AI-Driven Ensemble Model for Precision Weed Detection and Crop Yield Enhancement

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Abstract: *An AI-powered weed detection system autonomously identifies and classifies weeds in agricultural fields using advanced computer vision and machine learning techniques. The system integrates hardware components such as cameras or drones to capture high-resolution field images or videos. These images are processed by AI algorithms trained on extensive weed image datasets, enabling precise differentiation between crops and weeds. The AI extracts key features like leaf shape, color, texture, and growth patterns to enhance identification accuracy. The system allows farmers to implement timely and targeted weed control measures by providing real-time feedback. This study explores AI applications in weed detection, offering an efficient solution for automating this critical agricultural task. We compared an SVM classifier with a CNN classifier to evaluate performance and found that the CNN alone was insufficient. Therefore, we developed an ensemble model combining a weighted CNN (60%) and a random forest (40%), which outperformed the standalone CNN. The objective is to design a system that selectively sprays pesticides on weeds, reducing pesticide usage and waste. We validated our approach using a dataset of 1,300 labeled images of sesame crops and various weeds, formatted in YOLO and resized to 512×512 pixels. The results demonstrated that the SVM achieved 96.8% accuracy, a custom 5-layer CNN achieved 97.7%, and our ensemble model achieved the highest validation accuracy of 99.725%.*

Keywords: Artificial Intelligence, Weed Detection, Crop Monitoring, Classifiers, Ensemble Learning.

I. Introduction

Weeds are invasive plants that compete with crops for resources such as water nutrients and sunlight leading to reduced crop yield. Manual weed detection and removal are often time-consuming and labor-intensive making it a challenging task for farmers [1]. However, advancements in artificial intelligence (AI) offer a promising solution for automating weed detection in crops. This framework explores the application of AI in weed detection and provides a step-by-step approach for implementing an efficient weed detection system.

1. Data Collection:
The first step in the framework involves collecting a diverse and representative dataset of crop images contaminated with various weed species. This dataset should ideally include images captured under different lighting conditions plant growth stages and weed densities. The dataset should be labeled with ground truth annotations indicating the presence or absence of weeds.

2. Preprocessing and Augmentation:
Preprocessing techniques like image resizing normalization and noise removal are necessary to ensure consistency and effective training of the AI model. Additionally, data augmentation techniques such as rotation flipping and cropping can be applied to increase the diversity and size of the dataset leading to better model generalization.

3. Model Training:

The next stage involves training an AI model to accurately detect weeds in crop images. Convolution Neural Networks (CNNs) have shown remarkable performance in image classification tasks and can be utilized for weed detection as well. Transfer learning where a pre-trained CNN model is fine-tuned with the crop weed dataset can significantly reduce training time and improve detection accuracy.

4. Weed Detection and Localization:

Once the model is trained it can be deployed to detect and localize weeds in new crop images. The AI system analyzes the input image and generates a weed probability map highlighting the areas suspected of weed presence. This information can assist farmers in identifying the specific locations where weeds need to be targeted for removal.

5. Weed Management:

The final stage involves integrating the weed detection system into a larger weed management strategy. Farmers can utilize the information generated by the AI system to implement targeted weed control methods such as precision herbicide application robotic weeding or manual weed removal. By precisely targeting weed-infested areas farmers can reduce chemical inputs save costs and improve crop productivity.

1.1. Background Details:

Weed detection in crop refers to the process of identifying and distinguishing weeds from crops in agricultural fields. Weeds are unwanted plants that compete with crops for resources such as water nutrients and sunlight [2]. Identifying and removing weeds from crop fields is essential for ensuring their healthy growth and maximizing crop yield [3, 4].

