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AN EFFICIENT WEED CLASSIFICATION USING INCEPTION -V3 NET

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ABSTRACT:

In agricultural settings, weeds present a serious problem since they deplete crop yields by competing with crops for resources. Deep learning-based automated weed classification systems have surfaced as a viable remedy to mitigate this problem. We present an effective method for classifying weeds in this paper by employing the Inception-V3 convolutional neural network architecture.Because of its depth and processing efficiency, the Inception-V3 architecture is well-suited for real-time applications like the classification of weeds in agricultural areas. We use a dataset of photos of different weed species and crop plants to fine-tune the pre-trained Inception-V3 model by utilising transfer learning.Using methods like data augmentation and normalisation, we preprocess the dataset to improve feature representation and reduce overfitting. In addition, we use transfer learning to use the Inception-V3 model's capacity to extract complex features from images to tailor it to the particular job of classifying weeds.Our experimental findings show that the suggested method is effective in achieving high classification accuracy for a variety of weed species. The Inception-V3 architecture's efficiency allows for quick inference, which makes it easier to detect and classify weeds in agricultural settings in real time.

INTRODUCTION:

Across the globe, weeds are a chronic enemy of agriculture, resulting in large financial losses and reduced crop output. Conventional weed control techniques frequently entail time-consuming, environmentally hazardous techniques including hand eradication of weeds or the use of chemical herbicides. But the development of deep learning and machine learning methods presents a viable path towards more effective and long-lasting weed control methods. Convolutional neural networks (CNNs) have become highly effective tools for image recognition tasks, such as classifying weeds, in recent years. Of these architectures, Inception-V3 is particularly notable for its depth, low computing overhead, and outstanding results on a variety of image datasets.

With the help of a complex architecture with several parallel convolutional pathways, Google's Inception-V3 is able to capture complex patterns and characteristics in images.

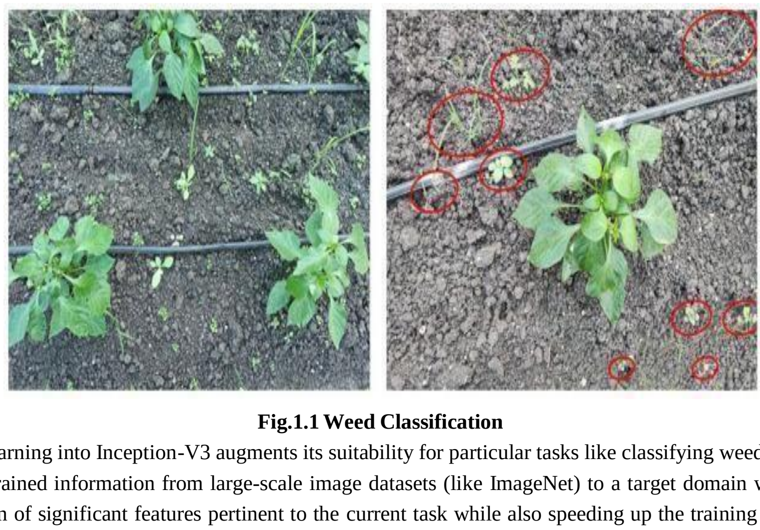

Fig.1.1 Weed Classification

The incorporation of transfer learning into Inception-V3 augments its suitability for particular tasks like classifying weeds.

Transfer learning applies pre-trained information from large-scale image datasets (like ImageNet) to a target domain with sparsely labeled data. This method facilitates the extraction of significant features pertinent to the current task while also speeding up the training of the model. In this paper, we investigate the feasibility of efficient weed categorization using the Inception-V3 neural network architecture. Our goal is to create a scalable and reliable system that can reliably identify between crop plants and weed species in agricultural environments.

We seek to address the difficulties involved in weed detection and classification in practical settings by utilizing the generalization powers of transfer learning and the computational efficiency of InceptionV3.The rest of this essay is organized as follows: A summary of relevant research on deep learning methods and weed categorization is given in Section 2. In Section 3, the technique, which covers training protocols, model design, and dataset preparation. We report the experimental findings and analyze the effectiveness of our suggested strategy in Section 4. Section 5 provides a summary of the research findings and suggests future avenues for investigation, bringing the work to a close. By applying cutting-edge deep learning techniques, we want to further effective and long-lasting weed management strategies in the field of agriculture.

