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Weed Detecion and Classification in Cotton fields using Resnet152V2 and inceptionn V3

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ABSTRACT:

Agriculture,the main pillar of our nation's economy, is experiencing many difficulties, which is forcing many farmers to look for other sources of income owing to the increased hazards. India has long relied heavily on cotton as a revenue crop, but one of the biggest risks it faces is weed infestations, which prevent plants from growing. The existence of multiple weed species complicates the procedure of weed detection. In this paper, we focus mainly on the cotton crop. This survey explores weed detection and classification methodologies across many models of Machine Learning and Deep learning namely— SVM,KNN, CNN, YOLOv8, Inception V3, and Resnet 152 V2—to identify weed infestations by classifying plants as weeds or not, identifying the type of weed, and recommending appropriate growth-controlling strategies. The traditional template matching procedure is replaced by these methods.We believe that the Weed detection system, by utilising the capabilities of DL models like Resnet and Inception, can significantly enhance safety of cotton crop. This hybrid model of Inception V3 and Resnet 152V2, which deviates from the conventional template matching method, is used to process the images. With its improved accuracy, versatility, and potential for real-time weed detection, this upgraded technology will revolutionise weed management in cotton farming and support India's agricultural sustainability.

Keywords: CNN,Inceptionv3, Resnet 152v2, YOLOv8

1. Introduction

An essential agricultural crop, cotton is produced annually in an astounding 27 million metric tonnes worldwide. It is used in many industries, such as industrial threads, medical supplies, and apparel. India, a major participant in this market, boasts an impressive output of cotton that directly affects the lives of about 6 million farmers. Cotton cultivation is highly challenging despite its economic significance because cotton plants are easily attacked by a wide variety of weeds. The quantity and quality of crops can be significantly decreased by these invasive species. Farmers frequently rely on their own judgement or ask locals for help while farming in rural areas where traditional agricultural methods are prevalent. This takes time and effort and can result in incorrect diagnoses and poor weed control. Thus, the need to create a system that gives farmers exact instructions suited to their unique weed-related problems is urgent. To fulfill the urgency, this project consists of detection with YOLOV8 model and classification with Resnet152V2 and InceptionV3 deep learning models for enhancing the efficiency and effectiveness of weed management strategies in agricultural practices. This project also recommends the prevention strategies of the particular weed which helps farmers quickly tackle their growth. This project also addresses certain challenges associated with style transfer, such as ensuring usage of perfect herbicide for a particular weed, especially for rare species. Another key focus is the detection of the bounding box which specifies the location where the weed is present, which requires careful training of the algorithm. By working on these, the project aims to push the boundaries of weed detection and classification, exploring innovative techniques such as real-time weed detection using cameras.

Related Work

In recent years, significant research efforts have focused on weed detection technology, addressing critical issues in agricultural contexts. This includes utilizing weed plants as templates for detection and employing tools like Python, NumPy, and OpenCV for template matching [1]. Another study proposes an image processing algorithm for efficient weed control in crop plantations, utilizing thresholding, morphological processing, and erosion and dilation techniques [2]. Additionally, deep learning models such as CNN, Resnet 152 V2, and Inception V3 are employed for cotton leaf disease detection [3].

Advancements in image processing and machine vision for weed identification are examined, focusing on spectral properties, biological morphology, spatial
contexts, and visual textures [4]. Another article evaluates DL-based models for weed recognition, highlighting Inception V3's efficacy [5]. Moreover, a machine vision-based weed detection method is proposed, evaluating various object detectors for precision weeding [6]. A comprehensive system is

presented for automatic recognition and classification of crops and weeds, employing CNNs, feature extraction techniques, and classification algorithms [7]. Stereo vision technology is utilized for weed and crop classification in rice fields, employing hybrid metaheuristic methods for improved classification accuracy [8]. This study addresses weed identification in agricultural fields by employing neural networks and machine learning algorithms, enhancing YOLOv5 architecture, conducting image segmentation with Otsu's method, and evaluating algorithms for future research direction [9]. Another work utilizes machine vision to extract shape data from sugar beet farm images, employing SVMs and ANNs for weed identification [10].A
study focuses on real-time weed classification through adaptive image segmentation and ensemble classification methods [11].Additionally, feature extraction using Gabor Wavelet and Fast Fourier Transform, combined with SVMs, improves weed classification accuracy [12]. Another work provides an overview of YOLO on test datasets guide further refinements, ensuring robustness and accuracy in real-world applications.

