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Plant Variety and Weed Growth Identification: Trending Towards Machine Learning

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Abstract*: An important module in the agriculture 4.0 based plant monitoring is the weed growth control. In order to achieve the optimum profit on vegetable plantations the control of weeds plays an important role to ensure the precision of yield. Previous studies uses, ariel or portrait images in groups to identify the plants, weed infestation as well as intrusion detection. The motivation in this work of automation is to make the process as an autonomous system to upgrade it to agriculture 4.0 standards, by introducing Artificial Intelligence components in plant monitoring process to help the farmers with the trending technologies. This proposed research approach improves the accuracy of finding plant features from the images captured on vantage angles of the plant .We tried to classify the plants as well as the weeds through inclusion of portrait and ariel images for better classification and to aid automation that uses machine learning in plant and weed identification. Results obtained from the proposed AI system found to be appropriate and accurate in every classes of comparison.

Index Terms*: Agriculture 4.0, Convolutional Neural Network, Image processing, machine learning.

I. INTRODUCTION

Vegetable plants are called money plants by the small farmers since vegetables bring-in ready cash for the farmers as a part of their income and lifestyle. It becomes a practice and habitual for them to plant vegetables and millets during the post rainy season and before summer when the amount of water for irrigation reduced. There is more benefit in cultivating organic products now a day and farmer groups are attracted towards it as there is a growing market demand for such organic produce due to the alarming cautions on health hazards caused by chemical and poisonous pesticides and fertilizers. Demand for organic products in local markets and export markets increases day by day and brings premium profits for them. Aiming for more profit, the interest in introducing new plant varieties, and strange cultivation procedures encourages them to test novel methods and adopt innovative technology into their farming practices. One such new practice is to introduce automation of plant monitoring. Automated plant monitoring involves weed control, pest control and intrusion control. We as a continuous process of finding enhancement in plant monitoring, tries out new experiments to bring in newer technologies to find a fine tuned optimum remedy in plant monitoring using image processing techniques. The importance of such experiments are to clearly and timely identify the requirements of plants, like water stress, weed elimination, adequacy of nutrients and removal of cattle, birds and insects that destroys the plants. The farmers are using conventional techniques and facing a tough time in expelling animals, birds and insects like parrots, peacocks, grasshoppers, hare wild boar and elephants from vegetable plants and money plants like Corn, Peppers, green leaves, tapioca and radish. The proposed research work is to prevent the plants from deterioration by the said problem, as well as preventing man-animal conflicts to protect the animals and birds. It is important that the domain expertise and field knowledge of the farmers are to be included in the system in an enhanced level and at the same time things that cannot be done manually. Along with the many good systems that are created by researchers for this purpose, a significant improvement with a machine learning perspective to ameliorate automation technology is suggested in this work. The novelty of this paper reporting the proposed research work is the machine learning algorithm that follows a Convolution neural network in the identification of features. This is to unravel the existing image based system performance by giving augmentation to the level of intelligence based classification. In this proposed research work we implement plant identification with a view of controlling the weeds infestation by combination of image processing and classification technique to be a perfect solution to the problem [1],[2] .Apart from the plant identification and weed monitoring other few associated application also benefits the farmer like identification of intrusion and event detection [3],[4].This application requires periodical image acquisition either by fixed or moving cameras .These cameras can be fixed on post erected or strategic locations are embedded into flying drones the ultimate aim of propose work is to precisely identify and care individual plants in order to support precision agriculture .[5]

II. METHODS

A. Previous Work

Young Chen, Xiaojun Jin lie Tang (2013) and Young, S.L (2012). , were proposed weed management in the stereo images. Aditi shreeeya BaliDaziy R. Ravinder Kumar Kohli (2016) from their work we acquired about how to extract features from leaf and we also implemented in ladies finger plant with same concept. From the works of Hossein Neiari (2008) we acquired weed management in corn fields, but here we implemented for some common fields.

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K Ramesh, Andrews Samraj(2017) were described about identification of weed by singular value decomposition .
In this we upgraded the work by introducing neural networks. Hossain – Bari (2012) used digital images in weed management, from this work we also used aerial and portrait images in our work. Kalvina Rajendran, Ramaswamy Palaniappan (2016) was showed about feature extraction and which is a important part of research work. , Aung Soe Khaing(2014) "weeds and crop segmentation and classification using area thresholding". From the work of Lopez-Granados (2011), we implemented and acquired knowledge in real time approach. F.Truchetelb (2007) was described about weed discrimination in simulated images.