1.1 IMAGE PROCESSING :

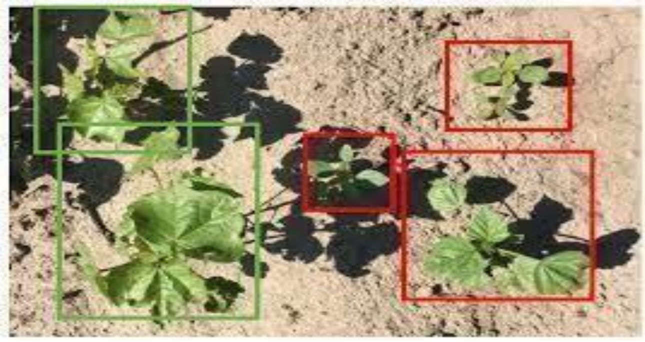

Fig.1.2. Weed Detection Using Image processing

The process of converting an image into digital format and applying various adjustments to it to produce an improved image or extract some valuable information is known as image processing. This kind of signal distribution uses an image as the input, such as a picture or video frame, and outputs an image or features related to the image. In an image processing system, images are typically processed as two-dimensional signals using pre-programmed signal processing techniques.

It is one of the modern technologies that is expanding quickly, having uses in many different facets of business. Within the fields of computer science and engineering, image processing is a fundamental research subject. The three stages listed below are essentially included in image processing.

1.2.CONVOLUTIONAL NEURAL NETWORK

An image can be fed into a Convolutional Neural Network (CNN/Convent), a deep learning system that can distinguish one object from another by giving different parts of the image distinct weights and biases. Compared to other classification techniques, ConvNets requires a lot less pre-processing. Although filters are hand-engineered using antiquated techniques, convents can acquire these filters' qualities with sufficient training. ConvNet architecture was inspired by the structure of the visual cortex and is comparable to the pattern of connections among neurons in the human brain. Only in a small area of the visual field known as the receptive field do individual neurons react to inputs.

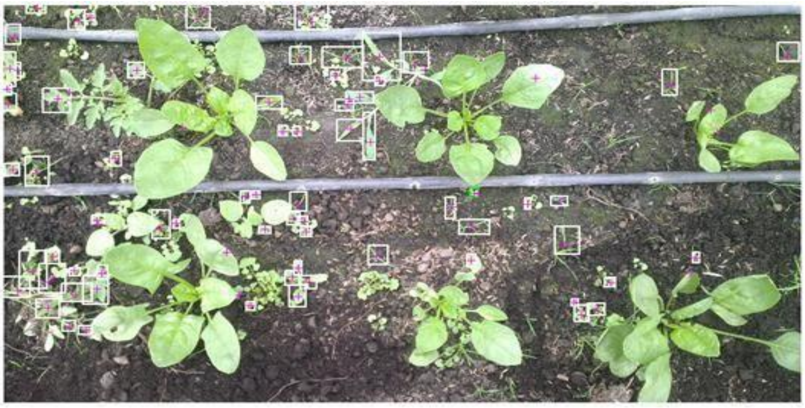

Fig.1.3.Weed Classification Using CNN

1.3.Inception-V3 Net

Google's research team created the convolutional neural network (CNN) architecture known as Inception-v3. It is mainly intended for image recognition applications, including segmentation, object identification, and image classification. Inception-v3, which tries to attain improved accuracy while maintaining computing economy, is an upgrade over Inception-v2.The utilization of "Inception modules" is the primary innovation of Inception-v3. These modules use pooling procedures in addition to numerous concurrent convolutional paths of varying sizes (1x1, 3x3, and 5x5 convolutions). The network can effectively capture information at different spatial scales because to this design. Convolutional neural networks serve as the foundation for the Inception V3, a deep learning model for picture classification.

