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Onion Weed Detection and Alert System using Deep Learning

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Abstract:

To put it simply, agriculture is fundamental to human existence on our planet. Through farming, it is possible to produce an abundance of food that can sustainably nourish a big population. The agricultural sector and the export of other consumer goods form the backbone of India's economy. Because of its central role in facilitating productive development and supplying sustenance to both the nation and its dependent nations, agriculture is an integral aspect of the Indian subcontinent. Identifying weeds on a farm is typically a labor-intensive, time-consuming process that might be nearly difficult for a single farmer to do on a large-scale operation. There are other, more important things that could be done with the time that this takes up. Weed detection and identification can be enhanced with the use of new technology. So, to address this issue, this method suggests a practical and efficient system for weed classification that makes use of Convolutional Neural Networks and Decision Making. Crucial to the methodology's performance realization has been the approach's successful evaluation through experimentation.

Keywords: Open CV, Convolutional Neural Network, Decision Making.

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I. INTRODUCTION

In order to build a healthy population and society, the agricultural paradigm is a crucial and necessary component. In addition to relying on hunting and gathering for food, early people also relied on agriculture. During the hunter-gatherer era, people lived in tight-knit communities that subsisted mostly on hunting for food. The tribes also collected fruits and berries, sorting out the edible ones from the toxic ones, and ate them for sustenance and vitality. As a result, for a number of years, people mostly subsisted on eating what they could find.

On the majority of occasions, there was insufficient or inconsistent food and other resources. This was recognized by the first humans, who were also clever enough to learn about seed germination and the intricate process of cultivating food crops. Since large groups of people could no longer be sustained by hunting and gathering, humans gradually shifted to an agricultural culture that relied on crop cultivation. The availability of increased nutrition allowed individuals to execute far more complex and strenuous tasks, which in turn improved the lifestyle of humans. Insecticides, pesticides, and fertilizers have greatly increased agricultural yields in recent decades, and there is a great deal of farmland available around the world. This is of utmost importance because our reliance on agriculture has grown substantially in the last several decades. The technical advancements have greatly improved the many aspects of the agricultural process, but they haven't done enough to get rid of weeds in the fields. This is a major issue because weeds can be quite tricky to spot and pull out by hand.

[1] With an emphasis on RMF and background detection, Guk-Jin Son et al. presented a method to detect foreign objects of any sort. For RMF prediction using U-Net, the author specifically suggested a way to efficiently gather the necessary training data. The efficient picture capturing technique allowed for the collection of training data capable of detecting RMF and alien objects without human annotation, which is a huge boon from a practical aspect. Using color and past experience, HBFOD was able to extract features from food and foreign item photos. Changes in illumination quickly deteriorated the method's performance, and it failed to recognize alien objects with colors comparable to RMF. In order to address the issue with the conventional method, this work employed a DNN-based foreign object detection method.

[2] in According to U N Mubarokhah et al., illness is one of numerous factors that affect the ideal onion plant output. If your shallot plants are healthy, you can tell by looking at their leeks. Anthracnose, a leaf rot disease, and purple spots are among the diseases that can affect green onions. The Alternaria Porri (Ell Cif) fungus causes purple spot disease, whereas the Collectotrichmm Gloeosprorioides Penz / Collectotrichmm Circinans (Berk) Vogl fungus causes leaf rot. The diseased leaves can be seen identified by their changed color and form. Visually analyzing leek illness requires specialized training and attention to detail. In order to make digital image processing a more effective tool for visually identifying leaf diseases. An optimally contrasted image is produced initially by enhancing the original image's contrast. By transforming the color components, the image will be transformed into a L * a * b image after the contrast is restored.
The symptoms of FBR disease in mature onion bulbs were studied by Subhankar Mandal et al., who devised objective quantification methods [3]. Digital pictures of the basal plates were shown by confocal microscopy, which also recorded strong autofluorescence emission in the blue-green part of the visible light spectrum, which was produced by the FOC-infected area, and successfully differentiated between healthy and diseased tissue. Visual estimation using digital images was found to be the most effective way for objectively quantifying FOC infection of the basal plate, according to a later comparison with two image analysis methodologies. The automated stepwise picture segmentation method under-estimated FOC infection, although being more accurate than visual estimates alone. To improve the efficiency of disease resistance breeding in onions, a more effective image analysis procedure, like one that uses machine learning algorithms, might replace visual scoring and significantly cut down on the time needed to screen bulbs resistant to FBR.

