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A Novel Deep Learning Technique For Weed Plant Identification In Crops Using Data Augmentation

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Abstract: Weeds in rice fields are a major problem because they compete with rice plants for nutrients, light and space, resulting in reduced yields and economic losses. Physical detection of weeds is problematic when human labor is scarce. The proposed solution includes a deep learning approach that uses a specially pre-trained DenseNet-121 model to increase efficiency in solving the problem of the negative impact of weed growth on rice crop by distinguishing between visually similar weeds and crops. This model is refined with a dataset created from images of rice fields, and data augmentation techniques are used to improve the reliability of the model. This approach implements and evaluates various metrics and improves accuracy by displaying test results. This method helps in accurate weed control which ultimately improves yield and reduces economic losses. The system underwent evaluation using a dataset of images sourced from a paddy field, demonstrating its capability of identifying and eliminating weeds with a precision exceeding 99%. The suggested approach has the potential to greatly minimize labor and environmental impacts associated with weed management, while enhancing the efficiency and precision of weed detection and removal in crop production.. In future integrating this model with real-time observation systems and applied knowledge will further improve its practical applicability in agriculture.

***Index Terms* – Deep Learning , Data Augmentation , Weed Dataset**

I. Introduction

Weeds are often defined as detrimental and undesirable plants, weeds prevent the efficient use of land and water resources and have a significant impact on human well-being. Often described as "unfit for plants," weeds compete with beneficial and desirable vegetation in a variety of environments, including farmland, forests, and aquatic systems. They also cause significant problems in uncultivated areas such as industrial areas, transport corridors (roads and railways), airports, landscape plantings, reservoirs and waterways. Weeds are a major problem in land and water management. Their impact is strongest in agriculture, where they cause more damage than any other class of agricultural pests. In particular, weeds account for 45 percent of the total annual loss of agricultural produce, followed by insects at 30 percent, diseases at 20 percent, and other pests at 5 percent. This significant impact highlights the importance of effective weed control strategies in maintaining and improving agricultural productivity and sustainability [1]. Particularly weeds present in paddy fields have the significant problem in agriculture. In the contemporary agricultural sector, precise identification of crops and weeds is essential for enhancing productivity, minimizing production costs, and attaining sustainable agricultural growth. Manual weeding constitutes a substantial labor burden and is also ineffective in promptly identifying weeds. The sole resolution to the issue is to augment personnel; nonetheless, this will ultimately elevate agriculture expenses. Mechanical weed control is very effective for managing weeds in organic agriculture and can also be beneficial in conventional farming. Conversely, the use of machinery may adversely impact crops and the environment through damage and erosion. Recently, Deep Learning approaches have been extensively employed for the identification and detection of crops and weeds, yielding several research findings. A considerable quantity of research papers has been published regarding the application of deep learning approaches for weed identification.

This paper focused to work on these problems by applying deep learning methods to detect weeds from crop images and successfully detected the weeds in crop plants.

II. LITERATURE REVIEW

In recent times, a lot of research has been conducted on the identification and detection of weeds and crops using DL approaches. Many research studies on the use of DL techniques for weed identification have been published. This section provides a quick review of the principles behind many Deep Learning approaches that are used to identify weed in crop images.

