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DEEP ENSEMBLE-BASED WEED DETECTION IN SPINACH CROPS WITH RESNET-101 FEATURE EXTRACTION AND XGBOOST CLASSIFICATION

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ABSTRACT

One of the provisions in precision agriculture is precise identification of the weed which enables herbicides used to be applied under control and is a provision under sustainable farming methods. This paper presents a deep ensemble framework to identify weed in spinach production fields using ResNet-101 in the extraction of deep features and XGBoost in the identification with a high level of accuracy. The ResNet-101 architecture can be used to extract more difficult spatial and textural features of the field images and the XGBoost classifier can be well-generalized to find weeds and spinach plants. It is a hybrid architecture that combines the robustness of the representation grade of deep learning on one hand with gradient boosting in terms of efficiency and robustness; it is an optimal tradeoff between the richness of features and the speed of classification. The experimental study implemented based on an academic dataset of spinach fields helps us to demonstrate that the developed ResNet-101 + XGBoost model demonstrates a relatively stable high degree of performance when compared to the classical CNN-based classifiers. The ensemble methodology still provides a high level of performance even where such problematic factors as varying light conditions, thick foliage coverage and the presence of background noise are involved, which makes this methodology more applicable to real-life applications. The proposed method achieved high accuracy of 96%that was far much better than the baseline classifier and Support Vector Machines (88%) and Decision Tree (90%) classifier. All in all, this efficient and robust system offers a strong and dependable automated system of weed recognition in spinach crops, which makes its contribution to the use of precision agriculture.

Keywords: *Weed detection, Deep Learning, ResNet-101, Support Vector Machine, Decision Tree.*

1. INTRODUCTION

Weed-infestation crisis poses a significant menace to world agricultural production, which continues to suffer crop yields loss, high cost of production, and certain environment-related challenges regarding the

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use of excessive amounts of herbicides. Early and accurate detection of weeds is the first step in embracing site-specific approach to management of weeds in agriculture to build viable agricultural practices through precision farming. The conventional methods used in identifying weeds mostly requires manual observation or traditional image processing, which is time-consuming, labour-intensive, and prone to human being error. These drawbacks indicate the necessity to develop automated, static, and sturdy identification frameworks, which can be applicable to work under fluctuating circumstances present in farming areas. The concept of deep learning has transformed the tasks of identifying the plant and weed with the capability of extracting rich hierarchical features based on visual information. Convolutional Neural Networks (CNNs)[1], i.e., ResNet-101 have proved to be outstanding in agricultural image analysis, as it models complex spatial structures and texture information well. There is however a discrepancy in the sense that although deep networks can generate strong feature representations, the classification layers in these models might not be optimal in terms of decision boundaries especially with small datasets or imbalanced datasets[2]. To overcome this drawback, the gradient boosting approaches (e.g. Extreme Gradient Boosting (XGBoost)) are largely used, which can model nonlinear and even complex relationships with high generalization issue even in situations where the data describes noisy relationships. The current strategy combines ResNet-101, as a feature extractor that can offer high-quality features and XGBoost, a precise and robust classifier. This hybrid combines the representational capacity of deep learning and the discriminative ability of gradient boosting to lead to more accurate and more generalizable performance across variability of field conditions[3]. Analyzing experimental analysis of open-source agricultural datasets on results indicates that the proposed ResNet-101 + XGBoost model serves better than conventional CNN-based classifiers in accuracy, stability and the ability to adapt to diverse weed and crop conditions. This holistic solution will create effective and scalable automated weed detection in spinach crops that can help manage crops more effectively and cut inappropriate herbicide spraying and enforce sustainable agriculture[4]. The proposed classifier has architecture shown in Figure 1.