There are various methods and technologies available for detecting and managing weeds in crops. Here are a few commonly used approaches (figure 1)

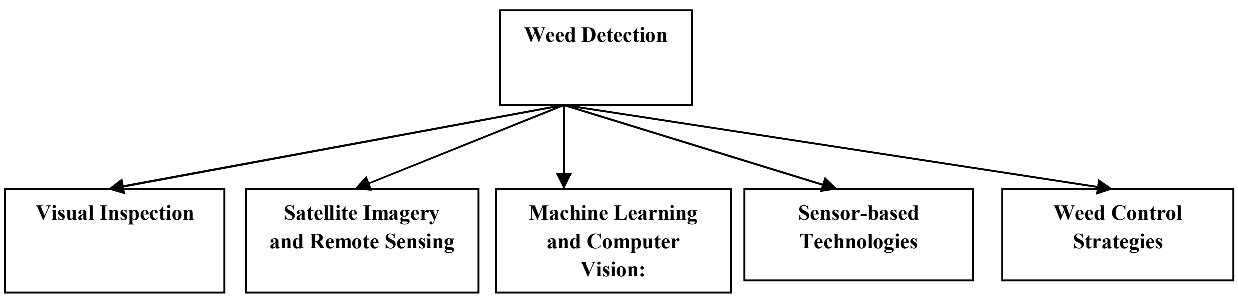

Figure 1. Weed detection methods

1. Visual Inspection: Visual inspection is one of the simplest and most common weed detection methods. Farmers or agricultural workers visually examine the crop fields and manually remove the weeds. However this method can be time-consuming labor-intensive and may not be suitable for large-scale or commercial farming operations.

2. Satellite Imagery and Remote Sensing: Satellite imagery and remote sensing techniques have become increasingly popular for weed detection in crop fields. Advanced sensors mounted on satellites or drones capture high-resolution images of agricultural fields which can be analyzed using image processing algorithms. These algorithms can identify and differentiate weeds from crops based on their shape size color and texture.

3. Machine Learning and Computer Vision: Machine learning and computer vision techniques have been applied to weed detection in crops. Using a large dataset of images of both crops and weeds algorithms can be trained to automatically detect and classify weeds in real-time. These algorithms can be integrated into automated farming systems or robotic devices enabling efficient and accurate weed management.

4. Sensor-based Technologies: Various sensor-based technologies including optical sensors electromagnetic sensors and thermal sensors can be used for weed detection in crops. These sensors analyze specific plant characteristics such as chlorophyll content plant height or thermal signature to distinguish weeds from crops. This information can help farmers make informed decisions regarding weed control measures.

5. Weed Control Strategies: Once weeds are detected various weed control strategies can be implemented. These may include manual removal mechanical weeder's use of herbicides mulching cover cropping crop rotation or

integrated weed management practices. The choice of weed control strategy depends on factors such as weed species weed density crop type and environmental considerations.

Efficient and accurate weed detection in crops is crucial for reducing the negative impacts of weeds on crop yield and overall farm productivity. By using advanced technologies and management strategies farmers can effectively identify and manage weeds ensuring healthier crops and higher agricultural productivity.

1.2. AI in weed detection

- **Support Vector Machine:**

SVM represents a support vector machine, which is notable for its more exact and, surprisingly, quickest results than some other machine learning models with no need for additional training [14]. In any case, it requires more assets for playing out its computational work. We can say it draws a hyperplane that isolates the subspace into two sections, the initial segment comprises vectors that have a place with some gathering, and the subsequent part comprises residual vectors which have a place with no gathering. It is a supervised machine learning algorithm that was first introduced in 1995 that maximizes the margin between different classes while minimizing the empirical classification error. High dimensional data categorization can be accomplished with little difficulty using SVM's kernel, or radial basis function. Most of the data sets are divided into train and test datasets. The effectiveness of SVM's classifiers by the training set is evaluated using this test dataset.

- **Convolution neural network**

Convolution layers are used in a convolution neural network, a type of deep neural network, to separate the input data and features. It is modeled after the idea of biological neurons, where characteristics from the previous layer of convolution are used in high-level feature abstraction [15][23]. Numerous artificial neurons work in various layers to compute the weighted sum of the input and output of an activation value as shown in figure 2.