2.1 A Comprehensive Study and Techniques for Deep Learning-Based Weed Identification

The review commences with an introduction to the essential concepts of deep learning as they pertain to weed detection [2]. Deep Learning algorithms have the capability to automatically extract information from extensive datasets utilized to model intricate problems, making them well-suited for the detection and classification of weeds and crops. The initial steps involved in the deep learning process for weed identification are as follows Data collection can be conducted through self-collection methods or by utilizing publicly available databases. Secondly, data preparation involves obtaining data from various sources, which may not be suitable for the deep learning model. Therefore, it is essential to conduct data preprocessing . Third, the DL Model utilizes Initial fundamental approach A Convolutional Neural Network (CNN) is a commonly used deep learning model applied in various fields, including image recognition, video analysis, and natural language processing. The architecture of a CNN includes an input layer, convolutional layers, pooling layers, fully connected layers, and an output layer. The CNN utilizes convolutional processes to extract local features from the input data, while multiple convolutional and pooling layers progressively abstract and represent the input data in a layered manner. This technique is achieved through the use of convolutional kernels, which extract feature information from the input data at different levels and degrees of abstraction. The next essential approach is a recurrent neural network (RNN), a deep learning model specifically created to handle and convert sequential data inputs into their respective sequential data outputs and Develop the model and evaluate the performance metrics. In recent years, Generative Adversarial Networks (GANs) have emerged as a powerful tool for data generation. A deep learning architecture known as a generative adversarial network (GAN) is utilized. It instructs two neural networks to engage in competition to generate more authentic new data from a specified training dataset.

2.2 A Review of Deep Learning-Based Weed-Crop Identification for Intelligent Farm Machinery

This study reviews the existing research on enhancing crop and weed identification for intelligent agricultural machinery [3]. This article outlines the application of deep learning algorithms for weed identification in smart agricultural machinery, emphasizing the image recognition processes, which encompass data gathering, picture preprocessing, and feature extraction. Ample labeled data is necessary for deep learning-based weed inspection and classification techniques. Various types of sensors installed on smart agricultural equipment, such as multispectral and hyperspectral imagers, are mounted on tractors, drones, or robots to capture high-resolution field images, adding spectral information beyond the visible spectrum to improve the ability to distinguish between crops and weeds. It is necessary to prepare data for model training, testing, and validation after collecting data from various sources. Applying various image processing techniques, data labeling, using image enhancement techniques such as normalization, noise reduction and contrast adjustment and segmentation are the methods of preparing the dataset. Relevant parts of the image, such as individual plants, are identified and separated. To train the deep learning model, data annotation can be done by labeling the photos with crop and weed classifications. The CNN weed identification algorithm is developed to recognize the camera detection with an accuracy rate of over 92%. It outperforms machine learning in terms of accuracy rate and the experiments are conducted on five separate CNN models. To detect weeds in real time, they deployed MobileNetV2 on a small autonomous robot called SAMBot. They also used algorithmic models such as Swin transformer and DeepLabv3+.

2.3 An Effective YOLOv7-Based Real-Time Weed Detection Method

Deep learning has resolved issues linked to weed detection in agriculture. Recently, some researchers have endeavored to locate weeds in rice fields utilizing convolutional neural networks. This study applied the YOLOv7 approach to address the issue and significantly enhance cannabis recognition performance in the early weed dataset [4]. Data collection, model training, and multi-class plant species classification must be finalized prior to developing a framework for weed detection. This research utilized two principal datasets: 4weed and the Early Crop Weeds dataset. The input layer of the deep learning model standardized photos of varying resolutions to uniform dimensions within the dataset. After the formation of a suitable dataset, 90% of the gathered data is allocated for training, while 10% is designated for testing. Subsequently, YOLOv7 is taught to identify agricultural weeds using the provided data. This paper presents a computer vision-based technique for item detection and recognition. The latest version of the Yolov7 model was utilized. Yolov7 is a singular approach for object detection. The model was trained and assessed using the NVIDIA Tesla T4 GPU in the cloud-based Google colab environment. The training of the YOLOv7 model commenced utilizing pre-trained weights obtained from the COCO dataset instead than initiating from the beginning.

2.4 Deep Learning for Weed Detection

As a result of this study, we have created an application that is capable of identifying and detecting weed and paddy crop disease. This time, we used the SVM and CNN algorithms to create our approaches for transfer learning (Mobile Net). Convolutional layers are used in the process of extracting features from input photos. The picture can be made smaller by using the pooling layer. Last but not least, categorization is done using dense layers. Additionally, we have taken into account the dataset of photos of paddy leaves, which will include one weed image and three distinct types of leaves (Healthy, Brown Spot, and Leaf Blight). The dataset results were tested by uploading an image once it had been trained, and this allowed for a more accurate classification of weeds and illnesses of paddy leaves [5]. Therefore, it will be simple to identify any paddy leaf illnesses and weeds with minimal human work, and it will provide treatments for such diseases.

