	conv2d[0][0]
activation (Activation)	(None, 111, 111, 32)	0	batch_normalization[0][0]
conv2d_1 (Conv2D)	(None, 109, 109, 32)	9216	activation[0][0]
batch_normalization_1 (BatchNor	(None, 109, 109, 32)	96	conv2d_1[0][0]
activation_1 (Activation)	(None, 109, 109, 32)	0	batch_normalization_1[0][0]
conv2d_2 (Conv2D)	(None, 109, 109, 64)	18432	activation_1[0][0]
batch_normalization_2 (BatchNor	(None, 109, 109, 64)	192	conv2d_2[0][0]
activation_2 (Activation)	(None, 109, 109, 64)	0	batch_normalization_2[0][0]
max_pooling2d (MaxPooling2D)	(None, 54, 54, 64)	0	activation_2[0][0]

...

Total params: 22,468,397

Trainable params: 22,433,965

Non-trainable params: 34,432

Table 1 explains the depth of layers used to build the deep learning model, as well as position at which they are connected and how they are connected and also the param are noted on the side. As shown in the figure it gives info about the type of layer and the shape of the output obtained at the end of that particular layer.

```
Please use Model.fit, which supports generators.
Epoch 1/500
13/13 [==============================] - 67s 5s/step - loss: 4.6516 - accuracy: 0.1282 - val_loss: 301.0000 - val_accuracy: 0.0385
Epoch 2/500
13/13 [==============================] - 67s 5s/step - loss: 2.3733 - accuracy: 0.3051 - val_loss: 61.9860 - val_accuracy: 0.0769
Epoch 3/500
13/13 [==============================] - 68s 5s/step - loss: 1.5650 - accuracy: 0.5692 - val_loss: 107.8523 - val_accuracy: 0.1051
Epoch 4/500
13/13 [==============================] - 68s 5s/step - loss: 1.0693 - accuracy: 0.7000 - val_loss: 20.6492 - val_accuracy: 0.1154
Epoch 5/500
13/13 [==============================] - 68s 5s/step - loss: 1.6510 - accuracy: 0.6308 - val_loss: 48871.3750 - val_accuracy: 0.0769
Epoch 6/500
13/13 [==============================] - 68s 5s/step - loss: 2.9685 - accuracy: 0.4718 - val_loss: 31277.9922 - val_accuracy: 0.0769
Epoch 7/500
13/13 [==============================] - 68s 5s/step - loss: 3.0946 - accuracy: 0.3872 - val_loss: 107518.7266 - val_accuracy: 0.0769
Epoch 8/500
13/13 [==============================] - 68s 5s/step - loss: 2.6935 - accuracy: 0.4462 - val_loss: 109092.5781 - val_accuracy: 0.0769
Epoch 9/500
13/13 [==============================] - 69s 5s/step - loss: 2.2341 - accuracy: 0.4641 - val_loss: 8723.2861 - val_accuracy: 0.0769
Epoch 10/500
13/13 [==============================] - 69s 5s/step - loss: 3.0498 - accuracy: 0.4641 - val_loss: 7731681.0000 - val_accuracy: 0.0718
Epoch 11/500
13/13 [==============================] - 68s 5s/step - loss: 3.7623 - accuracy: 0.4026 - val_loss: 134992736.0000 - val_accuracy: 0.0769
...
13/13 [==============================] - 65s 5s/step - loss: 0.1030 - accuracy: 0.9744 - val_loss: 0.2483 - val_accuracy: 0.9769
Epoch 112/500
13/13 [==============================] - 66s 5s/step - loss: 0.0222 - accuracy: 0.9872 - val_loss: 0.1315 - val_accuracy: 0.9897
Epoch 113/500
Output exceeds the size limit. Open the full output data in a text editor
13/13 [==============================] - 65s 5s/step - loss: 0.0471 - accuracy: 0.9872 - val_loss: 1.1434 - val_accuracy: 0.8333
Epoch 114/500
13/13 [==============================] - 66s 5s/step - loss: 0.2175 - accuracy: 0.9513 - val_loss: 0.1985 - val_accuracy: 0.9667