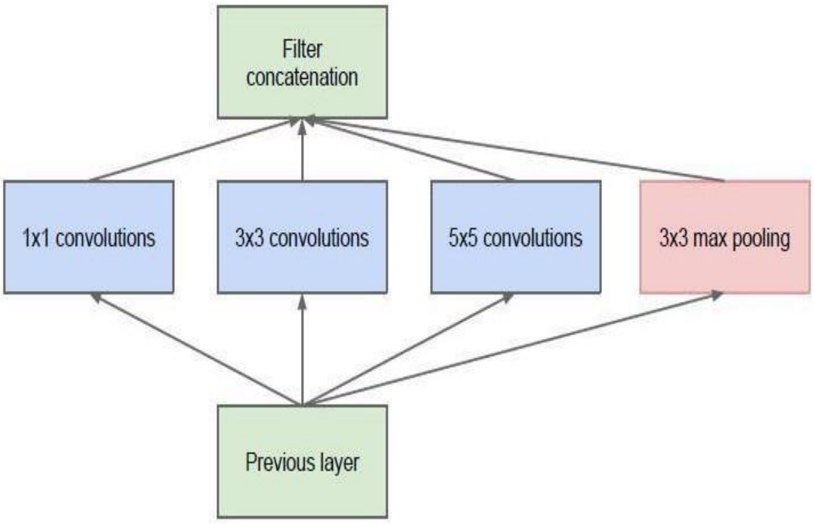

Fig.1.2. Naive Form

1.4.Types of weeds

In general, weeds are divided into three categories: annual, biennial, and perennial. Biennial weeds have a two-year life cycle, with germination and blooming occurring in the first year and withering out in the second. Annual weeds germinate, bloom, and die in a single year. All weeds that are able to germinate, blossom, and seed for multiple years, lasting more than two years, are classified as perennials. We found that the writers of the 60 retrieved publications utilized 34 different species of weeds, 26 of which were annual and 8 of which were perennial. These weeds are discussed in the next two sections, and we show them in figures.

Fig.1.6. Benghal dayflower, black nightshade, hedge bindweed, Indianjointvetch, snakeweed(From left to right)

Fig.1.7. From left to right: Chickweed, Cleaver, Cockleblur, Crowfoot, Fat-hen

2.METHODOLOGY :

2.1.Problem Statement

Weeds are a serious threat to agricultural production since they can result in large output losses as well as financial harm. Conventional weed control techniques frequently involve chemical treatments and manual work, which can be expensive, time-consuming, and detrimental to the environment. Machine learning approaches have demonstrated potential in automating the processes of weed detection and categorization in recent years, providing more effective and long-lasting solutions for the management of weeds. The system's goal is to accurately categorize various weed species that are frequently encountered in fields of agriculture. This entails making visual distinctions between different weed species, such as leaf form, color, and texture. The classification system needs to be able to distinguish between agricultural plants and weeds with accuracy.