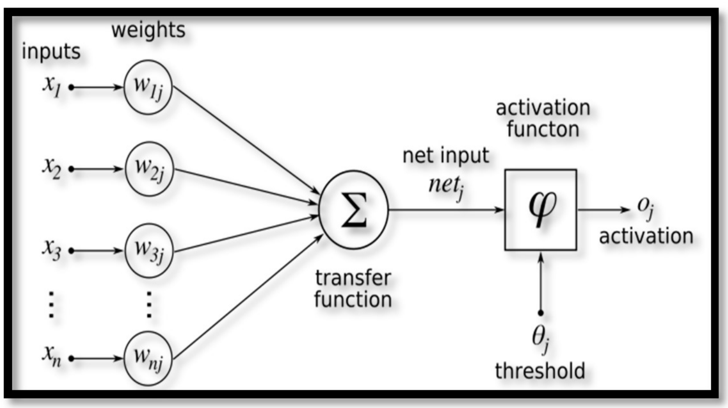

Figure 2. Artificial neuron with activation function

A neuron's behavior is characterized by its weight, which CNN's neurons may apply to pixels to extract the highlights from. Each layer creates an enactment map that includes the picture highlights when CNN receives an information picture. Each neuron now selects the pixels in a picture, copies the weighted shaded value, adds them, and then runs them via the execution capabilities.

- **Random Forest**

Random Forest is a well-known supervised learning technique that can be used for classification and regression problems in machine learning. To improve the performance as well as to address the issue of previous classifiers, RF is built which works on an ensemble model.

1.3. Objective:

Following are the objectives of the proposed work:

- Gathering real-time information on unwanted plants in wheat crops, which are subsequently processed before being used as input information for artificial intelligence models.
- Efficient development of artificial intelligence -based weed identification models so that they can later be employed in real-time detection models.

- Offering a comparison of detection accuracy, which reveals if the particular model is appropriate in terms of both inference time and accuracy.

1.4. Organization of Paper

The paper organization is as follows: In section 2 the literature survey has been described. Section 3 is about the materials and methods. Section 4 is about result analysis, and in section 5 the proposed work is concluded.

II. Literature Survey

A helpful technique for effective farming-related implementations is described in [5]: UAV In agriculture, aerial surveillance of UAV farms enables essential decision-making on the monitoring of crops. The accuracy and dependability of research using aerial photography in deep-learning models have further increased as a result of developments. Additionally, the author evaluated research works that apply deep learning to aerial photos for inadequate farming. Targeted weeding has been shown in [6] to significantly reduce or even completely eliminate the application of fungicides and pesticides in agricultural settings. To achieve high precision, it is vital to choose only the right weeds, identify plants at minimal cost, and work quickly. To categorise weeds and crops in lettuce fields, the present approach combines a size differentiation technique with combined red, green, and near-infrared reflectance.
In this study, the author suggested a pre-trained deep learning model, Mobile NetV2 [7], for a real-time weed detection tool. The 90% test accuracy achieved with weeds and crops as well as distortion, blur, and shadows is a significant step towards precision weed management in the real world.

The author of this research [8] presented a reliable and simple detection method to produce weed maps under dense soybean fields. The findings show that leaf alignments compromise useful characteristics for weed-crop cluster discrimination. A projected 75% reduction in the use of expensive herbicides is made possible by the suggested system design's ability to precisely and effectively identify infested zones with a precision of 93.19%.

A model for identifying the presence of weeds in soybean fields using deep learning has been suggested in this paper [9] [17]. Convolution Neural Networks, which were utilized in this study, are an example of a Deep Learning architecture that has had outstanding success with picture identification [24]. They have used Caffe-Net architecture for the training of datasets, and for result analysis, they have compared four well-known machine learning techniques with the proposed technique. The feature selection is done based on shape, color, and texture. As a result, utilizing Conv-Nets, this work obtained above 98% accuracy in detecting broadleaf and grass weeds when compared to soil and soybean, having an accuracy average across all photos exceeding 99%. A new set of data (i.e. Carrot-Weed) for weed detection was presented by P. Lameski et al. [10] under varied lighting conditions. The collection contains RGB photos of immature carrot seedlings collected in February, the author conducted a preliminary analysis of the dataset and presented preliminary results acquired using CNN designs.

Machine learning algorithms may be able to distinguish between several species of weed based on their form and texture contours [11]. To validate weed identification, authors in Ref. [12] introduced wavelet texture features. Each image went through the designed discriminating process before being fed into the neural network system. Using Principal Component Analysis (PCA), 14 features were chosen out of 52. The image's segmentation was carried out per the labeling method, which used a neural network.

The wavelet texture traits were demonstrated by the author in [12] to be effective at distinguishing weeds from crops, particularly when significant leaf occlusion or overlapping occurs. To compress three-dimensional vectors of an image produced by three different image processing techniques, the author of the paper [13] used the Principal Component Analysis (PCA) method. The three image processing techniques are crop row detection, 3D-Otsu's method, and picture segmentation. Using the suggested method in Ref. [13], it was possible to identify and classify weeds from crop rows in real time.