Epoch 115/500
13/13 [==============================] - 65s 5s/step - loss: 0.0705 - accuracy: 0.9821 - val_loss: 1.0289 - val_accuracy: 0.8769
Epoch 116/500
13/13 [==============================] - 66s 5s/step - loss: 0.0666 - accuracy: 0.9744 - val_loss: 4.4523 - val_accuracy: 0.6308
Epoch 117/500
13/13 [==============================] - 65s 5s/step - loss: 0.4309 - accuracy: 0.9026 - val_loss: 12.9331 - val_accuracy: 0.8256
Epoch 118/500
13/13 [==============================] - 66s 5s/step - loss: 0.2699 - accuracy: 0.9231 - val_loss: 2.3174 - val_accuracy: 0.8641
Epoch 119/500
13/13 [==============================] - 66s 5s/step - loss: 0.1880 - accuracy: 0.9538 - val_loss: 6.3620 - val_accuracy: 0.4923
Epoch 120/500
13/13 [==============================] - 66s 5s/step - loss: 0.1922 - accuracy: 0.9538 - val_loss: 2.1091 - val_accuracy: 0.6949
Epoch 121/500
13/13 [==============================] - 66s 5s/step - loss: 0.1756 - accuracy: 0.9821 - val_loss: 0.8996 - val_accuracy: 0.8462
Epoch 122/500
13/13 [==============================] - 66s 5s/step - loss: 0.1439 - accuracy: 0.9513 - val_loss: 1.9354 - val_accuracy: 0.7513
Epoch 123/500
13/13 [==============================] - 66s 5s/step - loss: 0.2509 - accuracy: 0.9513 - val_loss: 2.6774 - val_accuracy: 0.6718
Epoch 124/500
Epoch 459/500
13/13 [==============================] - 67s 5s/step - loss: 0.3367 - accuracy: 0.9359 - val_loss: 13.8680 - val_accuracy: 0.4333
Epoch 460/500
13/13 [==============================] - 67s 5s/step - loss: 0.6181 - accuracy: 0.8744 - val_loss: 5.8411 - val_accuracy: 0.5667
Epoch 461/500
13/13 [==============================] - 66s 5s/step - loss: 0.2354 - accuracy: 0.9359 - val_loss: 4.7825 - val_accuracy: 0.6564
Epoch 462/500
13/13 [==============================] - 66s 5s/step - loss: 0.1157 - accuracy: 0.9641 - val_loss: 1.1361 - val_accuracy: 0.8410
Epoch 463/500
13/13 [==============================] - 66s 5s/step - loss: 0.0363 - accuracy: 0.9897 - val_loss: 0.5913 - val_accuracy: 0.8769
Epoch 464/500
13/13 [==============================] - 66s 5s/step - loss: 0.0137 - accuracy: 0.9974 - val_loss: 0.4561 - val_accuracy: 0.8846
Epoch 465/500
13/13 [==============================] - 67s 5s/step - loss: 0.0447 - accuracy: 0.9795 - val_loss: 0.1362 - val_accuracy: 0.9667
Epoch 466/500
13/13 [==============================] - 66s 5s/step - loss: 0.0395 - accuracy: 0.9923 - val_loss: 0.0233 - val_accuracy: 0.9897
Epoch 467/500
13/13 [==============================] - 67s 5s/step - loss: 0.0152 - accuracy: 0.9949 - val_loss: 0.0342 - val_accuracy: 0.9923
...
Epoch 499/500
13/13 [==============================] - 67s 5s/step - loss: 0.0087 - accuracy: 1.0000 - val_loss: 0.0043 - val_accuracy: 1.0000
Epoch 500/500
13/13 [==============================] - 66s 5s/step - loss: 0.0211 - accuracy: 0.9923 - val_loss: 0.0055 - val_accuracy: 1.0000
```

Figure2: Epoch run for 500 times

Figure 2. Shows the epoch for using the training dataset to train the model different times and the corresponding losses are shown accordingly and also the value of the loss is also shown beside it. This epoch can be run for variable number of times to have a visual representation for how the model is getting trained at each step in the neural networks.