2.5 Data Augmentation

Finding new data instances to train a model is known as data augmentation. One practical way to provide more information from less data is through data augmentation.[6]

The data augmentation technique is the most suitable to provide good prediction results when a dataset is too little or unbalanced to train a model. In order to improve the diversity of data for the machine vision system, the data augmentation method is employed during the training phase [7]. It helps avoid overfitting and improves the model's overall performance.

Over the past few decades, researchers have used a variety of strategies for data augmentation. It is commonly categorized as a synthetic data generator approach, an operation-based manipulation approach, and certain hybrid techniques that have been developed by various researchers for data augmentation.

Operation-based manipulation uses mathematical operations on real-input images to create new images. This approach's general techniques include rotation, flipping, cropping, edge improvement, noise, and jittering. Using traditional picture augmentation techniques can create new images [8]. The final images created using traditional techniques, however, have a distribution that is equal to that of the input image. These methods might not work if the synthetic items cause data to be dispersed among several participants.

GAN, image registration, and PCA are examples of synthetic data-generating techniques that use existing images to create new synthetic images. When synthetic samples must depict data distribution across numerous participants, these methods might be appropriate. For deep learning-based techniques to produce reliable results during training, a sufficient dataset is needed. A time series data creation technique that made use of high-quality plant leaf photos was presented [9]. It suggests two new time series data production methods (T-copy-paste and T-mixup) and acknowledges three perspectives for plant growth prediction.

III.PROPOSED SYSTEM

This paper focused to work on several reviews done by applying deep learning methods to detect weeds from crop images and it has been successfully implemented and detected the weeds in crop plants with the help of data augmentation [10]. The proposed system can detect and eliminate weeds autonomously, reducing the need for manual labor and herbicides. The crop images can be captured by a camera and loaded into the dataset, which are processed by a Deep learning model of Densenet 121 for weed detection.

3.1 Densenet Architecture

DenseNets, or Densely Connected Convolutional Networks, represent an advancement in the evolution of deepening convolutional networks. As convolutional neural networks (CNNs) increase in depth, they encounter complications. This occurs because the information's transmission from the input layer to the output layer (and the gradient in the reverse direction) becomes so extensive that it may vanish before reaching the opposite side.

Layer-to-layer connectivity is made simpler by DenseNets. Due to the elimination of duplicate feature map learning, DenseNets require fewer parameters than a comparable standard CNN. Due of the previously described gradients and information flow, training very deep networks posed another challenge. This problem is resolved by DenseNets since each layer has direct access to the original input image's gradients as well as the loss function. Using a composite of operations, traditional feed-forward neural networks link the layer's output to the subsequent layer. Typically, the composite consists of an activation function, batch normalization, and a convolution operation or pooling layers. For this, the equation would be:

$$x_l = H_l(x_{l-1}) \qquad (1)$$

DenseNets do not sum the output feature maps of the layer with the incoming feature maps but concatenate them [13].

Consequently, the equation reshapes again into:

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}]) \qquad (2)$$

DenseNets are separated into DenseBlocks, where the number of filters varies across blocks but the feature map dimensions stay the same inside a block. These layers, which are referred to as Transition Layers, handle the downsampling by using 2x2 pooling layers, 1x1 convolution, and batch normalizing.

This channel dimension is growing at each layer as a result of concatenating feature mappings. We can generalize for the l-th layer if we set H_l to consistently generate k feature maps:

$$k_l = k_0 + k * (l - 1) \qquad (3)$$

The growth rate is represented by the hyperparameter k. The amount of information added to each layer of the network is controlled by the growth rate.