Section 2 In this study provides a literature review of pertinent works; Section 3 Detail the methodology used in the study; Section 4 Analyzes the results of the experiments; and Section 5 ends by outlining potential areas for future research.

II. LITERATURE SURVEY

To transform the imputed data into a numerical value, the encoders in the LSTM model described by Shubham gade et al. in [4] employ the minmaxscaler function. The temporal fusion transformer (TFT) makes effective use of the trained model that is obtained by deploying an LSTM model in the encoded data. To retrieve target values from the past, TFT employs a look-back window of a fixed length. The next step is for TFT to build the unknown input using permutations, resulting in properties of the external input that depend on time. Lastly, TFT uses static covariates to give contextual metadata about the things being evaluated that is independent of time. Implementing a deep learning model in hybrid mode is made easier by combining LSTM with a convolution neural network.
[5] This study article by Nilesh Dagadu Navale et al. describes the goal of accomplishing weed categorization on an onion crop. It is the python programming language that has enabled the offered technique. In the traditional model, farmers would manually sort weeds in their fields. There is no way around the amount of time and effort required for this procedure. There is a risk of reduced

agricultural yield if weed plants are not adequately removed from the land. This occurs because the weed crop is vying for the same field resources as the onion crop. Unfortunately, this problem has a solution that this method suggests using computer vision to avoid.

[6] An successful and cost-effective method for detecting plant diseases is described by David Duarte-Correa et al. as utilizing grayscale photographs to identify affected areas. The findings also showed that the plant tissue might be simplified, which could make image-processing methods more efficient in terms of computational cost. Additionally, this method offers a non-destructive alternative to measuring wet places in the crop, which helps farmers target areas with sustained humidity to avoid blight and fungal damage. When used to non-uniform weed growth, the weed-detection method did not perform up to par.

[7] A noteworthy development in precision agriculture is the weed detection system for onion crops that Navale Prathmesh et al. implemented using convolutional neural networks (CNNs). Weeds in onion fields can be easily and accurately identified using this method, according to extensive testing and evaluation. The CNN model has the potential to completely transform weed management techniques for onion agriculture due to its remarkable adaptability to different environmental circumstances and its remarkable ability to differentiate between weeds and onion plants. Improved crop output and quality are the results of the automated detection procedure made possible by the CNN model, which decreases the need for manual work and allows for timely intervention to control weed infestations.

[8] According to Mrs. Reshma Shivraj Bhalke et al., weed detection in vegetables is more challenging than in crops because of the varied plant spacing in vegetable plantations. So far, there is a dearth of literature on the topic of weed detection in vegetable gardens. The majority of the research on conventional methods for weed detection in crops has concentrated on direct detection of weeds. Weed species, however, can differ substantially. But this study presents a novel approach that combines machine learning with video/image processing tools. Making bounding boxes around vegetables using a trained center Net model was the initial stage. Weeds were the next designation for the remaining verdant items that spilled out of the border containers. [9] An approach to weed identification in vegetable plantations using deep learning and image processing was proposed by Dr. A. A. Dandvate et al. [9]. There were two stages to the algorithm. Vegetable detection was taught to a YOLO v3 algorithm. The rest of the green stuff in the color picture was then thought of as weeds. The goal is to remove background weeds. So long as the model is limited to vegetable identification, it will not deal with weeds of any kind.

[10] An innovative method for multi-level grading of onion purple spot disease, which can have a significant economic impact, was introduced in this paper by Govindharaj I et al. using a CNN-VGG16 hybrid model. Overall, the model demonstrated an impressive 93.5% accuracy, surpassing some of its leading competitors. This development proves that convolution neural networks and other deep learning techniques can help with precision agriculture illness diagnosis and severity grading. The effective extraction of complicated visual aspects of onion leaf disease symptoms suggests that this model's deep learning architecture has been successful..