Data Collection:

- Obtain high-resolution images of cotton plants from various fields to ensure dataset diversity and representativeness.
- Implement a rigorous curation process to eliminate low-quality or blurry images, maintaining dataset integrity.

Data Preprocessing

- **Resizing:**Resize images to dimensions compatible with different Convolutional Neural Network (CNN) architectures, such as 224 x 224 pixels for ResNet152V2 and InceptionV3, and 128 x 128 pixels for a compact CNN.
- **Data Augmentation:**Apply data augmentation techniques including resizing, shearing, zooming, rotation, and horizontal flips to augment the training dataset, enhancing model robustness and generalization.

Model Selection

InceptionV3
approach's object detection capabilities, showcasing its advantages and limitations, especially regarding small or complex objects [13].
Furthermore, a study automates weed identification and evaluation in agricultural fields using a hyperspectral sensor and statistical features, presenting a comprehensive framework for weed detection [14].

Proposed Method

Our method for weed detection and classification in cotton fields combines diverse image datasets with advanced deep learning
techniques. Through meticulous curation and preprocessing, we enhance dataset quality for training CNN models like Inception V3 and ResNet152. We strategically fuse these architectures to create a hybrid model, optimizing training parameters for optimal performance. Subsequent deployment and evaluation

Convolutional neural network systems like Inception v3 are well known for their ability to analyze images and recognize objects. This architecture in Figure1 was first designed as a GoogLeNet module, but it has now developed into a stand-alone model with unique features. The fundamental technique used by Inception v3 is a set of inception blocks made up of many convolutional and pooling layers. Together, these building components improve the network's capacity to identify complex characteristics and patterns in incoming pictures. By lowering total processing costs, the integration of several convolutional and pooling layers into inception blocks not only enables more accurate results but also increases computing efficiency. The inception architecture, with its intricate design and thoughtful utilization of convolutional and pooling layers, has played a pivotal role in advancing the field of image analysis, making it a key player in the landscape of convolutional neural networks.

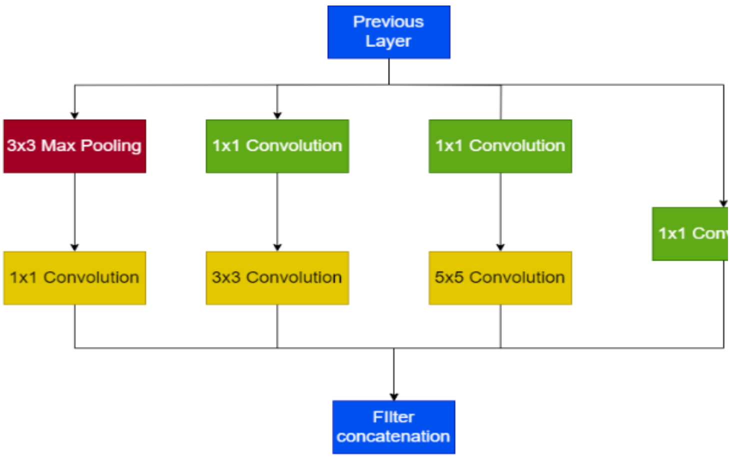

Figure.1 InceptionV3 Architecture

3.3.2 Resnet152V2

Residual Network (ResNet),a well-known deep learning based model for computer vision applications uses an architecture of Convolutional Neural Networks (CNNs) that can support several convolutional layers. In contrast to earlier CNN architectures that struggled to scale effectively with an increasing number of layers, ResNet addresses the prevalent "vanishing gradient" problem encountered during training. ResNet introduces a groundbreaking solution termed "skip connections", which enhances training efficiency by compressing the network into fewer layers as shown in Figure 2.