The feature maps could be viewed as the network's information. Each layer can access the collective knowledge by referring to its previous feature maps. Then, in concrete k feature maps of information, each layer contributes fresh information to this collective knowledge. It represents in Figure 1

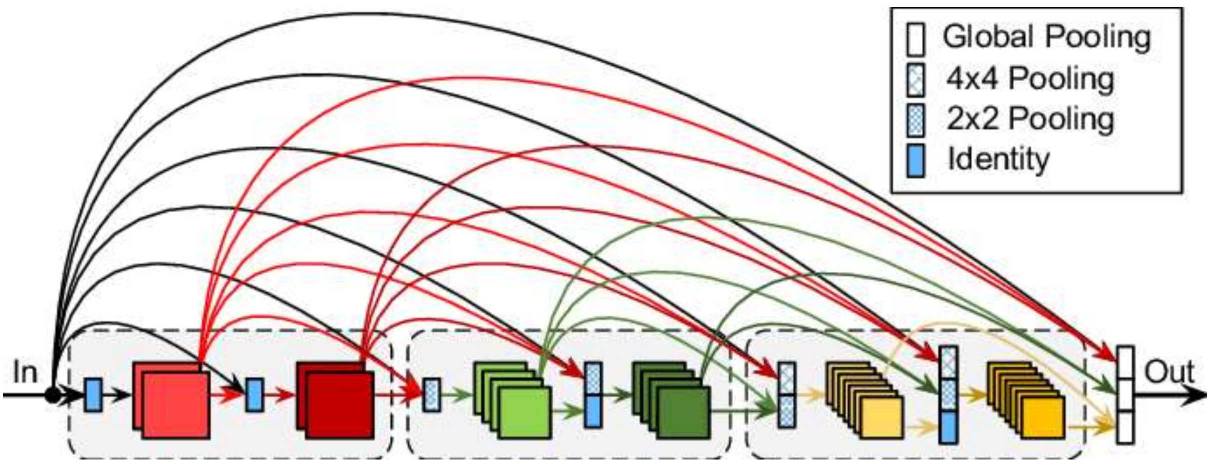

Fig 1: Densenet Architecture

The General workflow for weed detection based on deep learning. A typical Deep Learning process for weed detection can be represented in the Figure 2

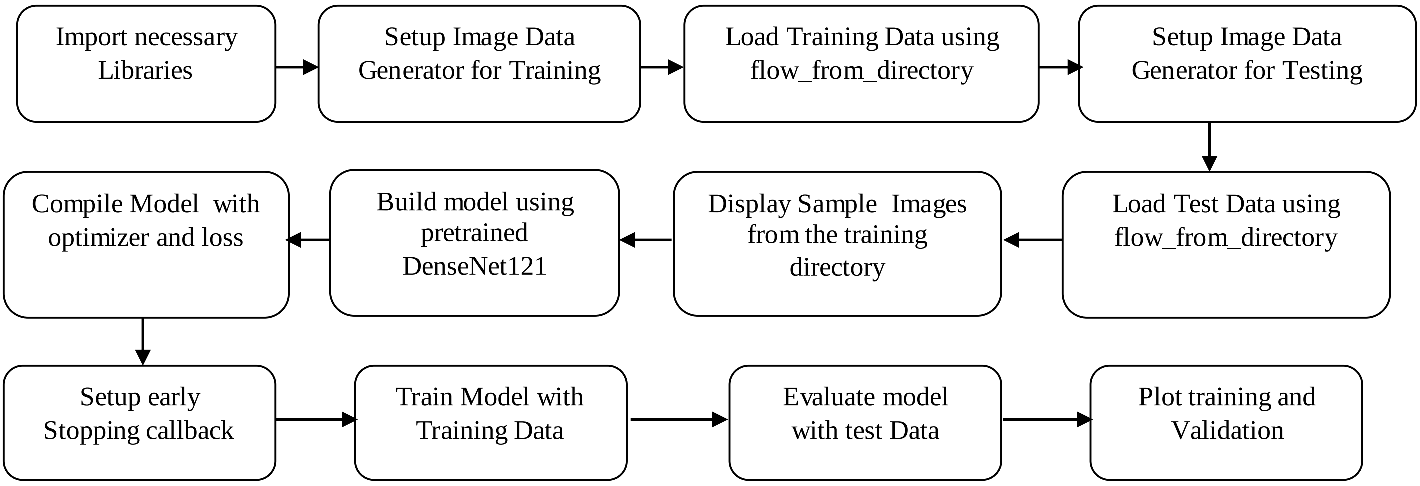

Fig 2. Deep Learning Process for Weed Identification

A typical DL process for weed identification involves the following steps: setting up data generators, displaying sample images, building the model, compiling and training the model, and evaluating its performance.

