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Identification of Weeds in Maize Crop Using CNN

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Abstract— Deep learning is the nucleus in machine learning discipline which uses knowledge representation of learning. Learning can be supervised, semi-supervised or unsupervised. Many Deep learning architectures are available which includes deep belief networks, deep neural networks and recurrent neural networks of which it has been applied to most of the fields. The commonly used applications of deep learning are vision related, audio, video, language processing, social media, medical, game and many more programs where they have produced a promising accurate result comparable to and in few cases superior to human experts. Smart agriculture is an area that can benefit from the latest advances in expert systems. One of the objectives is to remove the weeds by reducing the use of herbicides used, the risk of pollution of crops and water. The image of the crop field is given as input training examples. By using the extracted feature, the images with weeds are detected and classified. A deep learning model is developed using convolution neural networks to detect weeds with a good accuracy so that the model could be used to detect the weeds in the crop field in a shorter time.

Keyword-Image Segmentation, dataaugmentation, Convolutional Neural Network, Deep learning,RGB extraction. (keywords)

I. INTRODUCTION

Successful cultivation of maize depends largely on the efficacy of weed control. Weed control during the first six to eight weeks after planting is crucial, because weeds compete vigorously with the crop for nutrients and water during this period. Annual yield losses occur as a result of weed infestations in cultivated crops. Crop yield losses that are attributable to weeds vary with type of weed, type of crop, and the environmental conditions involved. Weeds are notorious yield reducers that are, in many situations, economically more harmful than insects, fungi or other crop pests.If weed growth is not stopped at a critical time, it results in massive crop loss, sometimes as varied from 10% to 100%. The presence of weeds at the harvest stage of some crops may reduce the quality and their values. According to Nave and Wax's [1] study the soybean harvesting before weeds was dried out resulted in great threshing and separating losses when the speed increased from 1 to 2 and 3 mph. Stubble, lodging, and stalk losses almost doubled in the pigweed and foxtail infested plots compared with the ones without weeds.

In the present day scenario, the quality of soil is slowly depleting due to the weeds and in some areas the land is completely not fit to grow anything and besides that we have the rising population. Weeds cause annual crop loss of $11 billion in India.

The motivation in this project is to achieve more efficient gardening in agriculture. If we identify weeds early on and can distinguish them from the plants we want to grow we can take action earlier.

II. LITERATURE REVIEW

In a present-day scenario different method have been attempted, among which manual weeding by hand or using simple hand tools has been used for centuries and is still being used in small scale fields nowadays. However, this manual testing is time consuming and needs many labor thus increase in labor cost, making this method not useful for modern weeding. Controlling of weed is a critical farm operation and can affect the crop yield. Herbicides applications have vital importance in weed control and high crop yield. Weeds are not uniformly distributed in the field, they clumped together in patches [2] herbicides are applied to the whole field, representing significant portion of the variable cost of agricultural production. In these days, there

is a clear tendency of reducing the use of chemical agents in agricultural cultivations.

New weed detection technologies have been developed to improve the speed and accuracy of weed detection, mitigating the conflict between the goals of improving soil health, and to achieve weed control for profitable farming. Literature review is done for all weed detection techniques and methods in recent five years and divided into two categories :digital image sensors based and non-digital image sensors based [3].

Digital image sensors :
Weed detection based on digital imaging processing and computer vision is the most examined and widely used technique. Image processing is one of the common tools used in weed detection; its typical procedures include pre-processing, segmentation, feature extraction, and classification.