B. Image Acquisition

The pictures of Brinjal, Ladies finger, Ragi, in their various forms were captured from different angles and are resized in their digital form with uniform lighting. The camera used for this process in our experiment is a 5MP, f 2.4 autofocus with an LED flash light. This camera is positioned in oblique aerial and portrait angles while taking pictures of the plants of all varieties considered for this experiment. Throughout the process of image capturing a uniform distance is maintained and picture is taken in a distributed way from all over the plant bed. The camera is positioned from a distance of 3 feet from the ground level for all the pictures captured for this experiment.[6],[7]We have taken 30 pictures of each plant varieties and used only 8 - 10 images randomly in our experiments.


a. P icture of Ladies finger *b. Picture of weed grown Plant in Ariel view with Ladies finger*


c. Picture of Ragi Plant *d. Picture of Brinjal in Ariel view vegetable in Ariel view*

Figure 1: Aerial images of the plants used in this experiment.


a.Picture of ragi plant b.Picture of Brinjal in Portrait view plant in Portrait view

Figure 2: Portrait images of the plants used in this experiment

C. Preprocessing

The captured multi angle images were in both aerial and portrait directions .The raw images are in different sizes, for which there is a need for preprocessing to bring them into a uniform size. Max pooling is used to reduce the size of the image into the standard size. The size of the max pooling is 2 x 2. There are totally 128 hidden layers are present in the model. For test images we need to preprocess the data as we do earlier for train data, because it is a raw dataset .For preprocessing the test data we use "VGG 16" model. VGG16 model is mostly used for image identification.

Table 1: Number of Images Used in this Experiment

S.no	Images	Train	Test	Total
1	Brinjal	8	8	16
2	Ladies Finger	8	8	16
3	Ragi	9	9	18
4	Ladies Finger with Weed	9	9	18

D. Convolutional Neural Network classifier

We used a Convolutional Neural Network (CNN) for setting up a classifier that can classify images of this kind[8]. Hence we followed a training module to train the network and use it for testing with three classes as an initial step.

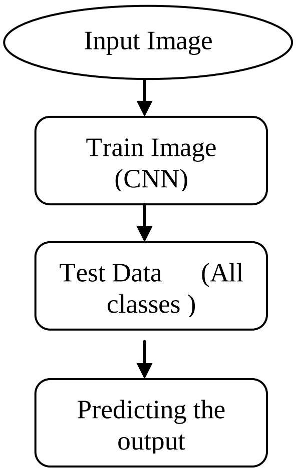

Figure 3. Flowchart of Convolutional Neural Network (CNN)

After Preprocessing, the images are admitted into the CNN process model which consists of two major parts "Training" and "testing" to predict the given image with the class as the output. We adopted Max-pooling of CNN in this work to select the predominant feature of every block of interest from the given image. Max pooling is done by applying max filters, which divides the images into a standard square matrix. [9] Max-pooling adopts a sample data discretization process, where it transfers continuous functions, model, variable and equations into discrete process.

This process is used to carry out as a first step towards making them suitable for numerical evaluation and implementation during the process.

To find the matching between trained pools of images with the test image we made the images into an uniform size of 512Kb. The test image has to undergo the same reduction process that of the training images to make the process uniform and accurate for matching. We used 2×2 max pooling size throughout the experiment for all the images.

$$F(x) = \max(x, 0) \qquad (1)$$

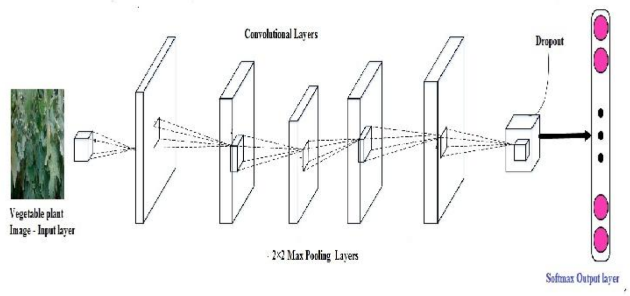

Figure 4: 2x2 Convolutional Neural Network Classifier

In this experiment, we used two activation functions namely, Relu and Softmax to setup the layer architecture of the CNN. The Relu is used to increase the non-linearity in images, since the images are naturally non-linear.