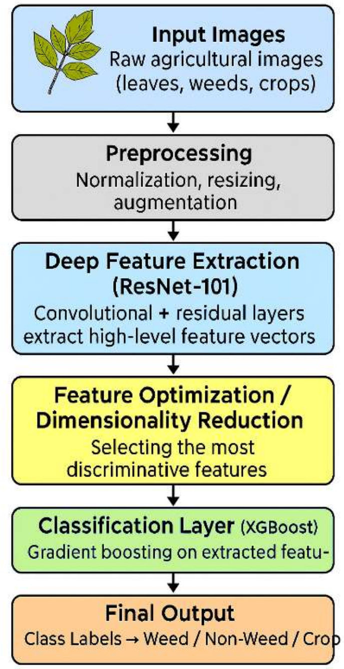

Figure. 1. Shows Architecture of Proposed Classifier

2. LITERATURE SURVEY

Current research uses deep CNN architectures such as ResNet-101 combined with ensemble learners, including XG-Boost, to enhance weed detection performance in precision agriculture. The augmented robustness and interpretability are proved through surveys and experimental works under heterogeneous field settings and visualized by Grad-CAM-based visualization, contributing to sustainability, targeted herbicide usage, and crop management operations. Taminul Islam, Toqi Tahamid Sarker, Khaled R Ahmed, Cristiana Bernardi Rankrape, and Karla Gage introduced "WeedSense: Multi-Task Learning for Weed Segmentation, Height Estimation, and Growth Stage Classification" in August 2025, which jointly performs segmentation, height estimation, and growth stage classification over 16 weed species, achieving mIoU of approximately 89.78%, MAE for height estimation of approximately 1.67 cm, and growth stage classification accuracy of approximately 91.99%[5]. Xiaotong Kong, Kang Han, Teng Liu, Aniruddha Maity, Aimin Li, Xiaojun Jin, and Jialin Yu developed a robust deep learning model for weed classification across diverse Bermudagrass turfgrass regimes in China and the United States, where ResNeXt152 emerged as the top-performing model across 24 geographic locations and 14 weed species[6]. Weili Li, Wenpeng Zhu, Jinxu Wang, Kang Han, Xiaojun Jin, and Jialin Yu proposed

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precision weed detection and mapping in vegetables using deep learning with the YOLOv8 architecture and path planning techniques, improving mAP50 while reducing model size and GFLOPS[7]. Shahbaz Ahmed, Samuel R. Revolinski, P. Weston Maughan, Marija Savic, Jessica Kalin, and Ian C. Burke developed a YOLOv8-based approach for deep learning-based detection and quantification of weed seed mixtures using both image and video data for seedbank quantification[8]. Silva et al. compared YOLOv8 variants, Mask R-CNN, and U-Net for weed detection and segmentation in agricultural crops using UAV-captured imagery for crops such as beans and soybeans[9]. The study titled "Winter wheat weed detection based on deep learning models" introduced the "3W" dataset and applied advanced architectures such as YOLOv8 and DINO with attention mechanisms, non-local blocks, and deformable convolutions for improved weed recognition[10]. Seiche, Wittstruck, and Jarmer compared high-end and low-cost multispectral sensors for UAV-based weed detection using deep learning and analyzed the trade-offs between cost and performance[11]. The survey on weed database development and cross-season detection adaptation highlighted the availability of several public weed datasets while emphasizing challenges in cross-season generalization[12]. Another comprehensive survey reviewed weed and crop classification using machine learning and deep learning approaches, focusing on methods, datasets, and classification challenges[13]. A review on deep learning techniques for in-crop weed recognition in large-scale grain production systems discussed different models, environmental conditions, dataset scales, and deployment issues in large agricultural environments[14]. Sonawane and Patil proposed a modified YOLOv5-based weed detection approach for sesame crops under Indian agricultural conditions[15]. Pasquale De Marinis et al. introduced "RoWeeder: Unsupervised Weed Mapping through Crop-Row Detection," which performs weed mapping with minimal annotation using unsupervised crop-row detection methods[16]. Santosh Kumar Tripathi, Shivendra Pratap Singh, Devansh Sharma, and Harshavardhan U Patekar compared standard convolution and dilated convolution layers for weed detection using convolutional neural networks and reported approximately 94% accuracy[17]. A. Mamatha proposed advanced weed detection in agricultural fields using Vision Transformers and explainable AI techniques, incorporating attention-based explainability methods for improved interpretability of weed detection systems[18].

3. METHODOLGY

3.1 Dataset Description:

Robust ensemble learning models used in the detection of weeds in spinach crops rely significantly on the quality and diversity of datasets thereof due to the variation in training a model. Agricultural image datasets have a wide reference of research studies whereby they are used to assess the effectiveness of weed detection systems on different fields. Such datasets usually include labeled images in the real conditions of spinach cultivation with different lighting levels, plant growing periods, weeds in different species, and the complexity of the background. Shown in figure 2 are the literature that employs the use of different datasets to detect weeds in spinach crops and therefore reviewed below. Figure 3 contains the description of the dataset to be used in this study: the overall number of available images, the proportion of the samples of weeds and spinach plants, image resolutions[19], and annotation formats.