The author of the paper [14] uses SVM for the classification of weeds and crops based on the parameters derived from images like their shape and texture. For feature weighting, they have used a unique combination of SVM with the RELIEF-F algorithm for lesser grain weed types. This work aims to identify weed species ("Cirsium-arvense *and* Galium-aparine") at an early stage, using this classifier has achieved an accuracy of more than 85%.

III. Materials and Methods

3.1. Site Description and Field Experiment:

The experiment was carried out on the weed and crop dataset collected from Kaggle (was created by Alessandro dos Santos Ferreira), we have taken 589 images to detect weeds in seseam crops through image analysis and artificial intelligence (AI). In the current study, a number of different sesame crop variants are taken, some sample images of which are shown in Figure 3. These data samples are employed to assess how well the model performed after various adjustments. Our objective was to assess the precision and effectiveness at several iterations in order to detect weed among the crops.

3.2. Image Acquisition

An aggregate of 1300 RGB ordinal pictures of weeds and sesame plants were reserved at Kaggel, with a resolution of 4000X3000 colors. We have taken 589 images to detect weeds in sesame crops through image analysis and artificial intelligence (AI). A diagram showing the steps of weed images collection is shown in Figure 4.

3.3. Data Preprocessing

The second step towards data sample processing after image acquisition is data cleaning, which is a crucial step since the detection model will perform worse if any faulty photos are left in the dataset. We now have 546 photos after cleanup. The next step towards processing of data samples is to convert all of our photographs to 512 X 5 12 X3 sizes because the original photo is of 4000X3000 colors in size, which is very enormous and will take a very long time to train. However, training requires more than 546 images, so we have to turn these 546 images into 1300 images. To increase the dataset, we used data augmentation techniques. Labeling picture data manually is an extremely tedious procedure! Drawing bounding boxes on photos—whether they are weeded or cropped—is required in this phase (figure 5).

3.4. Classification of sample data:

For training, we have taken 1000 images to train models and 300 images to test. The object annotation can be seen in Table 1. We have taken 1637 features to train and 435 features to test models. Complete steps for Yolo Label conversion is shown below.