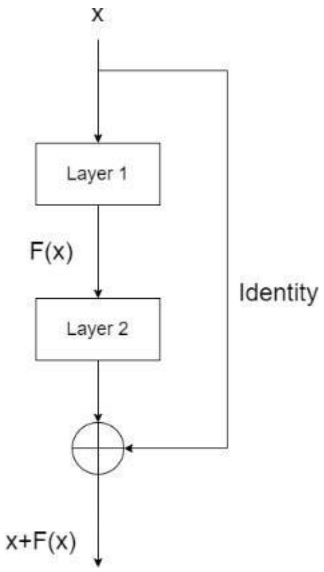

Figure.2 Resnet Architecture

3.3.3 Deep Fusion Model

This model is a combination of the Inception V3 and ResNet152V2 models. After obtaining the outputs from both InceptionV3 and ResNet152V2 branches, global average pooling layers (GlobalAveragePooling2D) are applied to each branch's output.Global average pooling reduces the spatial dimensions of the feature maps while retaining important information, resulting in a more compact representation suitable for classification.Finally, the output features from both branches are concatenated using the Concatenate layer. This merges the features extracted by InceptionV3 and ResNet152V2 into a single feature vector, effectively combining the representations learned by both architectures. Thus, this new feature vector would consider all important features effectively, which can be leveraged in the task of image classification.

Evaluation Metrics

In evaluating the performance of our weed detection and classification system we employ a set of widely-used metrics including accuracy, precision, recall, and F1- score.

Accuracy measures the overall correctness of our model's predictions, calculated as the ratio of correctly predicted weeds to the total number of predictions.

$$\frac{True\ Positives + \text{True}\ Negatives}{\text{Total Population}}$$

Precision quantifies the proportion of true weed predictions among all positive predictions made by the model, providing insights into the model's ability to minimize false positives.

$$= \frac{True\ Positives}{True\ Positives + False\ Positives}$$

Recall, on the other hand, assesses the model's capability to capture all actual weeds by measuring the proportion of true weed predictions among all actual weeds present in the dataset.

$$= \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

Where,

True Positives (TP) represents the number of correctly predicted weed instances.

False Positives (FP) represents the number of instances that were predicted as a class of weeds but are actually of some other class of weeds.

False Negatives (FN) represents the number of instances that were not predicted asa class of weeds but are actually of that class. F1-score, represents the harmonic mean of precision and recall, offering a balanced assessment of our model's performance by considering both false positives and false negatives.

$$= \frac{2 \times Precision * Recall}{Precision+Recall}$$

These evaluation metrics provide a comprehensive understanding of our weed detection and classification system's effectiveness in accurately identifying weeds in field image, enabling us to assess its performance across various dimensions and make informed decisions regarding its optimization and deployment.

4. Experimental Evaluation

In our analysis, we compare three transformer-based models: InceptionV3, ResNet152V2 and a deep fusion model of both to evaluate their weed classification performance in the given field image. Each model is fine-tuned on pre-trained ImageNet weights. These pre-trained weights are beneficial because they provide a good starting point for the model's parameters, leveraging the knowledge learned from ImageNet data, which includes a vast variety of images across different categories Following fine-tuning and validation, we assess the weed classification capabilities of each model on the test set using accuracy.

Results

Weed Detection

Users can detect weeds by using the webcam to capture a live image. This utilizes the implemented YOLOV8 (You Only Look Once) algorithm for real-time detection of weeds in images.

Figure. 3 Weed Image for Detection

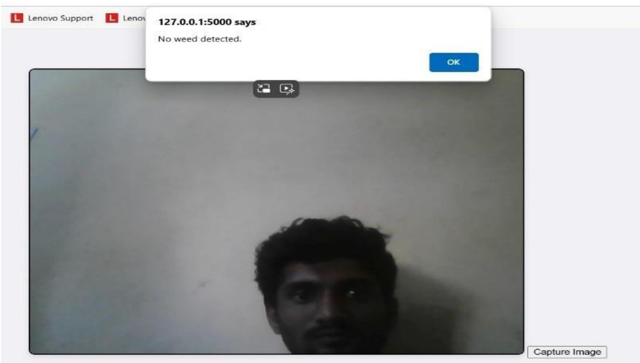

Figure. 4 Bounded box on the weed plant

Figure 4 illustrates the functionality of the camera within the detection module.When the camera is directed towards the weed depicted in Figure 3, it identifies the weed plant as Palmer Amaranth, with a bounding box outlining its exact position. This detection system holds potential for farm application, enabling farmers to identify areas where weeds are present efficiently.

4.1.2 Weed Classification

Users can classify weeds by uploading an image containing the weed of interest. This option utilizes deep learning models such as Deep Fusion mode, Resnet152V2 and InceptionV3 for accurately classifying the type of weed present in the image.

