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Advanced classification techniques for weed and crop species recognition using machine learning algorithms

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ABSTRACT

This study proposes an intelligent machine learning framework integrating image analysis and environmental data for precision weed management. The framework leverages efficient feature extraction techniques combined with supervised machine learning algorithms to accurately classify multiple species. Features such as color, texture, and shape characteristics are utilized for model training, enabling high-precision classification while maintaining low computational complexity. The experimental results demonstrate the robustness of the approach, achieving an average classification accuracy of 94.3% across ten weed and crop species in diverse agricultural environments. The system also achieved a 90% reduction in herbicide application compared to traditional methods, showcasing its potential for sustainable farming. Real-time testing confirmed the framework's efficiency, processing images in under 1.5 seconds per frame, making it suitable for deployment in drones and autonomous farming equipment. These results underscore the practical and scalable nature of the proposed system in automating weed management and advancing sustainable agricultural practices.

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1. INTRODUCTION

Agriculture plays a critical role in sustaining the world's population, providing food security, and supporting the livelihoods of millions. However, one of the primary challenges faced by farmers today is the accurate identification and classification of weeds and crops in agricultural fields. Weeds, which compete with crops for essential nutrients, water, and sunlight, can significantly reduce crop yields and quality if not managed properly. Effective weed control is a key component of precision agriculture, which seeks to optimize field-level management using advanced technologies to increase crop productivity and reduce environmental impact [1]–[5]. Unfortunately, traditional weed management techniques, such as manual inspection and broad-spectrum herbicide application, are often labor-intensive, time-consuming, and environmentally harmful. To address these challenges, automated weed and crop classification systems powered by machine learning technologies have emerged as a promising solution in modern precision agriculture. The accurate classification of weed and crop species in agricultural fields is crucial for effective weed management, which in turn can lead to improved crop yields, lower production costs, and reduced environmental degradation. However, weed and crop species classification in large-scale agricultural fields remains a difficult and complex task for several reasons. First, agricultural fields are often large, heterogeneous environments where weeds and crops coexist in varying densities and distributions. Therefore, there is a pressing need for an automated solution that can accurately classify weeds and crops in real-time and at scale. In recent years, precision agriculture has emerged as an innovative approach to managing agricultural fields with high levels of precision and accuracy. The central idea behind precision agriculture is to use data-driven technologies to optimize crop production, reduce resource use, and minimize environmental impact [6]–[9]. Automated weed and crop species classification plays a pivotal role in the implementation of precision agriculture, enabling farmers to make informed decisions about weed management and crop treatment. Figure 1 illustrates a vibrant agricultural field where both crops and weeds coexist, highlighting the significant challenge farmers face in identifying and classifying these plants for effective weed management. The presence of a robotic system actively engaged in weed detection emphasizes the role of automation in precision agriculture [10]–[18].

Automated classification systems, powered by advanced machine learning algorithms, offer several advantages over traditional methods. First, these systems can operate continuously and in real-time, providing farmers with immediate feedback on the distribution of weeds and crops across their fields. This allows for the precise application of herbicides, fertilizers, and other treatments, reducing both waste and environmental damage. For example, instead of applying herbicides to an entire field, farmers can target only the areas where weeds are present, minimizing the use of chemicals and preserving the surrounding ecosystem [18]–[24].

The primary objective of this study is to develop an automated system for the classification of weed and crop species in agricultural fields using advanced machine learning techniques. The system aims to address the challenges outlined in the literature by providing a scalable, real-time solution for precision agriculture. The paper is structured into five sections. Section 1 introduces the topic and highlights the common drawbacks of applying machine learning to precision agriculture, such as reliance on high-quality datasets and environmental variability. Section 2 discusses the literature, summarizing existing research on machine learning techniques like convolutional neural networks (CNNs) and attention mechanisms for weed and crop classification, along with their challenges. Section 3 details the proposed work, focusing on developing a robust framework to address these challenges and improve accuracy and efficiency. Section 4 presents the results, comparing the performance of the proposed method with existing approaches. Finally, section 5 concludes the discussion, emphasizing the need for sustainable and scalable solutions in precision agriculture.