1. Imports and Directory Setup The code begins by importing necessary libraries for handling images, building the neural network model, and performing data augmentation.

2. *Data Augmentation and Data Loading*

- *Training Data Augmentation:* It produces an ImageDataGenerator for training data with different augmentations to improve generalization and using a heat map, which is a map representation of data where colors correspond to data values. Heat maps are a useful tool for exploring large information and communicating correlations between data values. Proper classification and visualization of data are essential for accurate understanding of large-scale datasets[14]. To effectively and efficiently display a variety of datasets, heat maps employ kernel density estimation techniques and clustering analysis.
- *Training Data Loader:* Uses flow_from_directory to load training data from a specified directory.
- *Test Data Augmentation and Loading:* Similar to training data, but for test data.

3. *Displaying Sample Images:* Loads and displays the first five images from the training directory.
4. *Model Building*: Uses a pre-trained DenseNet121 model as the base, adds additional layers for fine-tuning.
5. *Model Compilation* Compiles the model with the Adam optimizer and binary cross-entropy loss function.
6. *Early Stopping Callback*: Sets up early stopping to prevent overfitting.
7. *Model Training:* Trains the model on the training data and validates it on the test data.
8. *Model Evaluation*: Evaluates the model on the test data and prints the evaluation metrics. 9. *Plotting Training Metrics* : Plots training and validation accuracy and loss over epochs.

IV. EXPERIMENTAL RESULT ANALYSIS

The results of our research are summarized in this section. This section is separated into two subsections: Experimental outcome & analysis and Experimental dataset.

4.1 Experimental Data Set

An open-access dataset for weed detection that includes manually annotated photos. Six food crops and eight weed species are detected in the dataset's 1118 photos, which include 7853 annotations overall. Three RGB digital cameras—the Sony W800, Canon EOS 800D, and Intel RealSense D435, were utilized to take the pictures. Food crops and weeds cultivated in field circumstances and controlled environments at various growth stages were photographed.

Fig 3: Sample Crop and Weed Dataset

4.2 Experimental Outcome Analysis

The original image can be used to conduct the experimental work and execute it using Red, green, blue, and near-infrared (NIR) information and create a heatmap with the help of density and overlay as mentioned in Figure 4

Density Map: Make a heatmap that highlights regions with higher densities of weeds. In order to accomplish this, the recognized weed pixels can be mapped onto a color scale, where warmer hues indicate more dense weed growth and cooler hues indicate less weeds.

Interpolation: To produce a seamless transition on the heatmap, interpolate the values between identified weed spots as necessary.

Map Overlay: To see the weed concentration directly on top of the original terrain, overlay the weed detection heatmap onto the original image.

Color Mapping: To show places with high weed density, use colors like red, yellow, or orange; for areas with lesser density, use cooler hues like green or blue.