Figure. 5 A weed Image for classification

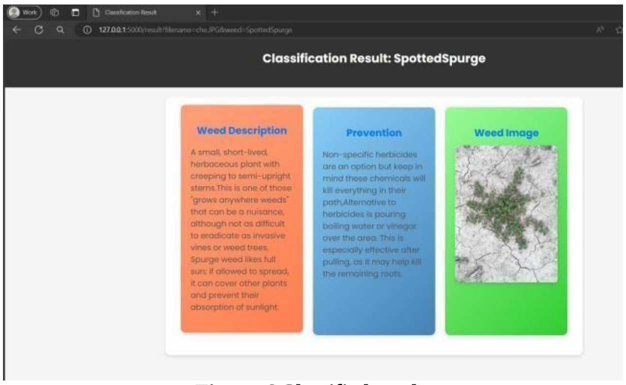

Figure. 6 Classified weed

4.2 Performance Analysis

In our examination of model performance, graphs are presented, illustrating the training accuracy of the InceptionV3, ResNet152V2 and deep fusion models. These visualizations offer insights into the learning

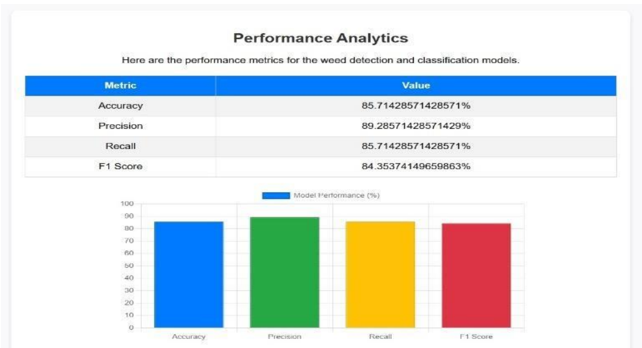

Figure. 7 Training and Validation Accuracy for InceptionV3

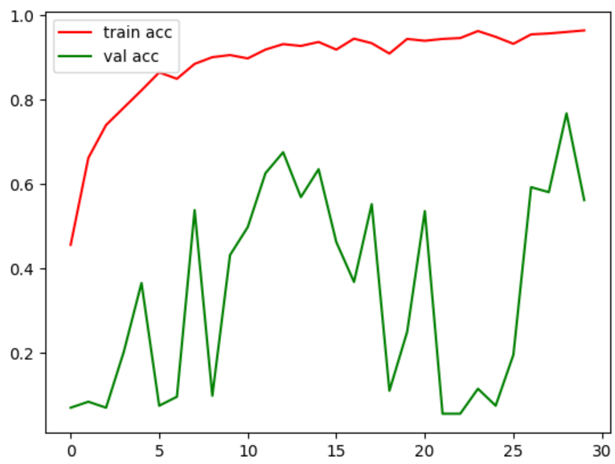

Figure. 8 Training and Validation Accuracy for Deep Fusion Model

TABLE I: MODEL PERFORMANCE

Model	Epochs	Accuracy
ResNet 152 V2	10	0.72
	20	0.75
	30	0.78
	40	0.79
	50	0.80
Inception V3	10	0.86
	20	0.92
	30	0.94
	40	0.95
	50	0.96
Deep Fusion	10	0.90
	20	0.94
	30	0.95
	40	0.95
	50	0.97

dynamics and generalization capabilities of each model during training and validation. Adam is utilized as the optimizer to facilitate efficient gradient-based optimization during training.

This table offers a comparative analysis of accuracy performance across 50 epochs for three models: InceptionV3, ResNet152V2, and a deep fusion model combining both architectures. ResNet152V2 demonstrates consistent improvement in accuracy metrics from epoch 1 to epoch 50, indicating progressive performance enhancement. Similarly, InceptionV3 exhibits a steady increase in accuracy throughout the epochs, with notably higher accuracy compared to ResNet152V2 at the last epoch. The deep fusion model, combining features of both InceptionV3 and ResNet152V2, shows a substantial rise in accuracy as epochs progress, indicating promising performance.

5. Conclusion and future scope

The utilization of deep learning models such as InceptionV3, ResNet152V2 and the Deep Fusion exhibits considerable promise in effectively addressing the issue of weed detection and classification in cotton fields. By training the model on a diverse dataset encompassing various coding styles and project complexities, the project aims to enhance the system's adaptability across different development scenarios. Efforts can be made in Integrating weed detection systems with existing precision agriculture technologies to further enhance their utility and impact. Also, leveraging Internet of Things (IoT) devices and sensor networks can provide valuable environmental data to complement weed detection algorithms.

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