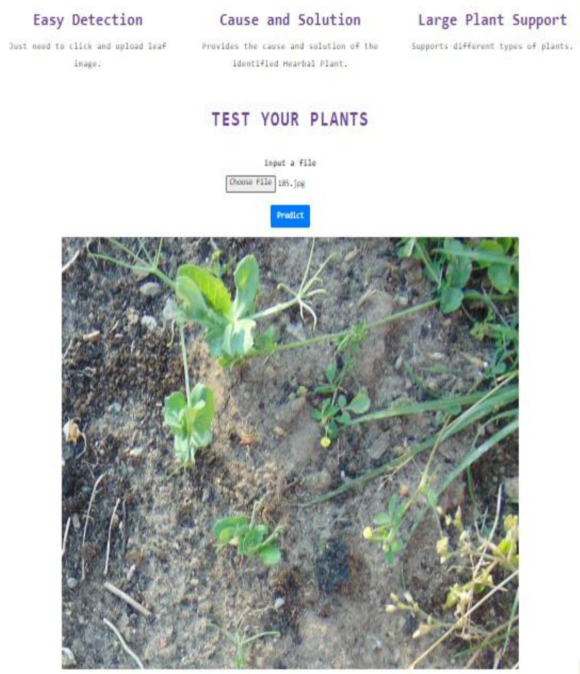


Figure 3 a). Input image from the dataset

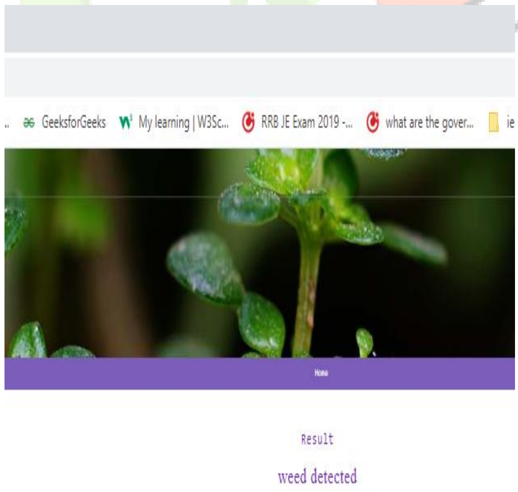


Figure3 b). Result obtained for the input image 3a

Figure 3.a depicts that the image is given as the model's input picture. The model analyses the source image and classify if it is a crop or the weed. The model classified the given image as weed and displayed the content "weed detected" as the result.

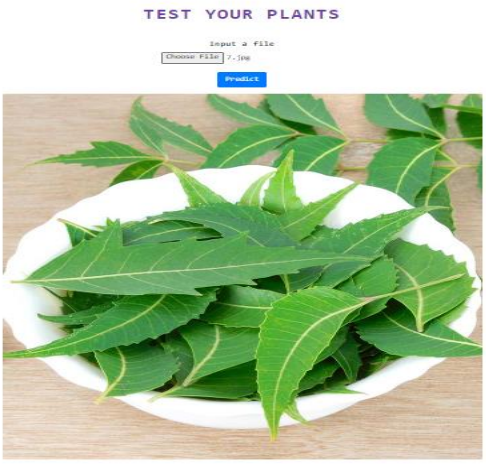
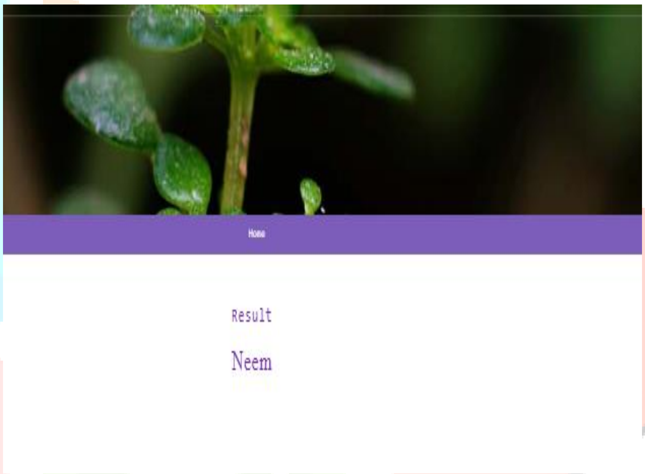


Figure4 a) Input image from the dataset.