Bakhshipour et al. [4] examined wavelet texture features to verify their potential in weed detection in a sugar beet crop. A discrimination algorithm was designed to determine the wavelet texture features for each image sub-division to be fed to an artificial neural network. Co-occurrence texture features were determined for each multi-resolution image created by a single-level wavelet transform. A neural network was finally used to label each sub-division as weeds or crops. Results showed that the wavelet texture features could discriminate weeds from crops effectively.
Another emerging method to detect the weed is using ML algorithms to directly extract crop features and classify weeds or crops based on the automatically extracted features [5].

dos Santos Ferreira et al. [6] used a convolutional neural network (CNN) to perform weed detection on soybean crop images collected using a drone, classified the weeds among grass and broadleaf, and applied the specific herbicide to detected weeds. Finally at the end this work reported about 97% accuracy using CNN in the detection of broadleaf and grass weeds without soil and soybean in the background.

Non-digital image sensors:
Pantazi et al. [7] proposed a method that tells us the difference between crop and weed species based on their spectral reflectance differences. The detection was based on one-class classifiers using neural networks. The recognition performance for different weed species varied between 31 and 98% for the self-organizing map and 53–94% for a mixture of Gaussians.

With the rapidly growing global population at a rate of around 1.09% per year, the demands for more food, feed, fiber, and fuel need to be increased correspondingly, which demands higher requirements for agricultural industry to provide increasingly higher yields. The global population is expected to reach 9 billion by 2050, and agricultural production must double to meet the increasing demands [8] [9].

Nowadays agriculture is facing challenges including the changing climate, shortage of rainfall and water resources, as well as the threat from diseases, pests and weeds [10]. Much effort has been made to weed control for decades by researchers and farmers to overcome the challenges that weeds have brought. Weeds appear everywhere randomly in the field, and compete with crops for water, nutrients and sunlight, which could result in a detrimental impact on crop yields and quality if uncontrolled properly [11] [12].

III. METHODOLOGY

The implementation process can be split into two main stages:

A. Preprocessing data stage
B. The classifier training stage

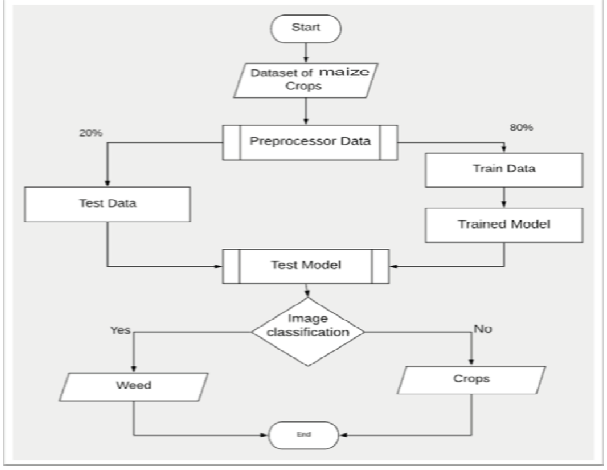

Fig 1: Flowchart

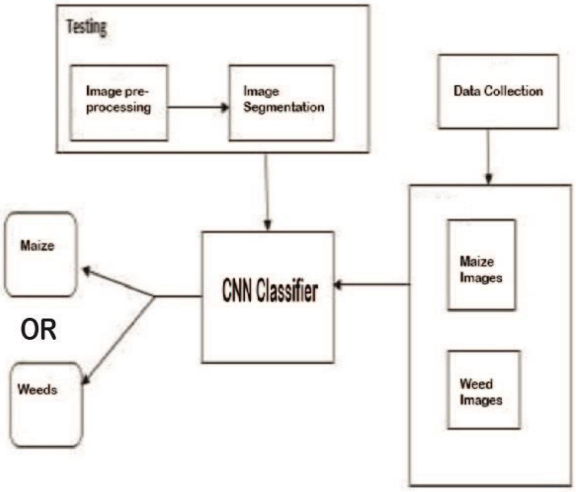

Fig 2: System Design

A. Preprocessing:

First we will attempt to remove the background from the images to see if we can find a method which generalizes well across all images, then this can be used to accelerate training by isolating the important part of the data. The strategy we are applying is to find upper and lower bounds within a color space which will only contain the green part of the plants. We will then turn the rest of the background black. In order to find the values for these upper and lower bounds,we will grab random pixels from random training images from each of 12 classes. Then we will take this random collection of pixels(here we have taken 50 pixels from each of 10 training images from each of 12 classes) and plot it in color space which is shown below.