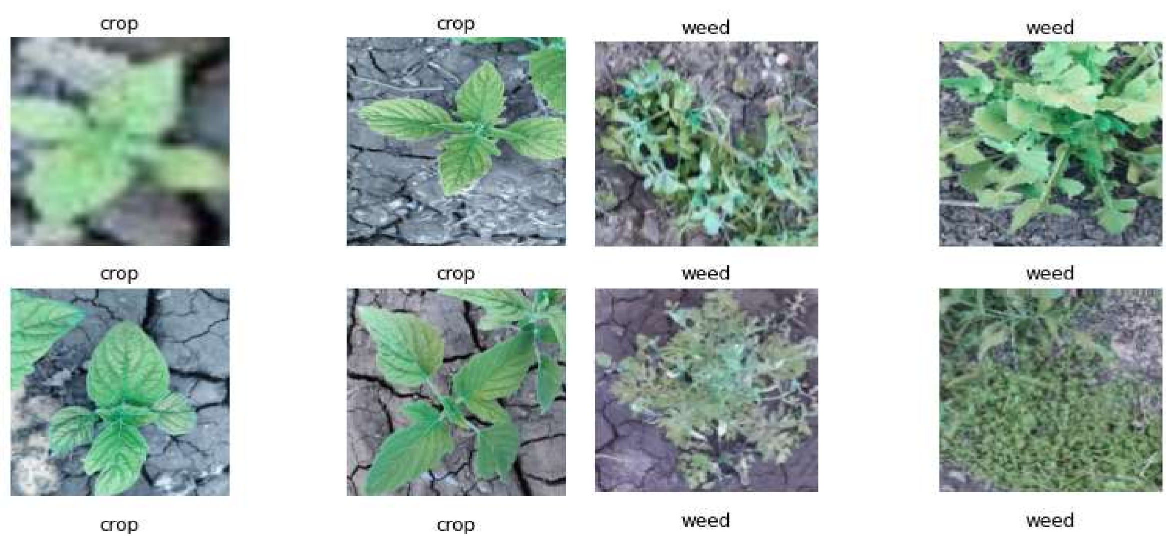

Figure 3. Crop and weed Image

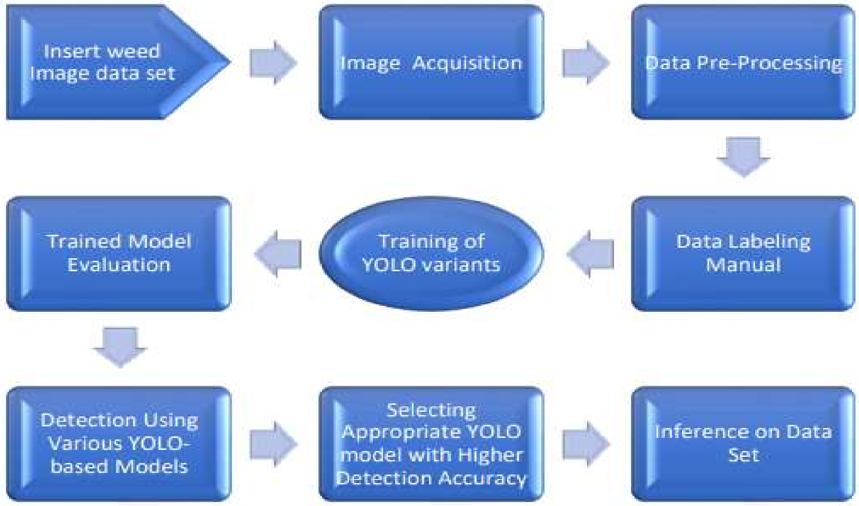

Figure 4. Weed Image Collection

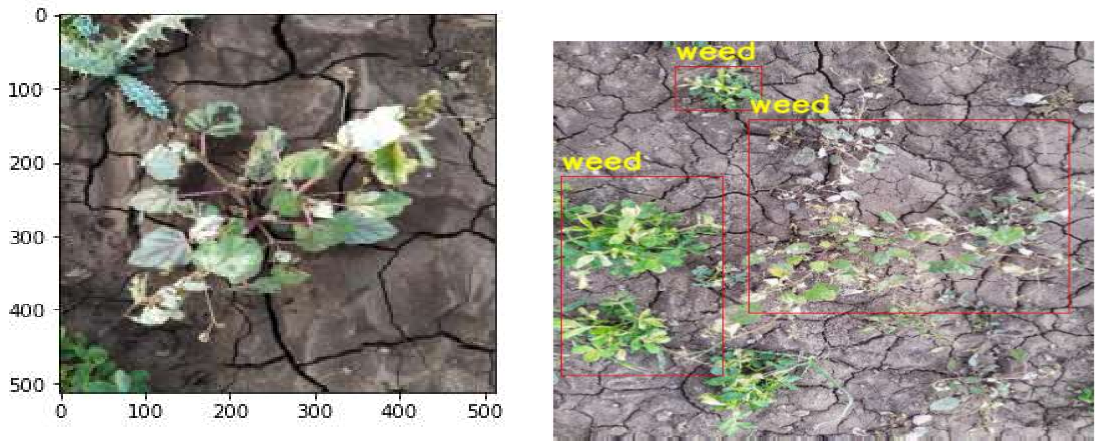

Figure53. Drawing bounding boxes on photos and label visualization

Table1. Converting dataframe to Pascal format

	filename	width	height	class	xmin	ymin	xmax	ymax
0	agri_0_9354.jpeg	512	512	weed	63	120	425	442
1	agri_0_9354.jpeg	512	512	weed	0	1	180	148
2	agri_0_7574.jpeg	512	512	crop	95	167	453	469
3	agri_0_8960.jpeg	512	512	weed	52	76	422	353
4	agri_0_417.jpeg	512	512	weed	7	75	511	411
...	...	...	...	...	...	...	...	...
2067	agri_0_2825.jpeg	512	512	weed	16	144	202	303
2068	agri_0_2825.jpeg	512	512	weed	291	94	471	304
2069	agri_0_9252.jpeg	512	512	weed	247	194	384	331
2070	agri_0_9252.jpeg	512	512	weed	37	104	179	246
2071	agri_0_8141.jpeg	512	512	crop	27	51	460	498

3.5. Efficiency appraisal metrics

To validate outcomes, various efficiency appraisals, including FP, FN, TN, and TP, are used. These evaluation metrics are used as measuring statistics by different academics to get the results [17][18][19][20][21].