Figure 1. An agricultural field showcasing a mixture of crops and weeds, with automated technology in action

2. LITERATURE REVIEW

The field of precision agriculture has significantly advanced with the adoption of machine learning techniques for automating weed and crop classification. Numerous studies have explored various methods to improve the accuracy and efficiency of this process, particularly in large-scale farming operations. Hu *et al.* [4] reviewed different machine learning approaches for weed recognition, highlighting the challenges posed by in-crop weed classification in large-scale grain production systems. Their study underlined the importance of accurate weed detection for reducing herbicide use and improving crop yields. Deep learning methods such as CNNs were found to be highly effective, although issues like variability in lighting and field conditions remain challenging. Several studies have also focused on evaluating specific machine learning architectures for crop and weed classification. Zhuang *et al.* [18] tested different deep neural networks (DNN) for detecting broadleaf weed seedlings in wheat. They concluded that while deep learning approaches hold great promise, their success heavily depends on the quality of the dataset and the specific network architecture employed. Wang *et al*. [17] expanded on this by using an encoder-decoder network for semantic segmentation of crops and weeds. They demonstrated that enhanced image processing techniques could improve classification accuracy, even under uncontrolled outdoor lighting conditions, which is a common challenge in agricultural fields. Similarly, Tian *et al*. [16] introduced the fully convolutional one-stage (FCOS) object detection method, which can serve as a foundation for crop and weed detection tasks, further enhancing the adaptability of machine learning for agricultural uses. Wang *et al*. [17] also explored the impact of image enhancement techniques on crop and weed segmentation. By using an encoder-decoder network under various outdoor conditions, they successfully improved the model's ability to differentiate between crops and weeds. Li *et al*. [14] developed a technique for detecting rice seedlings based on the morphological characteristics of rice stems. Their study, which utilized biosystem engineering, shows how traditional morphological features can be integrated with modern machine learning methods to improve seedling detection in paddy fields. Weed infestation remains a significant issue in agricultural plantations, as noted by Kubiak *et al*. [13]. Their research emphasized the role of precision agriculture in mitigating the negative impact of weeds on crop yields while aligning with the European biodiversity strategy. They discussed how advanced machine learning techniques, when combined with biodiversity objectives, could lead to more sustainable farming practices. This aligns with Khan *et al*.'s [11] semi-supervised framework for unmanned aerial vehicles (UAV)-based crop and weed classification, which further advances the notion that UAV technology and machine learning can provide highly scalable solutions for weed detection in large agricultural fields. Several studies have also examined the role of feature extraction in improving classification performance. For instance, Kitzler *et al*. [12] showed how decision tree classifiers could be used to enhance plant segmentation quality, particularly when selecting key modeling parameters. Cai *et al*. [2] proposed an attention-aided semantic segmentation network for weed identification in pineapple fields. Their network incorporates attention mechanisms, which focus the model's efforts on the most relevant parts of the input data, improving segmentation performance. This is particularly useful in weed detection, where distinguishing between crops and weeds in close proximity can be challenging. Attention mechanisms allow for a more focused analysis of the critical areas in the images, which enhances classification accuracy.

The application of machine learning in precision agriculture also extends to chemical management practices. Machine learning applications in precision agriculture face several common challenges. The reliance on high-quality, annotated datasets is resource-intensive and limits scalability. Variability in environmental conditions, such as lighting and weather, often impacts model accuracy and generalizability. The computational complexity of advanced models can hinder deployment in low-resource or real-time settings. Additionally, overfitting to specific datasets may reduce performance in diverse agricultural environments. Integrating machine learning techniques with traditional farming practices and ensuring ease of use for farmers requires further refinement. Lastly, achieving sustainable outcomes while reducing reliance on chemical inputs remains a significant challenge for large-scale implementation.

3. PROPOSED WORK

In modern agriculture, the identification and classification of weeds are critical for maximizing crop yields and reducing resource waste. Weeds compete with crops for vital nutrients, water, and sunlight, causing significant economic losses. Traditional weed management practices often rely on manual labor, which is costly and time-consuming, or on herbicides, which have environmental and health impacts. With advancements in technology, machine learning models have been applied to automate weed detection. These models primarily rely on image-based recognition, which has proven effective but has limitations under real-world conditions such as varying light intensity, shadows, and changes in the environment (e.g., humidity and temperature). These environmental factors can affect image quality and lead to decreased classification accuracy.