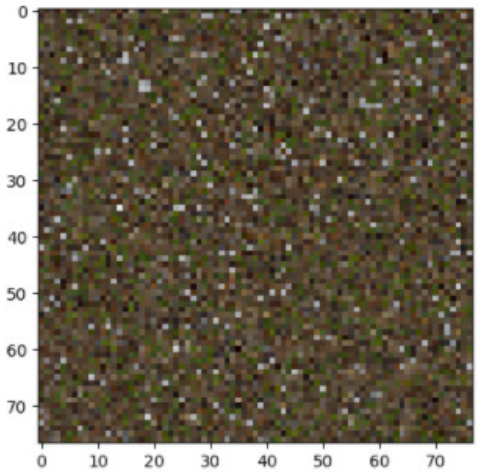

Fig 3:Random Samples

So now we have these pixels in color space.we will plot these pixels in RGB color space.

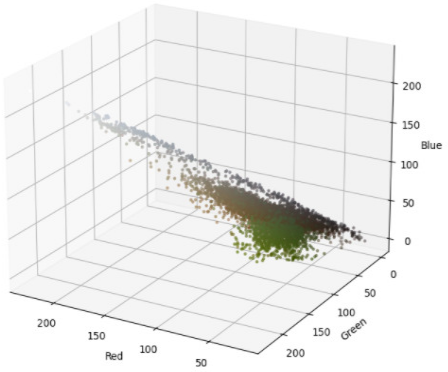

Fig 4:3D graph

From the RGB color space, we need only the green region so that we can understand if it is a weed or crop.now we have to separate the green region from the rest, but simply choosing bounds of RGB values will not work due to the shape of the distribution. Before we adopt more complex methods to isolate these pixels, let's look into a different color space basis that is Hue,Saturation,value (HSV).

In HSV space, it looks like clusters are more neatly separable by choosing upper and lower bounds of HSV values. Here we can clearly see that the green cluster comes from the plants/crop and the brown, white and grey clusters come from the dirt, rocks, and other things in the background. There is little variance along the V (value) axis, so lets plot this in 2 dimensions (H & S) shown in fig 5.

By using a 1D graph as shown in fig 6, we can point to an upper and lower bound. I will pick out pixels with Hue values ranging from 24 to 55 and Saturation values ranging from 50 to 255.

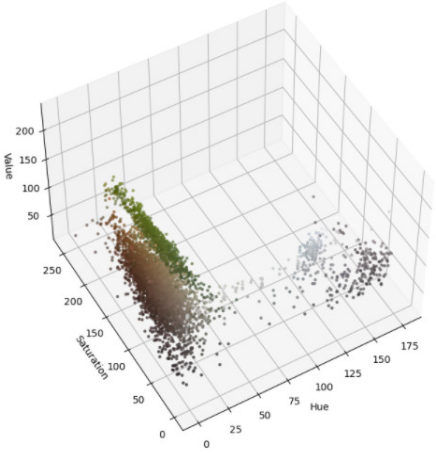

Fig 5:2D graph

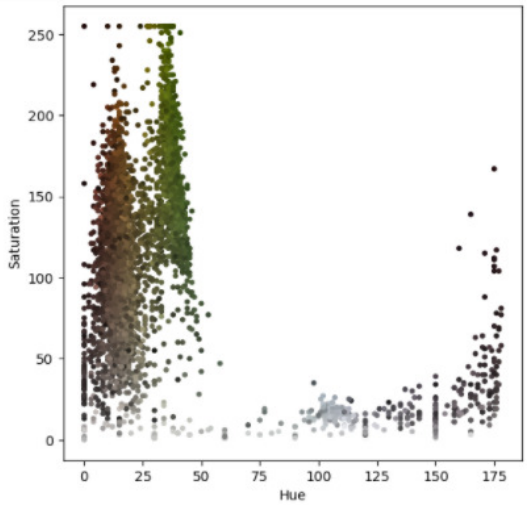

Fig 6:1D graph

Image Segmentation:

Now that we have got lower and upper bound values we need to remove the noise and the background from the image. We create a mask to remove the background of the image and get the required part for training and testing. Thefigure 7 displays the original and transformed images next to each other after image segmentation

B. Building classifier model and training stage:

Before building model,we will be using data augmentation technique during training.We will be using

ImageDataGenerator object from keras which will do random rotation,shiftingimages,rescalingetc in addition to the background removal function that we have defined.The benefit of using generators is that we can do training and validation in batches while also avoiding the need of storing of our data in local disks.This is very useful in when working with large datasets which may be too large to even store locally.

Next we will make a set of class weights to be provided during training to make sure there is no class imbalance.

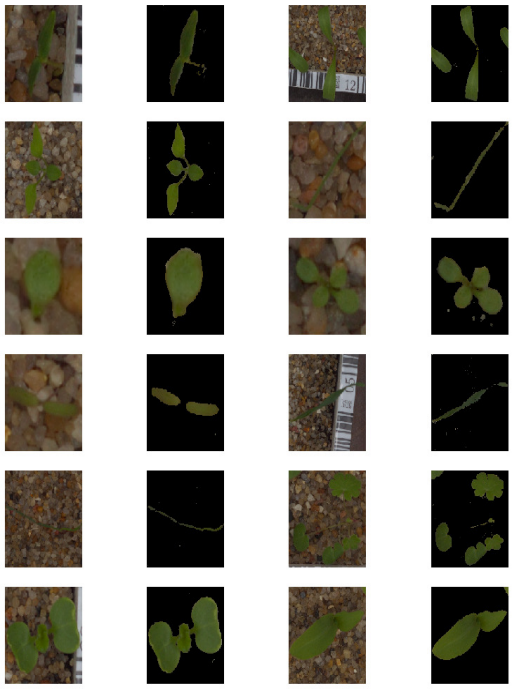

Fig 7:Image Segmentation

CNN ARCHITECTURE:

In general, Neural networks accept a single vector as input,transform it to a series of hidden layers, which in turn is made up of a set of neurons that are fully connected to all neurons in the previous layer. Neurons of the same layer are independent and do not share any connections. After the hidden layers, is the last fully connected layer which is also called the 'output layer', where each node outputs score for each class. The downside of regular neural networks is that they don't scale well to full images. It's mainly because with images of decent size, the number of neurons and weights that the network must accommodate becomes unmanageable. This is where the Convolutional Neural Network comes to rescue with its neurons arranged in 3 dimensions (width, height, depth).

Each of the layers in CNN accepts 3D input volume and transforms it into 3D output volume.

Following is a simple visualization of how CNN arranges its neurons in 3dimensions (width, height, depth):

Following are the layers that are used to build a CNN:

Input layer (w,h,d)

CONV layer:

The CONV layer will compute the output of neurons that are connected to local regions in the input, each computing a dot product between their weights and a small region they are connected to in the input volume. In this project we used 32 filters, CONV layer will output a volume equal to (148*148*32).

Activation functions

The purpose of the activation function is to introduce non-linearity into the output of a neuron.In this project we have usedReLU as activation function..

ReLU is the abbreviation of Rectified Linear Units. This layer applies the non-saturating activation function. $f(x) = max(0, x)$It increases the nonlinear properties of the decision function and of the overall network without affecting the receptive fields of the convolution layer.

The ReLU function is its derivative and both are monotonic. The function returns 0 if it receives any negative input, but for any positive value x, it returns that value back. Thus it gives an output that has a range from 0 to infinity.