Whereas 'Soft max 'is used before the output layer to converge the features towards the output. It must have same number of nodes as the output layer. The last step in training process is running the epochs and steps. In this experiment ten epochs and 5 steps were presented for the training. The Prediction stage is next to the training part.In the testing phase we used the same VGG16 model for handling the test data (raw data). Similar preprocessing steps were followed on the raw data to the trained classifier. During such test process the prediction was done for the given input image and it is shown as "Predicted label (Any one of the trained classes) = output (The test image)".

E. Experiments

A total number of 50 images were taken as shown in table2. Where the training and test images are equally distributed among all the given 3 classes namely brinjal (16), ladies finger (16), ragi (18). [10]

Experiment 1

In the first Experiment, we random picked 8 images of ladies finger, 8 images from brinjal and 9 images from ragi for training purpose. Three different class labels where assigned to the images according to the breed. All these images underwent preprocessing and completed the training. Once the notification of training completion is received, we started giving test inputs randomly selected from any of the 8 fresh images of ladies finger or 8 images from brinjal or any of the 9 images from ragi as input and the model subjected the test image also for preprocessing before matching it with the trained data. When the given image matches with any of the trained images then it prints the corresponding label as output as shown in figure4.

Experiment 2

In the second experiment we added a fresh 9 images of 'ladies finger with weed' as 4th label and get it trained completely. All the 9 images of this weed infested ladies finger were also underwent preprocessing and other formalities. Then the test image is randomly from any of the 4 classes, and the results are presented in table 4.

Experiment 3

In table 2. The first category of nine images are new and never been used to train the neural network, where as the second category of nine images are taken from the already used training data set images. In this third experiment we re-trained all the 68 images that includes plant images of ladies finger, brinjal ,ragi and ladies finger with weed, that forms 4 classes . In the third experiment we took the image of ladies finger with weed alone as our test data. Eighteen images of ladies finger with weed were presented as test input. These eighteen images were selected as two categories (train group and test group) with nine images in each. The first category of nine images are new and never been used to train the neural network (test group), whereas the second category of nine images are taken from the training data set images (train group).Train and Test images of ladies finger with weed were further separated into two groups. These two groups with nine images in each category were shown

Images used in training	Images used for testing
	
	
	
	

Figure 5: Image used for training and testing

Table 2: Two different categories of ladies finger with weed images

TEST DATA	TRAIN DATA
Test group 1 (5 images)	Train group 1 (5 images)
Test group 2 (4 images)	Train group 2 (4 images)

As a first part of this experiment, we gave the images of training group1 and test group1 from training and test classes respectively, as test inputs. Then we gave next set of data, which is test group2 and training group2 after that we gave the entire test and train data together and executed the program. The predicted result was "ladies finger" for this experiment that used "ladies finger with weed" as test input in this case In the second part of the experiment, we added new images of the ladies finger plants as test data and the training data is the same ladies finger images with weed. This part of the third experiment is similar to the first part, but we just added the test group with images of ladies finger plants without weed Even though the System predicted our test images as ladies finger class.

Experiment 4

In this experiment it differs from all the above three experiments. Because in this experiment we added a new class called intrusion . Intrusion consist of plant Images with farm animals like goat and rooster .in the natural circumstance the computer or machine need to identify the weed and there may be possibilities of farming animals in the field .we used another class named as crop . In this class it consists of images of brinjal plant and ragi each of five images .Then finally we gave the image of goat (intrusion) it predicted as intrusion which is the correct on the predicted . This experiment want to identify the intrusion rather than the type of the plant . we train the model we got the accuracy of 79. 8% .

Table 3: Identify the Intrusion and other foreign elements

S.No	Test Image	Predicted Image	Accuracy
1	Intrusion (goat)	Intrusion	100%
2	Intrusion (Rooster)	Intrusion	100%
3	Crop	Crop Image	100%

TEST DATA	TRAIN DATA
Test group 1 (5 images)	Train group 1 (5 images)
Test group 2 (4 images)	Train group 2 (4 images)

Figure 6: Different images of the same class used in training & testing

III. RESULTS

Table 3 shows the output of the first experiment with three classes and their classification accuracy. We got 100% matching accuracy for ladies finger and ragi, and got 87.5% accuracy for brinjal with a single wrong prediction due to less number of images we used for this simple first experiment. Output of brinjal was showed in the figure 4.