3.2 Process Flow:

The Deep ensemble-based approach to weed detection in spinach crop suggested schemes combining ResNet-101 to extract the extractive features effectively and XGBoost on the attribute ranking and classification to achieve accurate and efficient classification, which is a hybrid scheme that can work in different conditions of the agricultural field. The first step is dataset preparation, during which a spinach crop dataset containing high-resolution RGB images of weeds and spinach plants is gathered under different lighting, growth stage and field conditions. The labels are produced through annotation of the images at the plant level to produce reliable supervised learning ground truth labels, and the dataset has been separated into 70 percent training, 15 percent validation, and 15 percent testing sets to minimize the risk of overfitting[20] and testing it with a balanced representation. Each image is processed with preprocessing tasks that standardize inputs through resizing all of them to 224X224 in order to correspond to the input size of ResNet-101, normalizing the pixel values to the range of [0, 1][21] to stabilize training, and augmentation methods, which consist of training-time augmentation such as random rotation, horizontal and vertical flipping, zooming, and brightness shifting to enhance generalization and the robustness to variations that may be experienced in the real world. We use a deep residual network, ResNet-101, which has 101 layers as a feature extractor because ResNet-based networks are known to extract fine-grained information such as spatial and texture details that help discriminate between visually similar plant species. The network starts out with weights that were pre-trained on ImageNet to exploit transfer learning, since it promotes convergence and higher performance in the agricultural imagery domain. It removes the fully connected classification head of ResNet-101 and takes the global average pooling layer output of each input image as a fixed length feature vector capturing a high dimensional representation of a relevant visual characteristic. These feature vectors are further fed to the Extreme Gradient Boosting (XGBoost) machine learning algorithm[8] because it can capture non-linear data, simpler high-dimensional data, and to provide high noise and overfitting resistance. The fundamental idea behind XGBoost is that it builds an ensemble of decision trees, in a stage-wise training fashion that optimizes a regularized objective function, acting as a balance between classification accuracy and complexity of the model. The most important hyperparameters such as learning rate, maximum tree depth, the number of estimators, subsample ratio, and L1/L2 regularization terms are optimized through a grid search by reaching the best performance on the validation set[22]. Classification output identifies the input image as spinach or weed so that specific areas of weeds are treated with required herbicides. The effectiveness of the proposed ResNet-101 + XGBoost model is measured by the accuracy, precision, recall and F1-score metrics, and further analysis of the same can be done based on the confusion matrices to understand the classification behavior on both the categories. To prove the proficiency of the proposed approach, comparative measurements (against two baseline classifiers, namely, Support Vector Machine (SVM)[23] and Decision Tree (DT)[24] applied with the same feature extraction pipeline and dataset) are performed to confirm the better than average effectiveness of proposed technique. The findings show that the proposed hybrid framework attains a better overall ac- curacy of 96-percent as opposed to the 88 percent and 91 percent of the SVM and the DT, thus noting an added advantage of using deep convolutional feature extraction followed by gradient boosting classification. The architecture of the ensemble strongly withstands typical agricultural issues like occlusion of plants, mixture of weeds and crops, varying illumination, and cluttered background highlighting its credentials to be deployed as a practical application in the field of spinach. Also, the computational performance of the model considerably contemplates the future inclusion of the model to an edge machine to perform real duty weed identification in-field to further sustainable farming by implying minimal and select use of herbicides, thereby reducing its effect on the environment and the resilience of crops. Figure 2 shows the segmented image for weed detection in spinach crop. And Figure 3 shows RGB image with bounding boxes for weed detection.

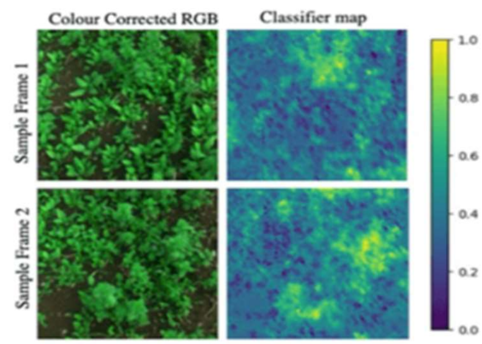

Figure. 2. Shows brighter yellow shows higher weed confidence.