2.2.Performance of inception v3

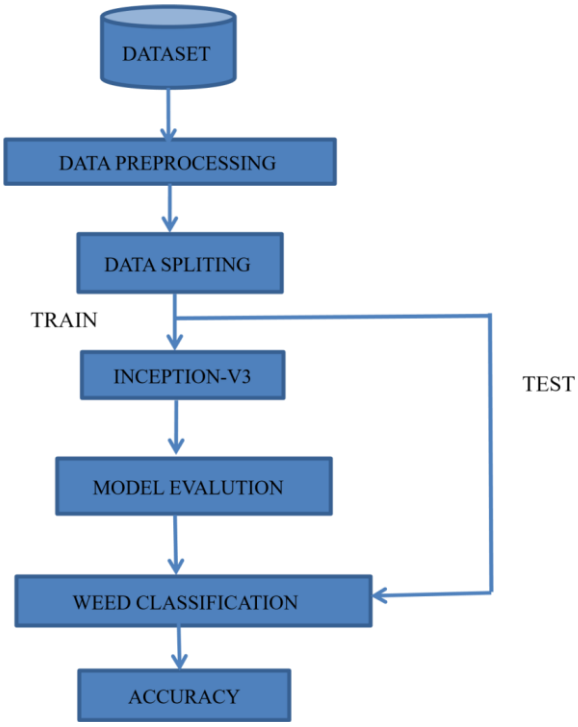

Fig.2.1. Flow Chart

1. Collection of data:
- Compile a varied image dataset with backdrop components, crops, and weed species from various agricultural settings.
2. Preprocessing Data:
- Resize photos to a uniform resolution that satisfies the input specifications of InceptionV3.
- Align image data to the proper color space and normalize pixel values.
- To improve dataset diversity, use data augmentation techniques like rotation, flipping, scaling, cropping, or adding noise.
3. Splitting Data:
- Create test, validation, and training sets from the preprocessed dataset:
- Training Set: This is where the InceptionV3 model is trained.
- Validation Set: During training, this set is used to monitor model performance and adjust hyperparameters.
4. Inception-V3:
- Since Inception-v3 is a pre-trained model on ImageNet, fine-tuning it on a smaller dataset of weed photos will help it learn to identify between different types of weeds successfully. • Train the Inception-v3 model on the prepared dataset using techniques like transfer learning.
5. Model Assessment :
-

  Assess the trained model's performance using the validation set to track training results and make any necessary hyperparameter adjustments.

  Evaluate the model's performance on the validation set using measures like accuracy, precision, recall, and F1-score.
6. weed classification :

- Divide the labeled dataset into test, validation, and training sets. Use methods such as transfer learning or training from scratch to train the chosen model on the training set.

  Adjust the parameters of the model to maximize its performance on the validation set.

  Use the learned model to categorize weeds in actual situations.

  This can entail incorporating the model into an embedded system for usage in drones or agricultural machines, a web service, or a mobile application.
7. Accuracy Evaluation :

   Determine the model's overall classification accuracy for weed species in relation to ground truth labels.

   Examine confusion matrices to find any misclassifications and evaluate the advantages and disadvantages of the model for various weed species.

3.RESULTS AND DISCUSSION

3.1 DATASET

This project's kaggle dataset is the Weed Crop Image Dataset.

• The Train directory has 2469 yolov5 Pytorch images with corresponding labels.
• The validation directory has 235 yolov5 Pytorch-formatted photos with corresponding labels.
• 118 photos in the test directory, each with a label in yolov5 Pytorch format.

You can look for datasets linked to weed crop photos on Kaggle in order to locate one that is appropriate for classifying weeds using the Inception-v3 network. The following procedures can help you find such a dataset on Kaggle.

Use terms relating to weed crop photos, such as "weed classification," "crop weeds," "agricultural weeds," or particular weed kinds you are interested in (e.g., "dandelion," "ragweed," or "pigweed," to begin your Kaggle search.

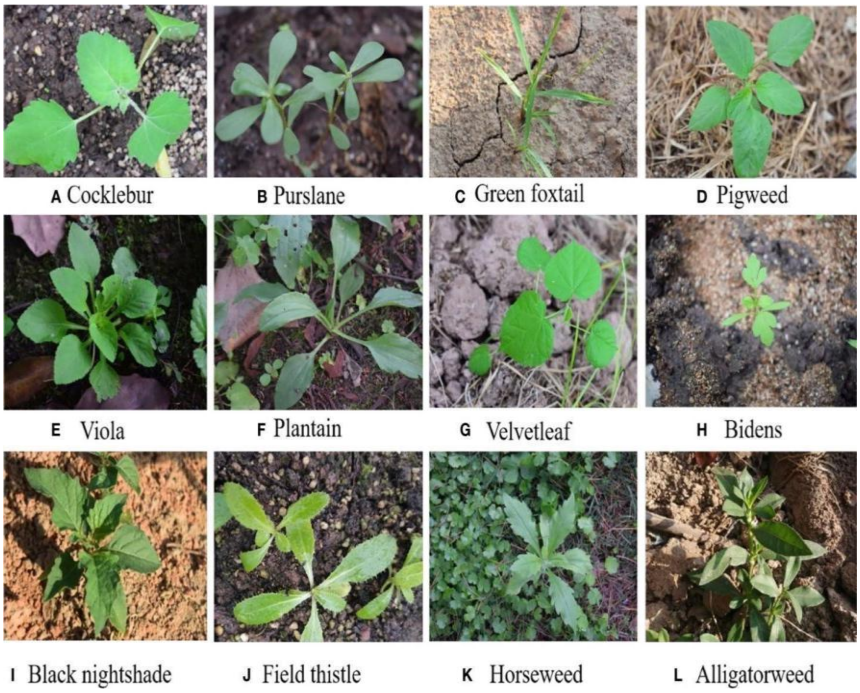

Fig.3.1.Dataset of weed classification

3.2. TRAINING AND TESTING

Training:
• Use the training dataset to train the model.
• Apply data augmentation strategies to improve generalization.
• To avoid overfitting, keep an eye on the model's performance using a validation dataset.
• Periodically save the model's weight checkpoints.