[11] the eleventh The authors Manuel de Jesús López-Martínez et al. suggest that the specific problems encountered by onion farmers can be addressed through the use of DL and transfer learning. Improved efficiency, sustainability, and resistance to environmental stresses could result from their implementation in agricultural operations. This study provides farmers in Zacatecas state with a solid groundwork for local onion production. It proves that new innovation, especially DL and CNNs, can improve farming. Using data-driven decisions, farmers may optimize crop yield and field resource efficiency by utilizing

these tools to their advantage. Combining ML algorithms like KNN with DL techniques like CNN greatly improves image classification tasks in agriculture.

[12] Burkinabe farmers of corn, tomatoes, and onions were the target audience for a new smartphone app developed by Obed Appiah et al. that makes use of AI models. Plant pests and diseases present significant problems for Burkina Faso's agriculture, as they do for many developing countries, endangering food production and economic stability. In response to these issues, PlanteSaine has developed a thorough solution that helps farmers detect pests and diseases in real time. Accurate diagnoses are provided by Plante Saine's AI system after farmers take pictures of diseased plants using their cellphones..

III PROPOSED METHODOLOGY

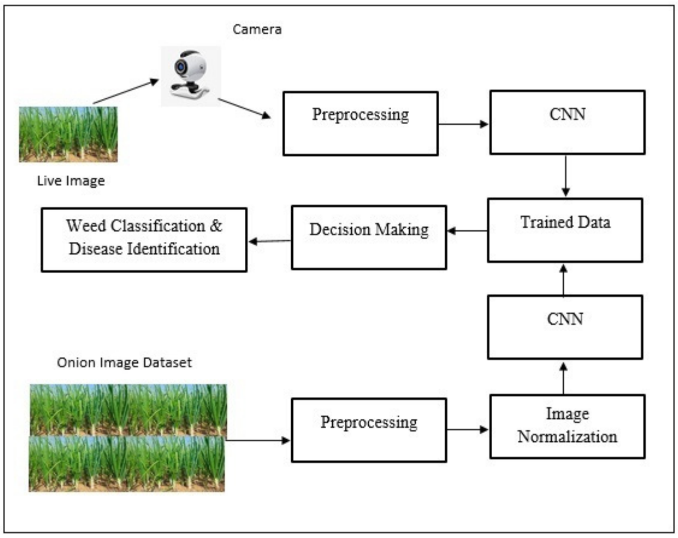

Figure 1: Proposed methodology

The method that has been suggested to establish a Onion Weed Detection System system depicted in the system overview in Figure 1 up top. The suggested method was based in part on the execution of the procedures detailed below.

Step 1: Dataset preparation*:* The onion crops are being grown in two plastic trays that are approximately 1 × 1 feet in size, and this is the first stage of the suggested technique. We keep one tray for our pure onion crop and supplement it with a few weeds. The opencv cv library, which is built using the python programming language, is used to gather around 2,000 photographs of both weed and non-weed crops. In order to train the proposed system to identify weeds, the acquired images are divided into training and testing sets.

Step 2: pre-processing *:* The keras python library class uses parameters such as a resizing factor of 1:255, a shear range of 0.2, and a zoom range of 0.2 to construct an object that generates image data. For the photos in each dataset, a resized size of 150 × 150 is chosen for 64 batches using class mode binary for both training and testing items. As will be detailed later on, the dataset is trained using a convolutional neural network with 500 adjusted epochs.

Step 3: Training with Convolution neural network (CNN)- : Using the keras and tensor flow libraries in Python, a convolution neural network is being used to train the obtained images. The three-layer neural network model chosen for deployment is a sequential one. Along with the activation function Relu and the color channel of 3, the first layer includes 32 kernels set to a 3×3 size.

An initial layer is inserted, followed by a max pooling layer. Building the second and third layers is very similar to the first layer as well. At the end of the third layer, there is a flattening layer that uses a dense layer with a size of 100 and an activation function called Relu to end the training process. Lastly, data is collected using an additional dense layer of size uni and the sigmoid activation function. After fine-tuning the neuron values with an adam optimizer, the result is trained data that can be saved in a file with the extension of H5. In the architecture table that is shown below, you can see the entire CNN learning process.