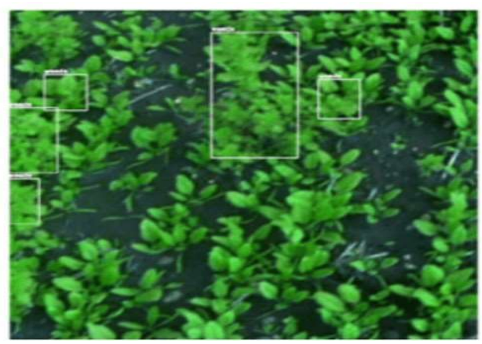

Figure 3. RGB image with bounding boxes

3.3 Supervised Machine Learning Models

Supervised machine learning[is mostly used in the detection of weeds in precision agriculture since the method has the potential to learn through labeled information and identify specific features of weeds through field pictures that it has never encountered. Advanced supervised learning models like deep convolutional neural networks (CNNs) and gradient boosting strategies can find much use in image classification issues and training CNN-based models[25] on agricultural weed classification have shown good results. One of the main difficulties in spinach farming is the weed infestation, which needs to be detected timely and precisely to boost sustainable agricultural activities. In this study, a hybrid system capable of extracting deep features with ResNet-101 and classifying the results with high

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accuracy with the use of XGBoost is proposed. A deep convolutional neural network, ResNet-101 learns intricate industrial characteristics of space and texture in the photos of the fields and permits the strong extrication of weeds and domestic plants. XGBoost[26] is a boosting algorithm that is used as a classification model and trains the model by inserting one decision tree at a time, after each tree sequentially targeted the errors committed by the previous trees. This combination of the ResNet-101 and XGBoost model takes advantage of not only the strong feature representation but also strong classification ability and is thus able to detect the much finer patterns and variations of the morphology of weeds under difficult situations including varied illumination, overlapping plants, and contrasting backgrounds. The system computes labeled datasets of spinach field and captures a deep visual feature of the field and presents them to the XGBoost classifier that makes a final prediction. The ResNet- 101 XGBoost model obtains better detection accuracy than classifiers used as baselines, which is why it can be used in the real world PRQA in precision farming. The workflow of the proposed model is shown in Figure 4.