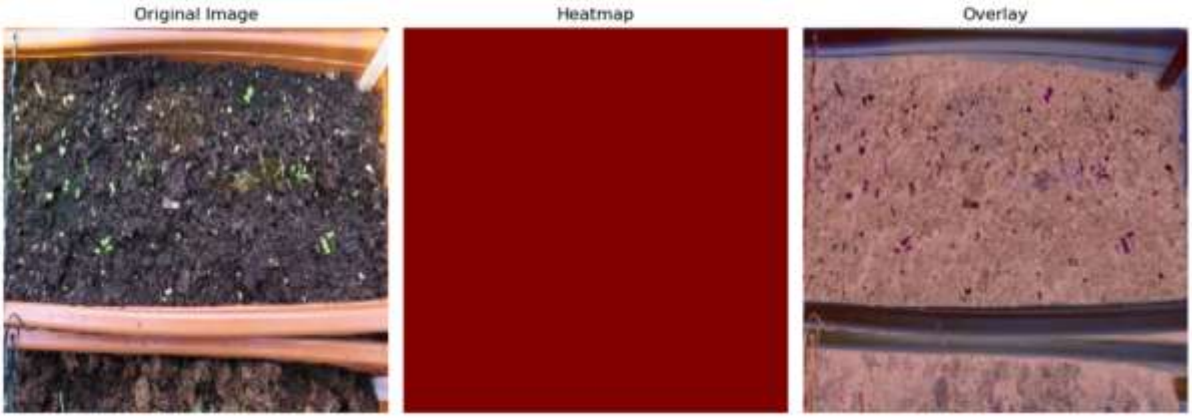

Fig 4 Data Augmentation – Heat map and overlay

We train the dataset over many epoch sizes to evaluate the model's performance. It facilitated the enhancement of the model's performance. Nonetheless, augmenting the epoch size above 50 leads to overfitting. Consequently, to mitigate the issue of overfitting, we restricted the number of epochs. Two distinct graphs, one for accuracy and one for loss, can be plotted to show the accuracy and loss for training and validation according to the number of epochs. These charts will demonstrate how the model's performance changes as it is being trained.
Accuracy Plot: As the number of epochs increases, you should typically see the training and validation accuracy increase, especially if the model is improving. If the validation accuracy plateaus or starts decreasing, it might indicate overfitting.
Loss Plot: The loss should decrease as the model improves. However, if the training loss decreases significantly while the validation loss increases, this could indicate overfitting.
For the Densenet121 model, the maximum training and testing accuracy are 99.9% and 100% mentioned as in the figure 5 and 6.It is a very powerful model with a large number of parameters. In some cases, such a complex model might easily overfit on a small or non-complex dataset, achieving perfect accuracy by memorizing the data.