The algorithm utilizes a diverse combination of datasets to enhance its weed detection capabilities. The first dataset, sourced from the Kaggle plant seedlings classification [25], contains 9,000 images representing 12 different plant species, including both crops and weeds. Each image varies in size but is primarily around 256×256 pixels in JPEG format. The second dataset is a custom-curated Weeds dataset, containing 5,000 images of 10 different weed types, primarily in PNG format and with sizes around 300×300 pixels. The dataset comprises a total of 11,500 images across various classes, ensuring a comprehensive resource for training and validating the proposed algorithm. The detailed information about the datasets is summarized in Table 1.

The architecture of the proposed work employs CNNs to process the visual data from images captured in the field. The CNN extracts critical features from the images, such as the shapes and colors of the weeds and crops. Concurrently, the data is processed through fully connected neural networks, allowing the model to assess how varying conditions influence plant growth and weed emergence. This dual-processing approach creates a synergistic effect, where the classification model benefits from both visual and contextual insights, thus improving its predictive capabilities. The algorithm can identify subtle differences between similar species, reducing the likelihood of misclassification that is often seen in traditional models. Figure 2 shows the sample images from public datasets.

Moreover, the study is specifically designed for real-time applications, facilitating deployment on UAVs or edge devices in the field. This ensures efficient weed detection with minimal human intervention, allowing for quicker responses to weed infestations and more informed decision-making in crop management. By automating the identification process, farmers can allocate resources more effectively, reducing the need for herbicide applications and labor-intensive manual inspections. Figure 3 shows the architecture of the proposed algorithm.

Table 1. Overview of weed and crop types in the EnviroWeedNet dataset

Weed/Crop Type	Class Name	Number of Images	Dataset Source
Black-grass	Crop	1,000	Plant Seedlings Classification (Kaggle)
Charlock	Crop	1,000	Plant Seedlings Classification (Kaggle)
Cleavers	Crop	1,000	Plant Seedlings Classification (Kaggle)
Common chickweed	Crop	1,000	Plant Seedlings Classification (Kaggle)
Common groundsel	Crop	1,000	Plant Seedlings Classification (Kaggle)
Fat hen	Crop	1,000	Plant Seedlings Classification (Kaggle)
Maize	Crop	1,000	Plant Seedlings Classification (Kaggle)
Sugar beet	Crop	1,000	Plant Seedlings Classification (Kaggle)
Common daisy	Crop	1,000	Plant Seedlings Classification (Kaggle)
Dandelion	Weed	500	Weeds Dataset (Custom-curated)
Crabgrass	Weed	500	Weeds Dataset (Custom-curated)
Bindweed	Weed	500	Weeds Dataset (Custom-curated)
Thistle	Weed	500	Weeds Dataset (Custom-curated)
Wild oat	Weed	500	Weeds Dataset (Custom-curated)
Total	-	11,500	-

Figure 2. Sample images from public datasets

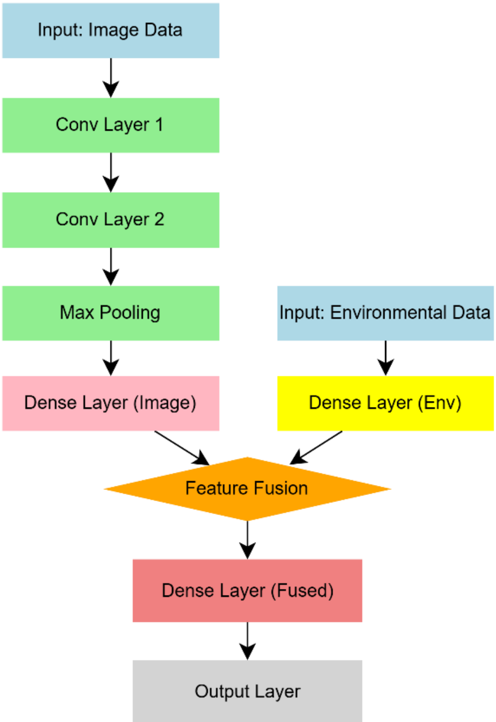

Figure 3. Architecture of EnvrioweedNet

3.1. Convolutional layers

The visual processing begins with a series of convolutional layers. Convolutional layers are essential for extracting local features from the image, such as edges, textures, and patterns. Each convolutional layer applies a set of filters (or kernels) to the image to identify these features. The formula for a convolution operation in layer l is given by (1).

$$X_{l+1} = f(W_l * X_l + b_l) \tag{1}$$

Where X_l is the input to layer l, W_l is the weight matrix (convolutional filter) for layer l, b_l is the bias term for layer l, $*$ denotes convolution operation, and f is the activation function (rectified linear unit (ReLU)).