Figure 10 illustrate Relu function:

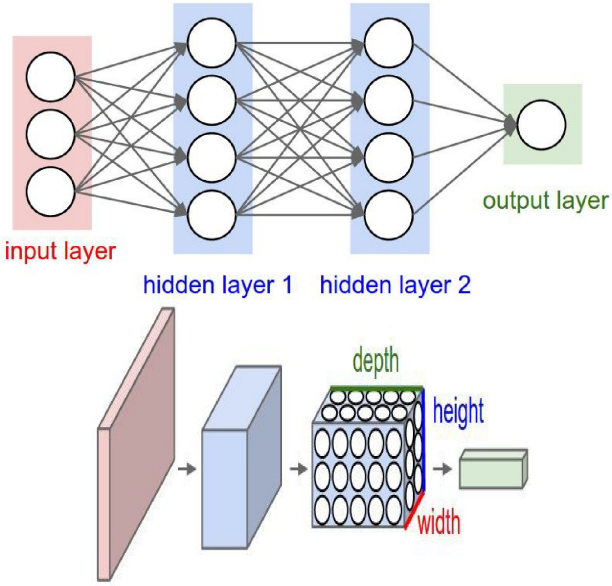

Fig 8:CNN Architecture

Layer (type)	Output Shape	Param #
conv2d_25 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_25 (MaxPooling	(None, 74, 74, 32)	0
dropout_37 (Dropout)	(None, 74, 74, 32)	0
conv2d_26 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_26 (MaxPooling	(None, 36, 36, 64)	0
dropout_38 (Dropout)	(None, 36, 36, 64)	0
conv2d_27 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_27 (MaxPooling	(None, 17, 17, 128)	0
dropout_39 (Dropout)	(None, 17, 17, 128)	0
conv2d_28 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_28 (MaxPooling	(None, 7, 7, 128)	0
dropout_40 (Dropout)	(None, 7, 7, 128)	0
flatten_7 (Flatten)	(None, 6272)	0
dropout_41 (Dropout)	(None, 6272)	0
dense_13 (Dense)	(None, 256)	1605888
dropout_42 (Dropout)	(None, 256)	0
dense_14 (Dense)	(None, 12)	3084

Total params: 1,849,804
Trainable params: 1,849,804
Non-trainable params: 0

Fig 9: summary of layers in CNN

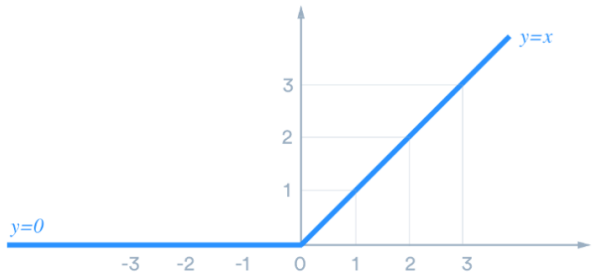

Fig 10:Relu layer

Optimizer :

We will be using Adam optimizer during training and also will be using ModelCheckpoint callback to save the best model during training. The model checkpoint considers the model with the lowest loss value to be the best. Since the Adam optimizer will dynamically adjust its learning rate throughout training

POOL layer:

Pool layer performs down sampling operation along the spatial dimensions (width, height), outputting a reduced volume than the previous layer that is (74*74*32)

Dense layer

Dense layer is also called a fully-connected layer, each neuron will be connected to all the neurons of the previous layer. Each of the nodes of the dense layer outputs a score corresponding to a class score.

In the end we used the features in two fully-connected (Dense) layers which are just artificial neural networks (ANN) classifiers.

In the last layer (Dense(10,activation="softmax")) the net outputs distribution of probability of each class.

Dropout layer

Dropout layer is used as a method of regularization of combat over-fitting of the training set. It 'drops' randomly neurons(setting their weights to zero), resulting in a simpler version of the CNN for each iteration and hence giving the model a hard time to overfit.

Flatten layer

It is used to convert the final feature maps into a one single 1D vector. This flattening step is needed so that you can make use of fully connected layers after some convolutional/maxpool layers. It combines all the found local features of the previous convolutional layers.