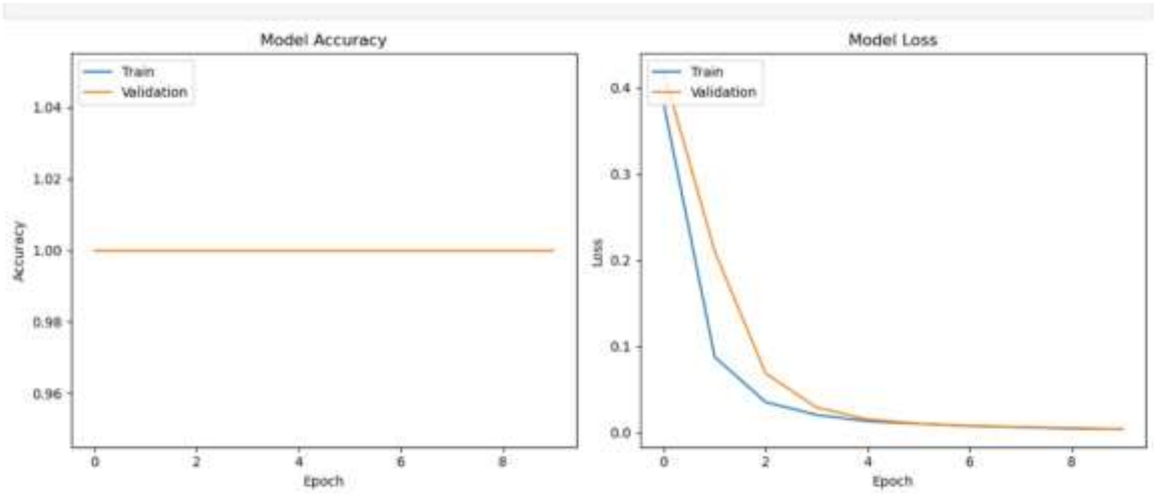

Fig 5 Accuracy and Loss Graph based on Epochs

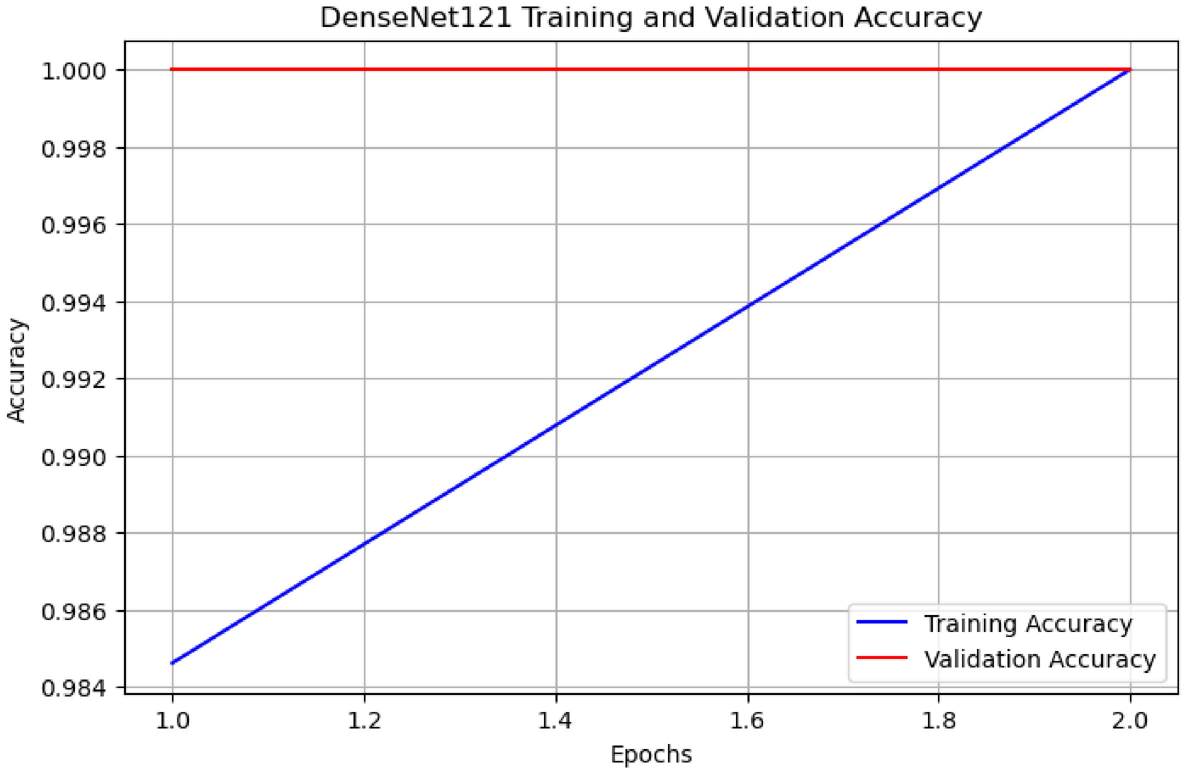

Fig 6: Training and Validation Accuracy

V. CONCLUSION

The accuracy and effectiveness of weed management in agricultural techniques could be greatly increased by using DenseNet121 for weed detection. It can do well when it comes to recognizing and distinguishing between crops and weeds. However, valid model evaluation, robust generalization, and real-time deployment optimization are important considerations to optimize its practical application. By reducing the use of herbicides and improving precision agriculture systems, DenseNet121 can support sustainable farming methods with additional refinements and practical testing. In controlled settings or under optimal training conditions, DenseNet121 has demonstrated itself to be a potent model for weed detection. For practical use, real-time weed detection in agricultural areas poses certain difficulties that need to be resolved. Understanding the benefits and drawbacks of each deep learning model's applicability is crucial when contrasting DenseNet121 with other models, particularly in dynamic, real-world situations. Here is how DenseNet121 stacks up against other deep learning models and how it might be applied to real-time weed detection

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