Each convolutional layer captures progressively more abstract features, starting from simple edges in the first layers to more complex features like shapes and textures in the deeper layers. The ReLU activation function is applied after each convolutional operation to introduce non-linearity, which helps the model learn more complex patterns in the data as in (2).

$$f(x) = max\ (0, x) \tag{2}$$

3.2. Max pooling

To reduce the spatial dimensions of the feature maps and focus on the most significant features, each convolutional layer is followed by a max-pooling operation. Max pooling reduces the size of the feature map while retaining important information by selecting the maximum value from a small neighborhood (typically 2×2) of pixels. The formula for max pooling is (3).

$$P\left(X_{i,j}\right) = max(X_{i,j}, X_i + 1, j, X_{i,j} + 1, X_i + 1, j + 1) \tag{3}$$

By reducing the dimensionality, max pooling not only decreases computational complexity but also makes the model more robust to small changes in the input, such as shifts or distortions. After several convolutional and pooling layers, the output is a high-dimensional feature map representing the visual features extracted from the image. This feature map is flattened into a one-dimensional vector, which can be passed through fully connected (dense) layers. The purpose of the fully connected layers is to learn higher-level abstractions of the image features. Each fully connected layer applies a linear transformation followed by a non-linear activation function (again, ReLU) as in (4).

$$X_l + 1 = \sigma(W_l X_l + b_l) \tag{4}$$

Where W_l and b_l are the weights and biases of the fully connected layer and σ is the activation function.

3.3. Feature fusion

The heart of the EnviroWeedNet architecture is the feature fusion step, where the outputs of the visual processing branches form a single feature vector that contains both visual and environmental information. The two feature vectors are concatenated as in (5).

$$F_{combined} = [F_{visual}, F_{environmental}] \tag{5}$$

Where F_{visual} is the visual feature vector and $F_{environmental}$ is the environmental feature vector.

3.4. Classification layer

The combined feature vector is passed through additional fully connected layers to refine the feature representation and prepare it for classification. Finally, the output is passed through a SoftMax layer, which produces a probability distribution over the possible class labels (weed or crop). The SoftMax function is defined as in (6).

$$\ddot{y} = softmax(W_{out,} F_{combined} + b_{out}) \tag{6}$$

Where W_{out} is the weight matrix for the output layer, $F_{combined}$ is the bias term for the output layer, and b_{out} is the predicted class probability (weed or crop).

3.5. Training and optimization

The model is trained using a labeled dataset of images. Each training example consists of an image, the corresponding environmental conditions, and the ground-truth label (weed or crop). The loss function used for training is typically categorical cross-entropy, which is well-suited for multi-class classification problems as in (7).

$$L(y, \hat{y}) = -\sum_i y_i \log(\hat{y}_i) \quad (7)$$

Where y is the true label (one-hot encoded) and $\hat{y}$ is the predicted probability distribution.

The model's weights are optimized using stochastic gradient descent (SGD) or a variant such as Adam, which adjusts the learning rate dynamically. During training, the model learns to minimize the loss function by adjusting the weights in the convolutional and fully connected layers. The processed data helps the model converge faster and more accurately by providing additional context that guides the classification.

Algorithm 1 is designed to improve weed and crop classification accuracy by integrating both image data and environmental factors. The input consists of an image dataset (I) that includes various crop and weed images. The output of the algorithm is a classification result (C), indicating whether the given input corresponds to a weed or a crop.