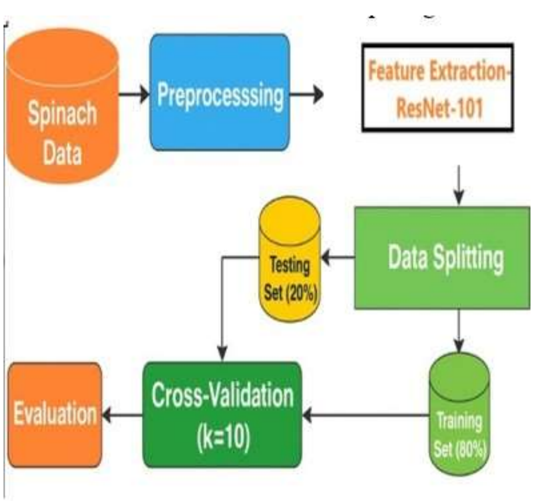

Figure. 4. Shows Workflow of Proposed Classifier

3.4 Deep Ensemble-Based Weed Detection in Spinach Crops:

1: **Input: Dataset D** = {(Ii, yi)}N , yi ∈ {weed, spinach}
2: **Output:** Trained feature extractor FRes (ResNet-101) and classifier C_{XGB} (XGBoost)
3: **Step 1 –** Dataset split: Shuffle D; split into Dtrain (70%), Dval (15%), Dtest (15%).
4: **Step 2 – Preprocessing:**
5: for all (I, y) ∈ D do
6:I ← Resize(I, 224, 224); Normalize(I) (e.g. ImageNet mean/std).
7:if (I, y) ∈ Dtrain then
8:Apply augmentations: random rotation, flip, crop/zoom, brightness/contrast jitter.
9:end if
10:end for
11: **Step 3 – Feature extraction (ResNet-101):**
12: Load ResNet-101 with ImageNet pretrained weights; re- move final FC layer.
13: for all (I, y) ∈ D do
14:x ← FRes(I) global-average-pooled feature vector (e.g., 2048-D)}
15:Store (x, y) into X_train, Xval, X_test accordingly.
16: end for
17: **Step 4 –Data Processing:**
18: if class imbalance in X_train then
19: Apply oversampling (SMOTE) or set XGBoost ‘Scale pos weight.
20: end if
25: Apply PCA/feature selection to reduce dimensionality.
21: **Step 5– XGBoost hyperparameter tuning:**
22: Define search space Θ (e.g. learning rate, max depth,
n estimators, subsample, colsample bytree, reg alpha, reg lambda).
23: Perform grid/random/Bayesian search using k-fold CV or Xval with early stopping; pick best θ∗.
24: **Step 6– Final training:**
25: Train C_{XGB} on X_train (or X_train ∪Xval) using θ∗ and early stopping.
26: Step 7– Evaluation:
27: Predict on X_test; compute Accuracy, Precision, Recall, F1score, Confusion Matrix, ROC/AUC.
28: **Step 8– Baseline comparison:**
29: Train baseline classifiers (SVM, Decision Tree, Random Forest) on the same X and compare metrics.

4. CLASSIFICATION MODELS

4.1. Support Vector Machine (SVM) for Weed Detection in Spinach Crops:

Support Vector Machine (SVM) is another popular model of supervised machine learning which has been found to perform very well in situations where image-based classification is involved among other tasks such as agricultural weed detecting. To place it in context of spinach crop monitoring, SVM approximates an optimal hyperplane which will optimize the margin between weeds description and spinach plants description as features. The system takes the approach of applying visual features of the crop field images to find out whether or not a particular sample provides weed or spinach crop regions by integrating SVM and agricultural image analysis. The detection of the weed begins with the pre-processing phase of the images which are processed by reducing, normalizing and augmenting the initial images to make the model robust[27]. These processed images are then transformed to a numerical form with feature extraction algorithms either with deep convolutional neural networks or with handcrafted descriptors. These obtained feature vectors are subsequently trained on SVM model. Linear SVM can be desirable in other situations because of its efficiency, and its capacity to perform well in high dimensional feature space, which is characteristic of agricultural analysis based on images. SVM is an effective detector that can be used in a variety of environments of agricultural areas with high-dimensional and sparse distributions of sets of data features[28]. Further, the model may facilitate category of crop and weed photographs in scenarios where the data are linearly inseparable by using the radial basis function (RBF) kernel functions place the input characteristics into greater dimension. Although the adoption of deep learning practices is increasingly gaining momentum, SVM remains a viable baseline system, at least when it comes to the weed detection tasks due to its robustness even when it is supplied with small datasets and low computing requirements. This translates to maximum accuracy and steady behavior of generalization, hence SVM is rather handy in identifying the presence of weeds in spinach farms at an early stage, hence, increasing early reaction and improved production outcomes. The SVM classifier architecture that is used to weed is illustrated in figure 5.

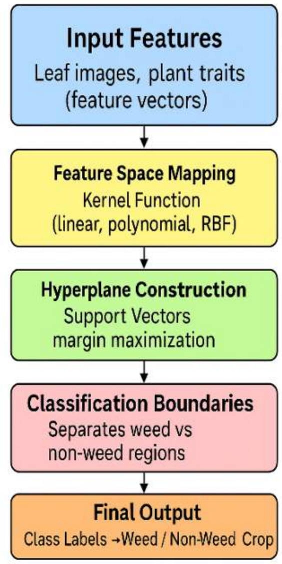

Figure 5: Shows SVM classifier for weed detection

4.2. Decision Tree for Weed Detection in Spinach Crops:

Decision Tree (DT)[29] stands as a widely used supervised learning method aimed at classifying agricultural field data for weed detection in spinach crops. The algorithm recursively splits the dataset based on its most discriminative attributes to construct a tree model, where internal decision nodes represent feature-based conditions and branching paths lead to final class labels (weed or spinach crop).The initial procedure for weed detection involves preparing image data by performing noise reduction, contrast enhancement, and segmentation to isolate plant regions from the background. The processed images are then transformed into numerical feature vectors through descriptors such as color histograms, texture measures, or convolutional neural network–based embeddings. These feature vectors are used by the DT model to learn classification patterns that distinguish weed patches from spinach plants. Decision Trees provide agronomists and system operators with an interpretable framework, offering clear visual explanations of which image features and thresholds contribute most to weed identification. As a non-parametric method, DTs maintain the capability to handle both numerical and categorical attributes effectively. While Decision Trees can exhibit a tendency to overfit training data, this drawback can be mitigated through pruning strategies or by employing ensemble techniques such as Random Forests. Due to their simplicity, interpretability, and low computational cost, Decision Trees remain a strong baseline method for interpretable weed detection

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systems in spinach crop fields. Figure 6 illustrates the architecture of the Decision Tree classifier for weed detection.