3.5.1. Confusion Matrix (CM)

The confusion matrix is used to find the correlation between the actual and expected class. It is also thought to be a helpful statistic for estimating AUC and ROC curves, specificity, precision, recall, and accuracy. Table 2 displays the confusion matrix.

Table 2. Confusion Matrix (CM)

Class	Actual Positive Class	Actual Negative Class
Predicted Positive Class	TP	FP
Predicted Negative Class	FN	TN

3.5.2. Accuracy

The percentage of instances that are correctly classified is calculated by:

$$\text{Accuracy} = \frac{\text{TP+}}{(\text{TP+TN+FP+FN})}$$

3.5.3. Error Rate

The percentage of predicted values that are incorrectly categorized is determined by:

$$\text{Error rate} = 1 - \text{Accuracy}$$

3.5.4. True Positive Rate

Utilizing this metric allows for the accurate measurement of actual positive proportions. The TPR is acquired using:

$$\text{True positive rate} = \frac{\text{TP}}{\text{TP+}}$$

3.5.5. False positive rate

If it is true, the null hypothesis is rejected. The FPR can be found by:

$$\text{False positive rate} = \frac{\text{FP}}{\text{FP+}}$$

3.5.6. True negative rate

The regular instances of the patterns are precisely identified. The TNR was discovered by:

$$\text{True negative rate} = 1 - \text{FPR}$$

3.5.7. False Negative Rate

The patterns are incorrectly categorized as common occurrences. The FNR can be acquired by:

$$\text{False Negative rate} = 1 - \text{TPR}$$

3.5.8. Precision

The patterns are accurately classified by the extent of their action. It is obtained by:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+}}$$

3.5.9. F-Measure

The appraisal of the accuracy is performed by it. It is obtained by:

$$\text{F-measure} = 2 \times \frac{\text{precision x recall}}{\text{precision+recal}}$$

IV. Experiments and Results

The presence of weeds in agriculture is undesirable. Weed consumes resources such as minerals, soil, water, and a lot more that could have been used by crops, which lowers the yield of the necessary crop [16]. Although using pesticides to get rid of weeds is common and effective, some chemicals can stick to crops and cause issues for people [22][25]. Our technology will only spray pesticides on weeds, not crops, which will lessen the issue of pesticides combining with crops and reduce pesticide waste. This dataset includes 1300 classifications for photos of various weed kinds and sesame crops. The size of each image is 512 x 512 in color. YOLO format is used for image labels. The proposed model can be seen from figure 2.

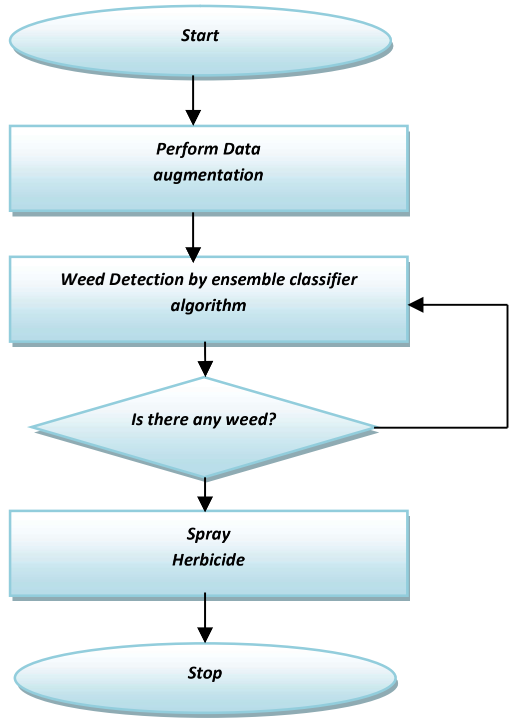

Figure 4. Proposed Model

The evaluation metrics of SVM and CNN with 1300 weed and crop datasets are calculated and analyzed here. Table 6 depicts the performance of the SVM algorithm which attained an accuracy of 96.85%, a precision of .968, a TPR of .96, and obtained F1 score of 0.86 for the given dataset. It is clear from the table that out of 1300 datasets, 1259 instances is there which are precisely classified and approx 41 instances of dataset are wrongly classified. Similarly, Table 7 depicts the performance of the CNN algorithm which attained an accuracy of 97.5%, a precision of .97, a TPR of .97, and obtained F1 score of 0.97 for the given dataset. It is clear from the table that out of 1300 datasets, 1267 instances is there which are precisely classified and approx 33 instances of dataset are wrongly classified.

