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Enhancing Agricultural Automation with Deep CNN-Based Classification of Seedlings

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***Abstract* – Controlling weeds is essential for agricultural uses. Finding weeds after a few days after plant germination is one of the most important duties, as it enables farmers to manage weeds early on and lessen adverse effects on crop growth. Therefore, our goal is to categorize crop and weed seedlings. In this study, we use the benchmark plant seedlings dataset to propose a classification system for plant seedlings. Images of 12 distinct species are included in the dataset; three of these are plant species, and the remaining nine are weed species. Three distinct deep convolutional neural network architectures—ResNet50V2, MobileNetV2, and EfficientNetB0—are used to implement the categorization framework. We use transfer learning to train the models and evaluate each model's performance on an 833-image test dataset. With an accuracy of 96.52% and an average F1-Score of 96.26%, we show that the EfficientNetB0 outperforms the other two models.**

***Index terms*—Convolutional Neural Network, Le Net, Alex Net.**

I. INTRODUCTION

Precision farming, which uses developing technologies to produce crops with controlled quality, is the revolution of traditional agriculture. In order to create organized, sustainable, environmentally friendly, and economically viable agricultural, it emphasizes the employment of drones, autonomous vehicles, robots, and information technology. One of the main issues with precision farming is weed control. Even though weeds are non-targeted plants that don't bring in any money for farmers, they nevertheless compete with target crops for nutrients and space, which slows down plant growth. Using human labor to pull weeds is costly and time-consuming. The undesired crops will be harmed even if the herbicides are applied consistently throughout the farms. By identifying and controlling weeds according to their location and density, the drawbacks of previous methods are lessened. These days, researchers have implemented numerous agricultural applications using the most advanced deep learning algorithms. We have even implemented the categorization of plant seedlings using deep CNNs. Many academics have used CNNs and a transfer learning technique to offer frameworks for classifying weeds and plant seedlings. Using Le Net, Alex Net, c NET, and s NET architectures, the authors in [1] executed the categorization of maize and weeds and outperformed c NET for real-time implementation. Using pre-trained ResNet50 and InceptionV3 architectures, the authors of [2] have developed a framework for classifying weeds in Australian rangelands. They have also suggested a real-time robotic weed control system that uses pre-trained ResNet50 that performs better than expected. The categorization frameworks for Philippine indigenous plant seedlings were proposed by the authors in [3] by optimizing pre-trained Alex Net, Google Net, and ResNet50 architectures. Compared to the other two architectures, ResNet50 performs better. The CNN was used by the authors in [4] to create a carrot and weed classifier.

II. LITERATURE SURVEY

Precise weed and maize classification through convolutional neuronal networks

In big data processing, deep learning is crucial for more precise modeling of typical production processes. It is extensively utilized in applications related to artificial vision, particularly in pattern identification. Precision agriculture is one of the many application areas where deep learning is utilized due to its versatility. The creation of an algorithm for image segmentation and classification is presented in this study. While classification aims to determine which photos belong to the two specified groups, segmentation aims to isolate the target plant from the original image. During the early phases of crop development, it uses a convolutional neural network (CNN) to distinguish between weeds and maize plants in real time. Since maize is a common staple crop in the Ecuadorian Highlands, it was applied to the crop. A dataset created during the segmentation stage was used to train the convolutional neural network. LeNET, AlexNet, cNET, and sNET network topologies were used to examine the network's performance. Based on its accuracy and processing time performance, cNET was the network architecture that produced the best training outcomes. This network architecture required a minimum working filter number of 16. The most effective processors and algorithms hold great promise for real-time autonomous weed and crop classification systems.

Philippine Indigenous Plant Seedlings Classification Using Deep Learning

Specialists in a particular plant species are known as plant taxonomists. The lack of these specialists and their uneven distribution around the world continue to be major issues on a global scale. They can develop solutions that would help them expedite the plant classification process using deep learning technologies. Three deep learning models are used in this study to categorize photos of native plant seedlings from the Philippines into five different species. For this, AlexNet, GoogLeNet, and ResNet50 were optimized. To accelerate learning, the fully linked layers' weight and bias learning rate parameters were both raised to 20 in the three pre-trained models.

III. PROPOSED SYSTEM

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The overview of our proposed system is shown in the below figure.

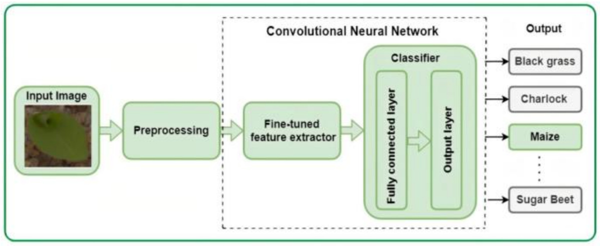

Fig. 1: System Overview

Implementation Modules

Dataset

- • The image dataset of plant seedlings is gathered from the internet in this module. All of the plant seedlings are taken. The pictures came in three different file types:.jpg,.png, and.jpeg. To train and evaluate the model, this image data is insufficient. We take the data argumentation step to the next level in order to enhance the size of the data.