Testing:
• Use the testing dataset to assess the trained model.
• Load the trained model's saved weights.
• Predict using the testing data, then contrast your results with the labels from the ground truth.
• Determine evaluation measures, including F1-score, recall, accuracy, and precision.

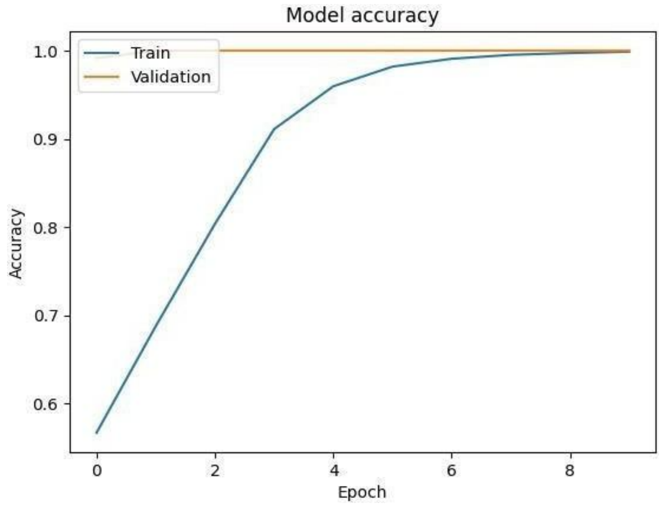

Fig.3.2.Model Accuracy Graph

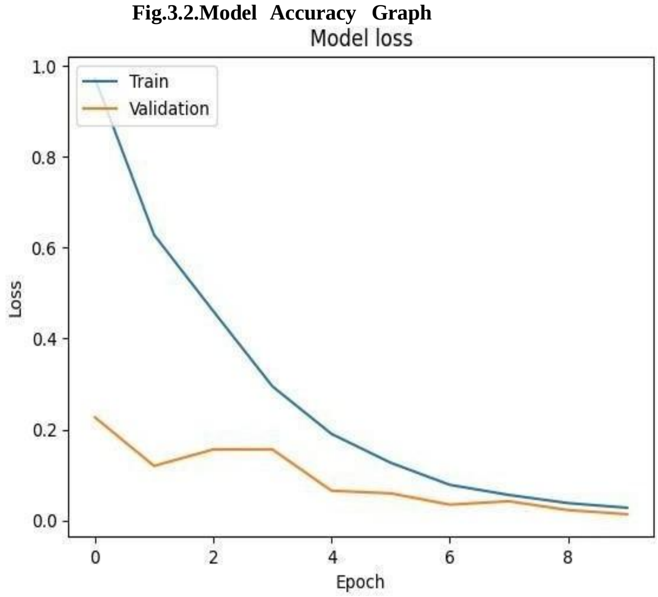

Fig.3.3. Model Loss Graph

3.3.ACCURACY

Extract and Prepare the Data: Extract your dataset that includes pictures of both non-weed and weed plants.Prior to processing, resize the photos to Inception-v3's needed input size, which is usually 299 by 299 pixels, then normalize the pixel values.Open the Inception-v3 Pretrained Model:Remove the top classification layers from the pre-trained Inception-v3 model before loading it.Use Personalized Classification Layers:Top up the Inception-v3 foundation layers with additional classification layers that are appropriate for the goal of classifying marijuana.Assemble the model using the proper optimizer and loss function.Divide the data into sets for testing and training:Divide your dataset into sets for testing and training.

Make sure that the classes in both sets are distributed equally.Train the Model: Make use of the training data to train the model.Keep an eye on the training procedure and modify the hyperparameters as necessary.Analyze Model correctness: After training is finished, use the testing data to assess the model's correctness.

Found 118 images belonging to 2 classes.