Layer	Activation
32 X 3 X 3 2D	Relu
MaxPooling2D	
32 X 3 X 3 2D	Relu
MaxPooling2D	
32 X 3 X 3 2D	Relu
MaxPooling2D	
Flatten	
Dense 100	Relu
Dense 1	Sigmoid
Adam Optimizer	

Figure 2: CNN Architecture

Step 4: Decision Making

: Whether the crop is produced in a plastic tray or in actual fields, this is the stage where the testing procedure is fed photos of a real onion crop. Finally, the photos are loaded into the CNN process using the trained model stored with the extension h5, and the images are streamed using the open CV object. utilizing a sample image and the obtained forecast, the decision is made to either crop for weeds or not utilizing weeds. The rules that notify the former employ Whatsapp.

IV RESULTS AND DISCUSSIONS

The proposed method for Onion Weed Detection and Alert System using Deep Learning.was developed using the Anaconda framework, Python, and the Spyder IDE. The development computer has 1 terabyte of secondary memory and 8 gigabytes of main RAM. A number of factors have been considered in order to determine how feasible the proposed plan is. In this part, we detail the results of the experimental study.

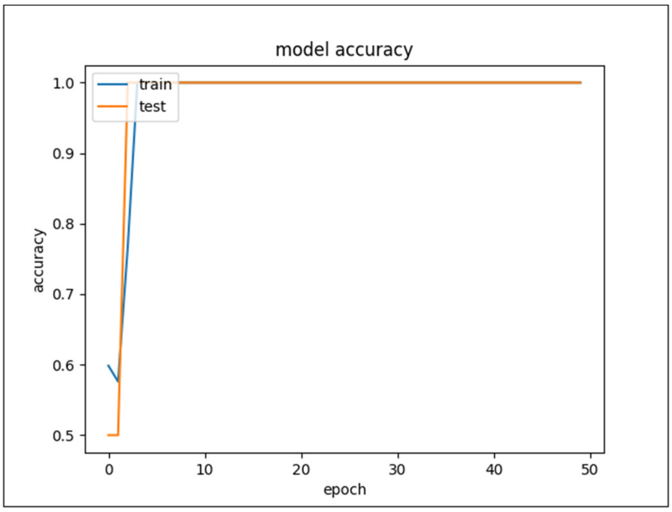

Figure 3: Model CNN Model accuracy for 50 epochs

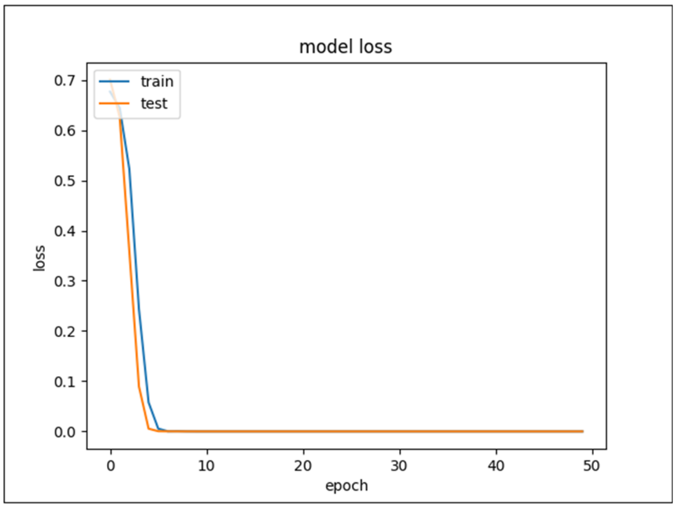

Figure 4: Model CNN Model Loss for 50 epochs

V CONCLUSION AND FUTURE SCOPE

In this study article, the methodology that has been suggested for classifying weeds in an onion crop is detailed. It is the python programming language that has enabled the offered technique. In the traditional model, farmers would manually sort weeds in their fields. Doing this takes a very long time and is very tedious. There is a risk of reduced agricultural yield if weed plants are not adequately removed from the land. This occurs because the weed crop is vying for the same field resources as the onion crop. This issue can be efficiently addressed by implementing the computer vision approach suggested here. Convolutional Neural Networks have been trained to evaluate weed plants using photos of actual onion crops. An strategy that has successfully identified weed plants with a decent degree of accuracy is also tested. A highly satisfactory performance has also been achieved as a consequence of the comprehensive evaluation of the strategy. The following are some ways this project could be expanded in the future to accommodate new areas of research:

API for convenience in integrating and evaluating The method can be improved for future research by training a neural network with photos taken at all stages of an onion crop, from germination to harvesting, in various fields and under diverse conditions. This would greatly increase the accuracy of the results.

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