Classification Layer (CL)

This is the final layer of the CNN that converts the output of Fully Connectedto the probability of each object being in a certain class. Typically soft-max types of algorithms are used in this layer.

IV. RESULTS

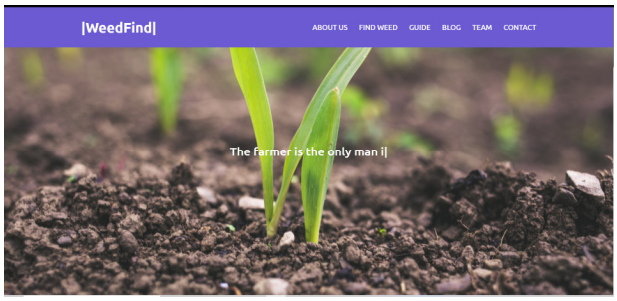

Fig 11:Front page of the project.

Find weed:Here the user by submitting the image can identify whether the image is crop/weed.

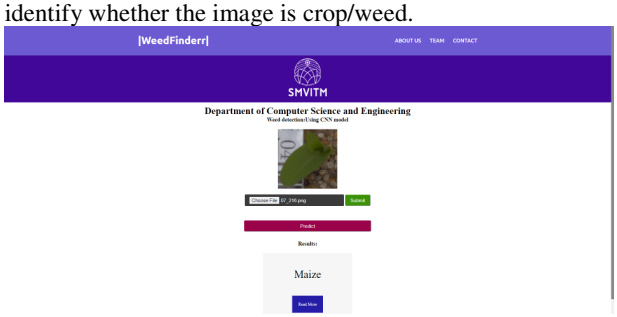

Fig 12:Find Weed

If the image submitted is crop/weed, find weed takes the user to respective results.Here all the control measures and products that are required for good cultivation are displayed.

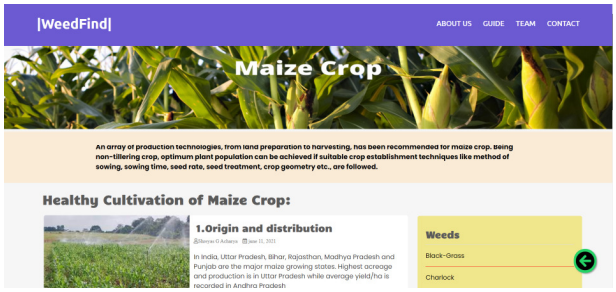

Fig 13:Control Measures

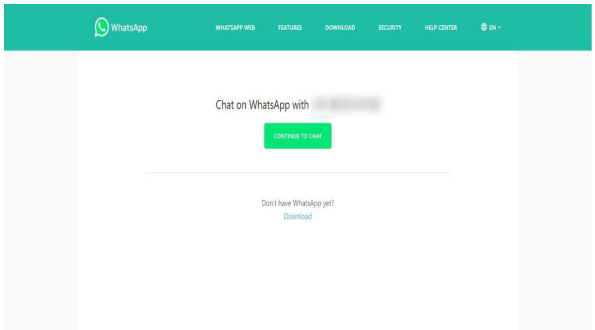

Fig14:Contact

V. CONCLUSION

Problem here is it's hard for users to identify different kinds of weeds and to take necessary.Our intention was to differentiate weeds from crops based on their images. We started from different data preprocessing methods which includes data augmentation, image segmentation or a highly usable training set. We've defined a customized CNN model with 4 convolutional layers and 2 dense layers.By applying a deep learning algorithm with adams optimizer we found 90% accuracy in detecting weeds which helps any persons or robotic system can find such weed and help in identifying weeds and gives control measures with required products which can be used for good cultivation.Currently we have took kaggledataset,so in near future there is a lot of scope to make this model a real world working model with some additional feature like automated sprayer or automatic drone sprayer with the help of GPS location.

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