Table 6. SVM Evaluation metric

Overall Instances		**1300**	
Instances that are classified precisely		1,259 approx (96.85%)	
Instances that are classified wrongly		41 approx (3.15%)	
Accuracy	TPR	Precision	F1 Score
96.85%	0.96	0.968	0.86
SVM CM (Confusion Matrix)			
a		B	
1240		6	
35		19	

Table 7. Evaluation metrics of CNN Model

Overall Instances		**1300**	
Instances that are classified precisely		1,267 approx (97.5%)	
Instances that are classified wrongly		33 approx (2.5%)	
Accuracy	TPR	Precision	F1 Score
97.5%	0.97	0.97	0.97
CNN CM			
a		b	
1260		3	
30		07	

We observed that CNN alone is not a very good approach for this kind of problem. Therefore we have used the ensemble model which will outperform the CNN model. Ensemble models combine the predictions of multiple individual machine learning models to make more accurate and reliable predictions. In the ensemble model with random forest, we used a weighted ensemble model in which the weight of CNN was 60% and the weight of Random Forest was 40%. In our customized ensemble model we have taken 5 layers of CNN where, the number of input Layers = 187, 1st layer = 32, 2nd layer = 64, 3rd layer = 128, a Flatten(), 1st dense layer = 512, 2nd dense layer = 1024 and 2 output layers. Table 8 depicts the performance of our model which attained an accuracy of 99.725%, a precision of .997, a TPR of .996, and obtained F1 score of 0.997 for the same dataset. It is clear from the table that out of 1300 datasets, 1296 instances is there which are precisely classified and only 4 instances of dataset are wrongly classified.

Table 8. Evaluation metrics of our model

Overall Instances		**1300**	
Instances that are classified precisely		1,296 approx (99.725%)	
Instances that are classified wrongly		4 approx (0.275%)	
Accuracy	TPR	Precision	F1 Score
99.725%	0.997	0.996	0.997
Proposed model CM			
A		b	
1290		1	
3		06	

Figure 5 demonstrates that the proposed method provides significantly better accuracy outcomes than the prior best results because the work has employed an ensemble model which is a combination of two well-known machine learning models i.e. CNN + Random forest.

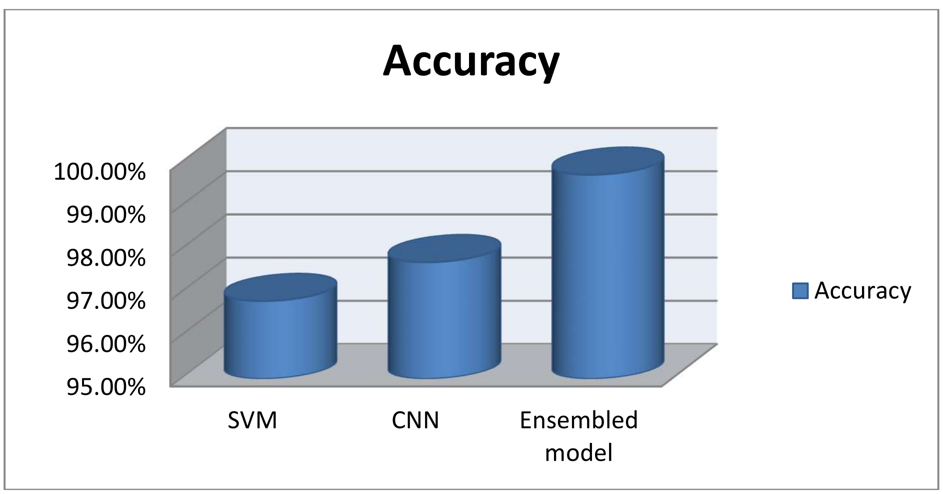

Figure 5. Accuracy comparison of various classifier's

The proposed model's real time accuracy can be seen from figure 6.