4 b). Result obtained for the input image 4a

Figure 4.a depicts that the image is given as the picture used as the model's input. Processing of the input image by the model and classify if it is a crop or the weed. The model classified the given image as weed and displayed the content "Neem" as the result which is the name of the input image.

VI. CONCLUSION

This research demonstrated the potential of using CNN for detection of weeds, and its usefulness in operations. The Inception V3 model was tested against the Inception V2 model across multiple CNN models. Results showed that Inception V3 outperformed Inception V2 in terms of precision, accuracy, and loss. Future studies may explore weed and crop detection in real time, as well as employing intelligent weeders or weeders making decisions based on CNN models for site-specific herbicide application.

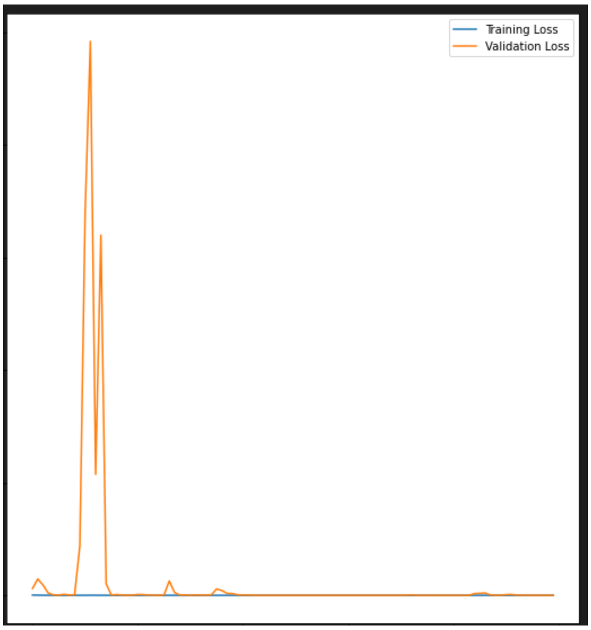


Figure 5a): Training and validation loss comparision of Inception V3 model.

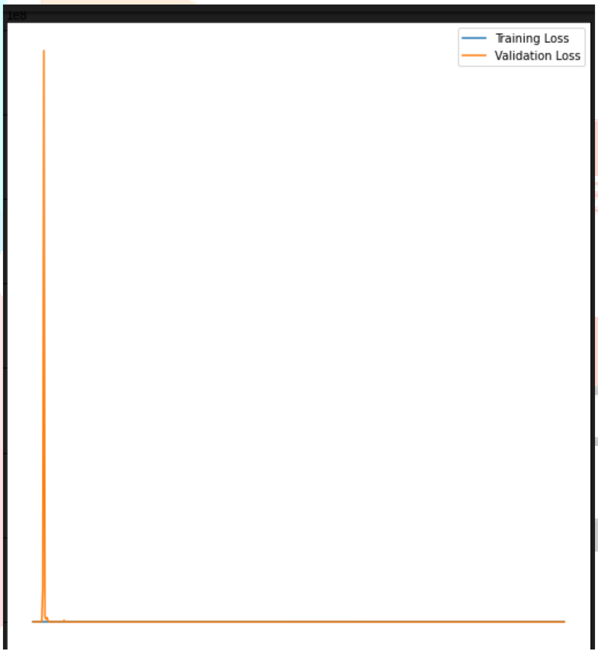


Figure5b): Training and validation loss comparision of Inception V2 model.

Figure 5 depicts that the performance of Inception V3 is much better compared to the performance of Inception V2 model. Inception V3 incorporated all the upgrades required for the Inception V2 and hence produces the better results and also the label smoothing than the Inception V2 model.

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