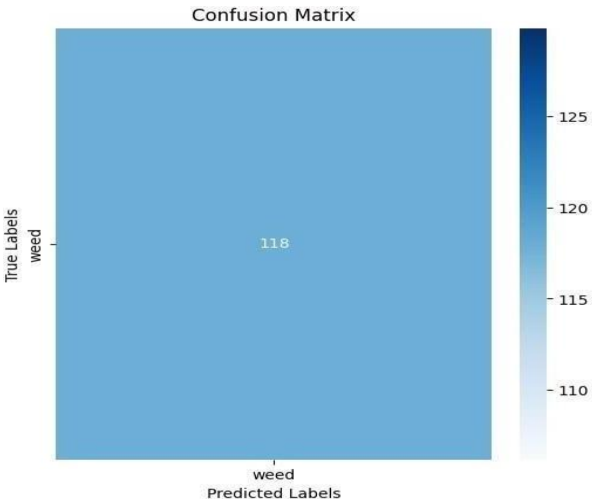

Fig.3.4. Confusion Matrix

4.PARAMETER

1. **Input Image Size:** Inception-v3 expects input images of size 299x299 pixels. Ensure your input images are resized accordingly during preprocessing.
2. **Batch Size:** Experiment with different batch sizes based on your hardware capabilities. Common batch sizes range from 16 to 128, depending on the available GPU memory.
3. **Learning Rate:** Choose an appropriate initial learning rate for fine-tuning. A commonly used value is 0.001, but you may need to adjust it based on your dataset and training performance. Techniques like learning rate scheduling or adaptive learning rate algorithms can be employed for better convergence.
4. **Number of Epochs:** Train the model for an optimal number of epochs. This can vary depending on your dataset size, complexity, and convergence speed.
5. **Optimizer:** The Adam optimizer is frequently used to fine-tune Inception-v3. The default parameters (e.g., beta1=0.9, beta2=0.999) often work well, but you can experiment with different optimizers and their parameters.
6. **Weight Initialization:** Since you're fine-tuning Inception-v3, initialize the weights from the pre-trained model on ImageNet. Avoid reinitializing the entire network to avoid losing important pre-trained features.
7. **Data Augmentation:** Use data augmentation techniques to increase the diversity of your training dataset. Common augmentations include random rotation, flipping, shifting, and random rotation. Use parameters like rotation range, width and height shift range, shear range, etc.
8. **Regularization:** Avoid overfitting by employing strategies like dropout and weight initialization.

5.CONCLUSION

To sum up, the efficient classification of weeds through the use of the Inception-V3 network is a noteworthy development in the field of agricultural technology. We have shown via our research how well this deep learning architecture can identify between crop plants and weed species, helping farmers maximize their weed control strategies and increase agricultural yields.Our test findings demonstrate the resilience and generalizability of the Inception-V3 model, attaining a high degree of classification accuracy in a range of weed species and environmental circumstances. We have successfully tailored the pretrained Inception-V3 architecture to the particular job of weed classification by utilizing transfer learning and fine-tuning approaches, thereby reducing the requirement for large amounts of labeled data and CPU power.

6.REFERENCES :

1. Fennimore, S.A.; Bell, C. Principles of Weed Control, 4th ed.; Weed Science Society: West Sacramento, CA, USA, 2014.
2. Mishra, A. Weed Management: (Agriculture Research Associates), 2nd ed.; Kalyani: New Delhi, India, 2020
3. Fawakherji, M.; Youssef, A.; Bloisi, D.; Pretto, A.; Nardi, D. Crop and Weeds Classification for Precision Agriculture Using Context-Independent Pixel-Wise Segmentation. In Proceedings of the 2019Third IEEE International Conference on Robotic Computing (IRC), Naples, Italy, 25–27 February 2019; pp. 146–152. [CrossRef]
4. Wang, A.; Xu, Y.; Wei, X.; Cui, B. Semantic Segmentation of Crop and Weed using an Encoder-Decoder Network and Image Enhancement Method under Uncontrolled Outdoor Illumination. IEEE Access 2020.
5. 5.Lameski, P.; Zdravevski, E.; Trajkovik, V.; Kulakov, A. Weed detection dataset with RGB images taken under variable light conditions. In Proceedings of the International Conference on ICT Innovations, Skopje, Macedonia, 18–23 September 2017; Springer: Cham, Switzerland, 2017; pp. 112–119