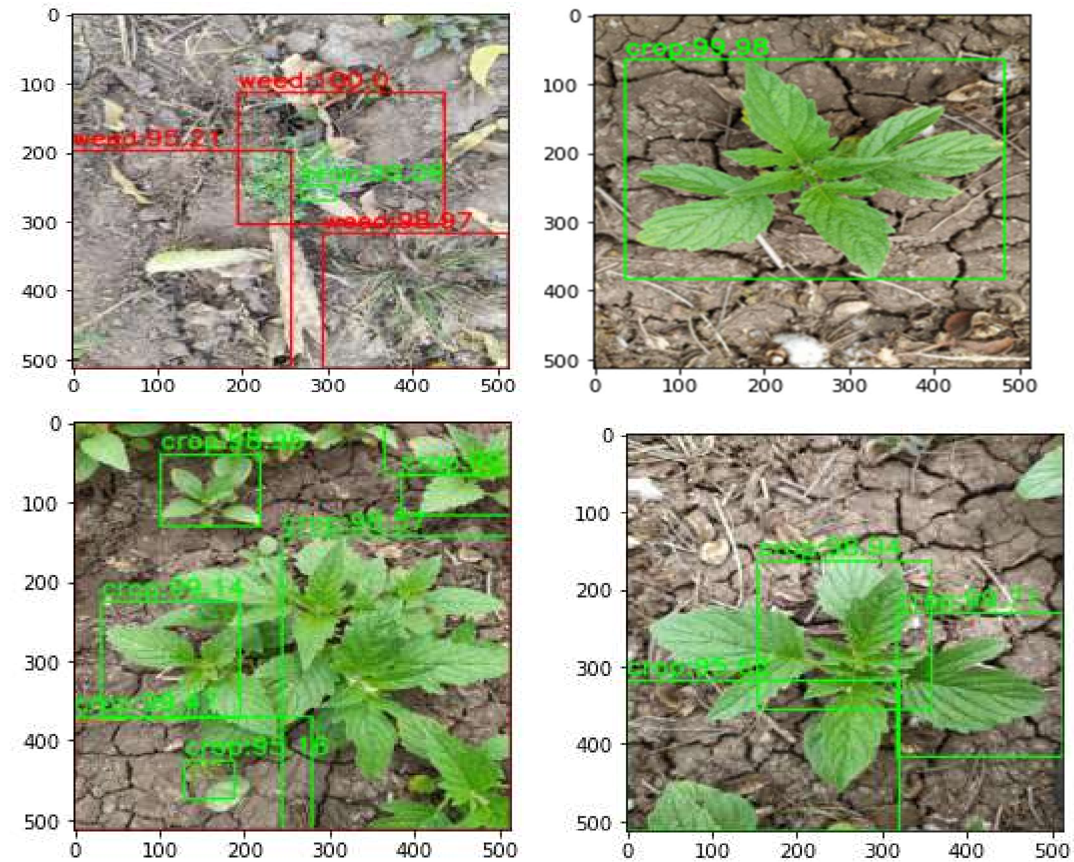

Figure 6. Real time detection of crop and weed

V. Conclusion and Future Scope:

In conclusion an artificial intelligence-based weed detection system offers significant advantages in terms of precision speed and efficiency compared to traditional methods of weed detection and control. By harnessing the power of AI and computer vision farmers can optimize their farming practices reduce reliance on chemicals and ultimately achieve higher crop yields. Moreover the system can provide valuable data and insights about weed infestation patterns helping farmers and agricultural experts improve their strategies for weed control and prevention. By detecting weeds at an early stage farmers can minimize crop yield losses and increase overall productivity. In this study, we compared the outcomes of our ensemble model, the CNN classifier, and the SVM classifier. The results also show that the accuracy achieved using SVM is 96.8%, while the detection accuracy for our ensemble model (CNN + Random Forest) is the highest at 99.725% and the validation accuracy for our customized 5-layer CNN architecture is 97.7%.

While machine learning models hold great promise in weed detection they should be combined with traditional weed management practices for optimal results. Integrated weed management which combines multiple strategies including cultural mechanical and biological controls in addition to data-driven technologies can provide a comprehensive approach to weed control in crops. In addition to this, segmentation of dataset can be done to achieve better results.

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