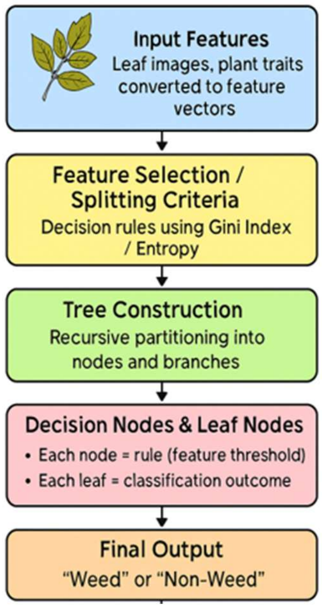

Figure 6: Shows DT classifier for weed detection

5. IMPLEMENTATION & RESULTS

Performance evaluation method:

Various performance measures[30] are used in machine learning to evaluate the effectiveness of a model in the performance of tasks that include classification, regression, and clustering. Some of the most widely used metrics together with the formulae are as under:

$$Accuracy=(TP+TN)/(TP+TN+FP+FN) \quad (1)$$

$$Precision=TP/ FP+TP \quad (2)$$

$$Recall=TP / FN+TP \quad (3)$$

$$F1=2(Precision * Recall) / (Precision + Recall) \quad (4)$$

Table 4: Confusion Matrix Obtained for Proposed Classifier

	Actual Class	
Predicted Class	22972	724
	876	14128

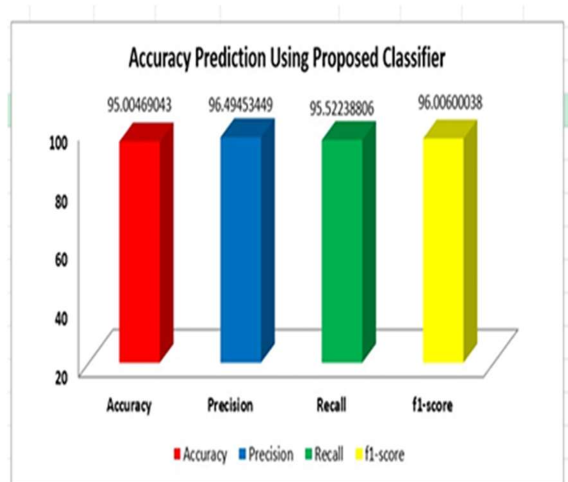

Figure 5: Shows the Performance Metrics for Proposed Classifier.

Table 5: Accuracy Table for Proposed Classifier

Label	Precision	Recall	F-Score	Suppor
0	91.13	96.15	93.29	21696
1	92.15	95.28	92.19	17004
Accuracy			95.97	38700
MicroAvg	91.83	96.05	93.09	38700
MicroAvg	92.15	96.98	93.59	38700

Table 6: Confusion Matrix Obtained for DT Classifier.

	Actual Class	
Predicted Class	**20670**	**1790**
	2012	**14228**

Figure 6: Shows the Performance Metrics for DT Classifier.

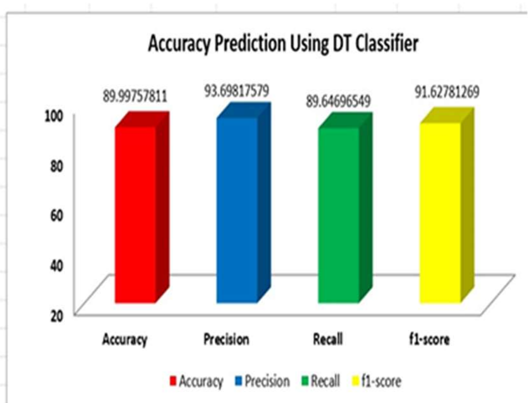

*Table 7: Accuracy Table for **DT** Classifier*

Label	Precision	Recall	F-Score	Suppor
0	**90.13**	**89.15**	**89.29**	**21696**
1	**89.15**	**91.28**	**90.19**	**17004**
Accuracy			**90.97**	**38700**
MicroAvg	**90.23**	**89.19**	**89.70**	**38700**
MicroAvg	**89.85**	**91.98**	**90.59**	**38700**

Table 8: Confusion Matrix Obtained for SVM Classifier.