Data Augmentation

- The process of expanding the amount of the data set is known as data augmentation. Among other methods, the process can be carried out by rotating, flipping, shearing, and introducing random noise. The addition of fresh photos to the dataset will aid in both network training and improving the classification effectiveness of either new or testing data.

Preprocessing

- The image data is pre-processed and converted into numpy array data in this module. To determine the characteristic of the image data, this phase is crucial. The array data and size are displayed for these extracted features.

Train Model

- This module's data is split into train and test data in an 80% and 20% ratio, respectively. The model can be trained using the train data, and its performance can be tested using the test data. In this project, we used the CNN model, and we used Python programming's fit() technique to train the model.

Classification

In this lesson, we classified the plant seedlings using the model we suggested.

Implementation Algorithms

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Convolutional Neural Network (CNN)

To create a feature map, the input image is convolved through a collection of filters in the convolution layers of a convolutional neural network model. The face expression is then identified as belonging to a specific class-based output of the softmax algorithm after each feature map is integrated to create fully linked networks.

IV. RESULTS

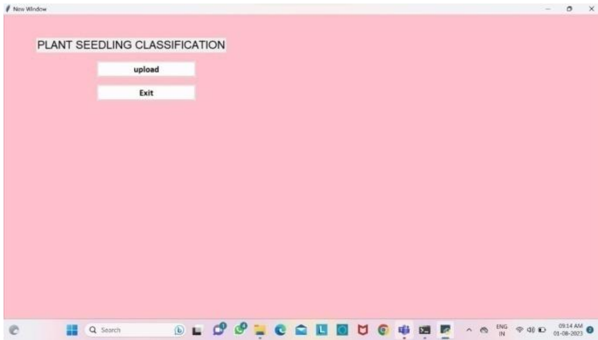

Fig. 2: Home Page

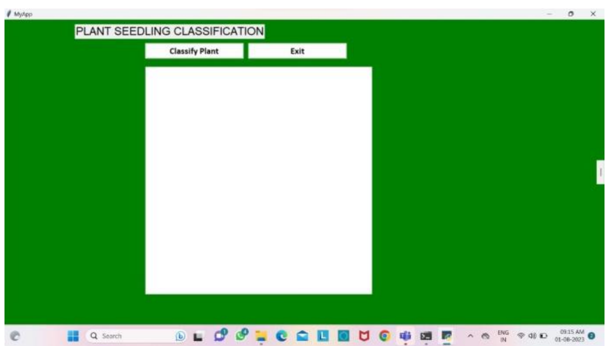

Fig. 3: Classification Page

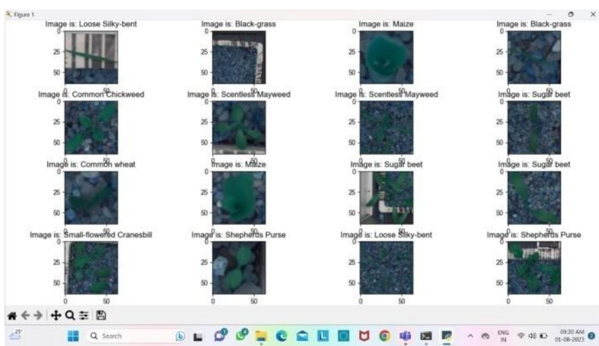

Fig. 4: Image Dataset

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Fig. 4: Heat Graph

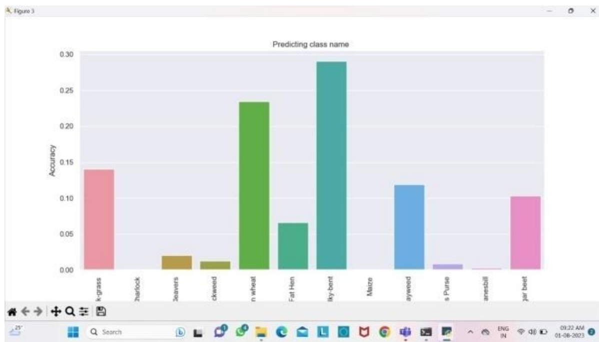

Fig. 5: Comparison Graph

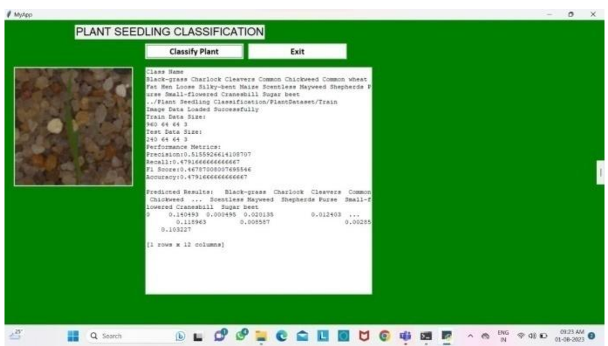

Fig. 5: Result Page

V. CONCLUSION

We used the ResNet50V2, MobileNetV2, and EfficientNetB0 architectures to develop a classification framework for plant seedlings. The benchmark plant seedlings dataset, which comprises 12 distinct species—three of which are plant species and the remaining nine of which are weed species—is used to validate the models. After comparing the models, we showed that the EfficientNetB0 model performed better, with an accuracy of 96.52% and an average F1-Score of 96.26%.

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