Table3: CNN experiment with three classes of plants in both aerial and portrait categories

S.no	Image	Train	Test	Classification	Accuracy %
1	Ladies finger	8	8	8-Aug	100
2	Brinjal	8	8	8-july	87.5
3.	Ragi	9	9	9-sept	100

```
[INFO] loading network and VGG16...
features= [[1. 0. 0.]]
index= 0
Predicted Array: [[1. 0. 0.]]
Predicted Label: brinjal
```

Figure4: Classification output for the given image

S.NO	Test Inputs	Result
1	Train group -1 Test group-1	Ladies finger- 80%
2	Train group-2 Test group-2	Ladies finger- 100%
3	Train group-1,2 Test greoup-1,2	Ladies finger- 89%

After the completion of training we gave the test data of 9 images of "ladies finger with weed" as the 4th class. The newly trained 4th class shows an accuracy of 88.9 in matching due to one picture reported error during the process of the test. (It reported as Ladies finger). Table 4 presents these results of all the four classes.

Table4: CNN experiment with four classes of plants in both aerial and portrait

S.no	Image	Train	Test	Classification	Accuracy %
1	Ladies finger	8	8	8/8	100
2	Brinjal	8	8	7/8	87.5
3.	Ragi	9	9	9/9	100
4	Ladies finger with weed	9	9	8/9	88.9

In the 3rd experiment we split into two parts. Part one consist of ladies finger with weed and ladies finger .In part one we got an accuracy of 100% for this 3rd experiment in the identification of Ladies finger plant even if we give ladies finger with weed picture. Secondly we gave training group2 and test group2 of the test and training images and it is predict as ladies finger with an accuracy of 75%. As the last step of the experiment we supplied the entire test and training data together to the neural network and it identified the plant as ladies finger with accuracy of 100% were shown in table 5.

Table 5: CNN experiment with ladies finger with weed images.

S.NO	Test Inputs	Result
1	Train group -1 Test group-1	Ladies finger-100%
2	Train group-2 Test group-2	Ladies finger-75%
3	Train group-1,2 Test greoup-1,2	Ladies finger-100%

In part two of experiment 3 we got an accuracy of 80% for the training group 1 and testing group1. Secondly we gave the training group 2 and test group 2, for prediction,. It predicted the input images as ladies finger with an accuracy of 100%. Finally we gave all the training and test groups for prediction for which it shows the accuracy of 89% and predicted the ladies finger correctly. Table 6 presents the results of ladies finger plant as test class.

Table 6: CNN experiment with ladies finger

S.No	Test Inputs	Results
1	Train group -1 Test group-1	Ladies finger-80%
2	Train group-2 Test group-2	Ladies finger-100%
3	Train group-1,2 Test greoup-1,2	Ladies finger-89%

IV. DISCUSSION

We used the open source platform for machine learning and data science called Microsoft azure cloud. This visual cloud platform contains some most commonly used libraries such as pandas, numpy , matlab , keras, etc to accommodate different algorithms from different source code . This Machine Learning Studio provides a framework to involve data science, cloud resources including Library functions, predictive analytics, and the user data sets to accomplish the target. We used Python code files of version 3.7 in this cloud along with the imported basic libraries required for the experimental work. We created a new file for uploading the training data set and then the training code was executed on the supplied training data. Once training is completed in the Azure cloud, it will be notified through the "training Completed" message, after 15 – 30 minutes for 68 images for ten epochs. Now the CNN is ready to give the prediction based on the given test input. The input is given as its path that was defined in the coding. If the given input is matched with any label, of the training data, then it shows the label name as output as in figure 4.

V. CONCLUSION

The machine learning approach we introduced in this work by CNN, integrated the previous system of plant identification by separate data sets that contain, portrait and Ariel images of the same plants. This approach reduced the time consumption and increased the accuracy in identifying the plant and weed. We didn't include any additional feature extraction algorithms since the max pooling process took care of all such processes. We further identified that the inclusion of more pictures from classes for training improved the results and accuracy of prediction. So any further addition of pictures in training will certainly improve the performance of the CNN.

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