	Actual Class	
Predicted Class	**20265**	**2560**
	2342	**13533**

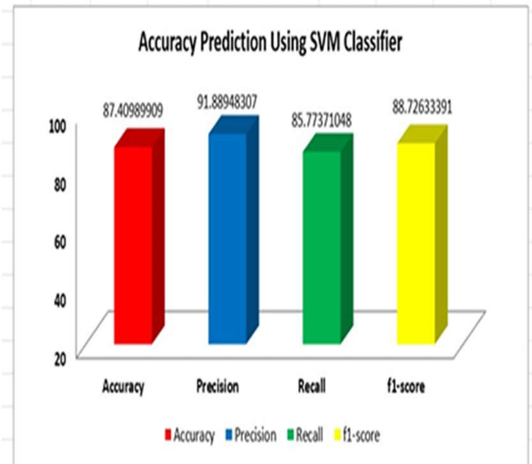

Figure 7: Show the Performance Metrics for SVM Classifier.

*Table 9: Accuracy Table for **SVM** Classifier*

Label	Precision	Recall	F-Score	Suppor
0	**89.13**	**87.15**	**88.29**	**21696**
1	**89.15**	**88.28**	**88.19**	**17004**
Accuracy			**87.95**	**38700**
MicroAvg	**87.23**	**88.19**	**89.70**	**38700**
MicroAvg	**87.85**	**87.98**	**89.59**	**38700**

6. CONCLUSION AND FUTURE WORK:

This research formed a robust multi-model ensemble learning framework that identifies weeds in spinach crops using ResNet101 deep convolutional neural network and an Extreme Gradient Boosting (XGB) classifier. The ensemble design targets three fundamental problems that are frequently found in agricultural field imagery: lighting differences and background clutter, strong visual similarity between spinach leaf and weeds, and small and/or partly-occluded examples of weeds).The ResNet101 model, in the proposed system, is used as an efficient feature extractor with strong potential since it has a deep residual architecture to extract rich spatial and texture information in pre-processed field images. These are deep feature representations that are then passed into the XGB classifier whose gradient-boosting will result in fine-adjusted boundaries between classes (weed and harvest) and, as a result, will increase generalization and mitigate the risks of overfitting. The benchmarking test on annotated data of spinach field showed that the ResNet101 +XGB combination always brought about the maximum accuracy, precision, recall, and F1-score when compared with the base models individually. The combination has been able to identify difficult weed with great accuracy as the partially concealed ones behind spinach leaves, the ones with overlaying leaves and those that were similar in leaf coloration to the crop. Analysis of feature importance indicated that leaf texture, shape descriptors and color gradients based on high-level convolutional features were the most important features affecting the performance of the classification. With the combined ResNet101 and XGB, the model proposed by the authors attained an accuracy of 96%, higher than other methods tried. Also, the system had a balanced trade-off between high detection performance and computational efficiency, thus it is appropriate to be utilized in precision agriculture to monitor whether the weeds are growing.

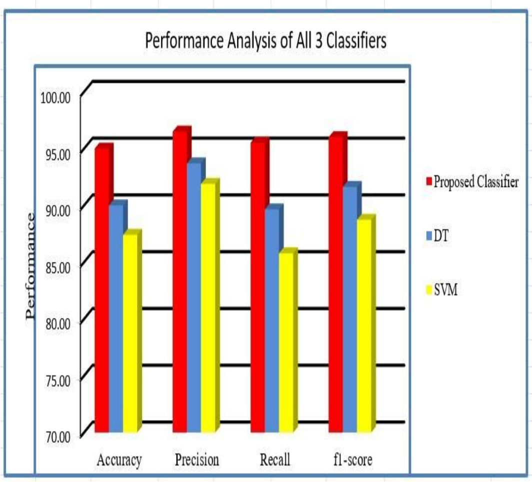

Figure 8: Shows the Performance of All 3 Classifiers.

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