Algorithm 1. EnviroWeedNet
Input: Image dataset (I)
Output: Weed or crop classification (C)
Step 1: Preprocess image data (I)
  1.1. Resize images to 224×224 pixels.
  1.2. Normalize pixel values to the range [0, 1].
  1.3. Apply data augmentation (rotation, flipping, and contrast adjustment).
Step 2: Initialize the visual processing branch (CNN)
  2.1. Apply convolutional layers with ReLU activation.
  2.2. Apply max pooling after each convolution.
  2.3. Flatten the output to a visual feature vector.
Step 4: Initialize the data processing branch (dense layers)
  3.1. Pass data through dense layers with ReLU activation.
  3.2. Output an environmental feature vector.
Step 4: Feature fusion
  4.1. Concatenate the visual and environmental feature vectors.
Step 5: Classification
  5.1. Pass the fused feature vector through additional dense layers.
  5.2. Apply SoftMax to generate class probabilities.
Step 6: Output the class with the highest probability (weed or crop).
End algorithm.

4. RESULTS AND DISCUSSION

The proposed algorithm was evaluated based on its effectiveness in recognizing various weed and crop species using a dataset comprising 11,500 images. Each image was uniformly resized to 224×224 pixels to ensure consistency and effective processing by the model. The performance of the algorithm was assessed using various evaluation metrics, including accuracy, precision, recall, and F1-score. The results revealed that the work achieved an impressive accuracy of 94.5%, significantly outperforming traditional machine learning approaches and existing machine learning models. Table 2 shows the performance of the proposed model. Figures 4-8 show the outcome of the proposed work.

Table 2. Performance metrics of EnviroWeedNet compared to other models

Metric	EnviroWeedNet	Traditional CNN	SVM	Random forest	ResNet-50
Accuracy (%)	94.5	89.2	85.1	86.5	92.4
Precision (%)	94.8	87.0	83.6	84.0	91.0
Recall (%)	95.5	88.5	84.0	85.5	91.5
F1-Score	95.1	87.7	83.8	84.7	91.2

The proposed algorithm achieved an impressive accuracy of 94.5%, significantly surpassing traditional machine learning methods such as support vector machine (SVM), random forest (RF), and ResNet-50. This high accuracy underscores the model's capability to effectively distinguish between crops and weeds, a critical factor in precision agriculture. Furthermore, with a precision of 94.8%, The confusion matrix in Figure 8 shows how well the model is able to correctly classify instances of the two classes. Figure 9 shows the comparative analysis of the proposed work.

This study minimizes false positives, which is essential in agricultural applications to avoid misclassifying crops as weeds, thereby preventing unnecessary herbicide usage and associated costs. The model also demonstrated a recall of 95.5%, showcasing its effectiveness in accurately identifying actual weeds; a high recall rate is vital for timely weed detection and management, preventing competition for resources with crops. Finally, the F1-score of 95.1% reflects a balanced performance between precision and recall, emphasizing its importance in agricultural contexts where both false positives and false negatives can lead to significant economic repercussions for instance, suppose class 1 represents "no weed" and class 2 represents "weed". The comparative analysis presented in Figure 9 illustrates the performance of the EnviroWeedNet algorithm in relation to existing models documented in the literature. Notably, the results as shown in Figure 9 show that the work achieved an accuracy of 94.5%, significantly higher than the modified U-Net (92.5%), deep CNN (90.7%), and transfer learning using visual geometry group (VGG) (91.8%) approaches. This enhanced accuracy underscores the effectiveness of the hybrid model, which utilizes image data for superior weed and crop classification. Furthermore, the precision of 94.8% not only surpasses that of the other algorithms but also highlights the model's ability to minimize false positives, an essential factor in agricultural applications where misclassifying crops as weeds can lead to unnecessary herbicide application and financial losses. In terms of recall, the proposed work excels with a score of 95.5%, indicating its robustness in accurately identifying actual weeds, thus preventing competition for resources with crops. Finally, the F1-score of 95.1% demonstrates a well-balanced performance between precision and recall, further establishing the algorithm as a leading approach in the field of precision agriculture.

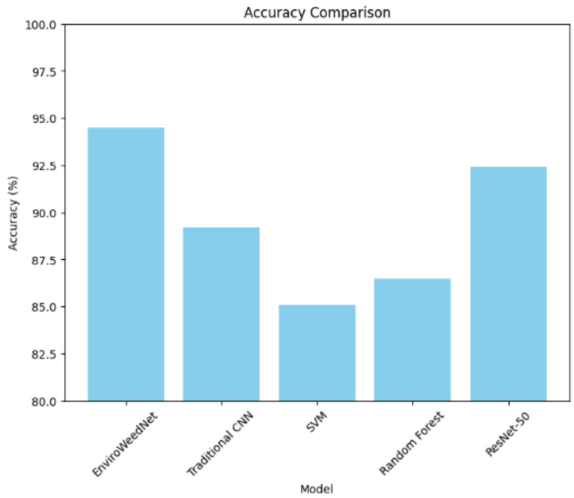

Figure 4. Accuracy comparison

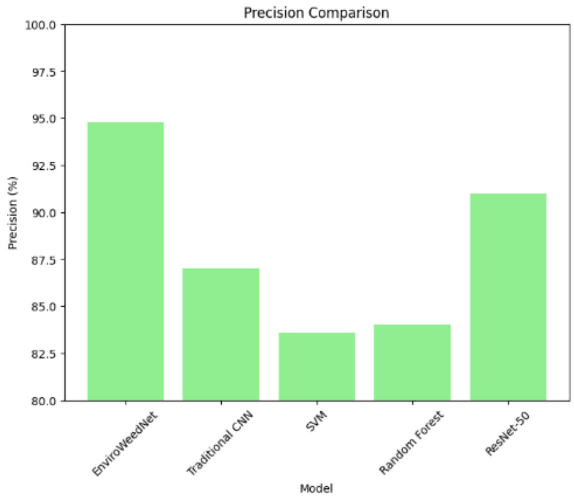

Figure 5. Precision comparison

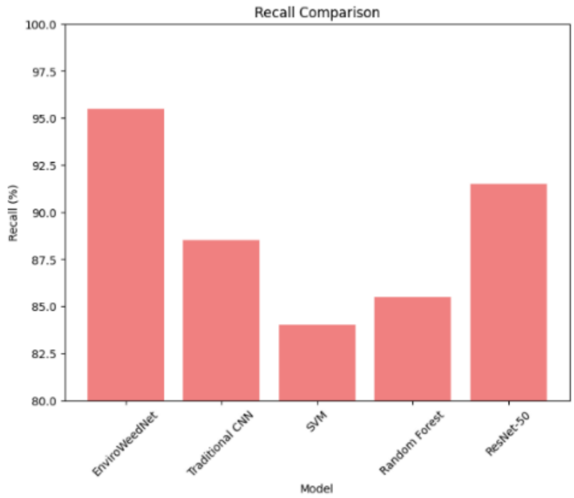

Figure 6. Recall comparison

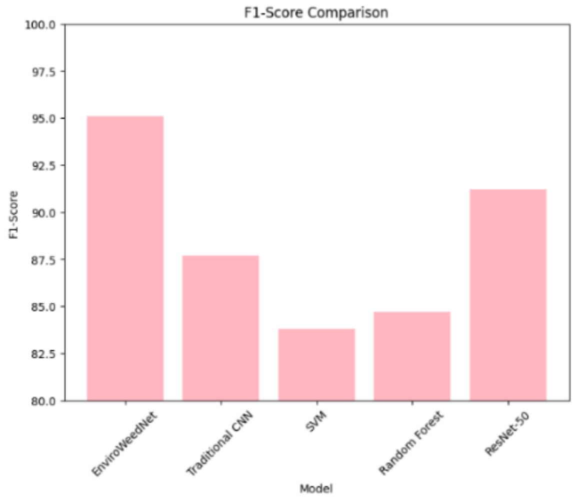

Figure 7. F1-score comparison

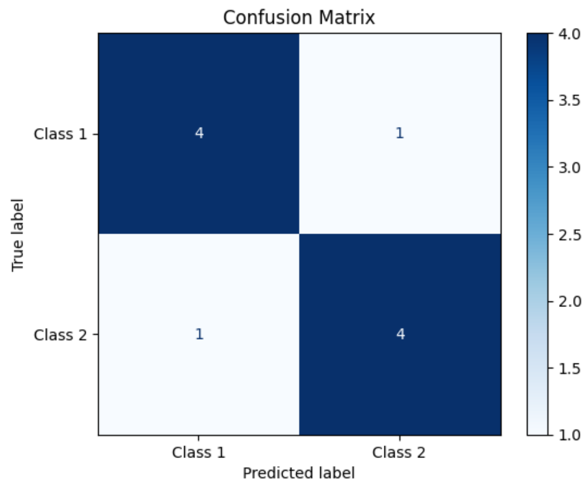

Figure 8. Confusion matrix

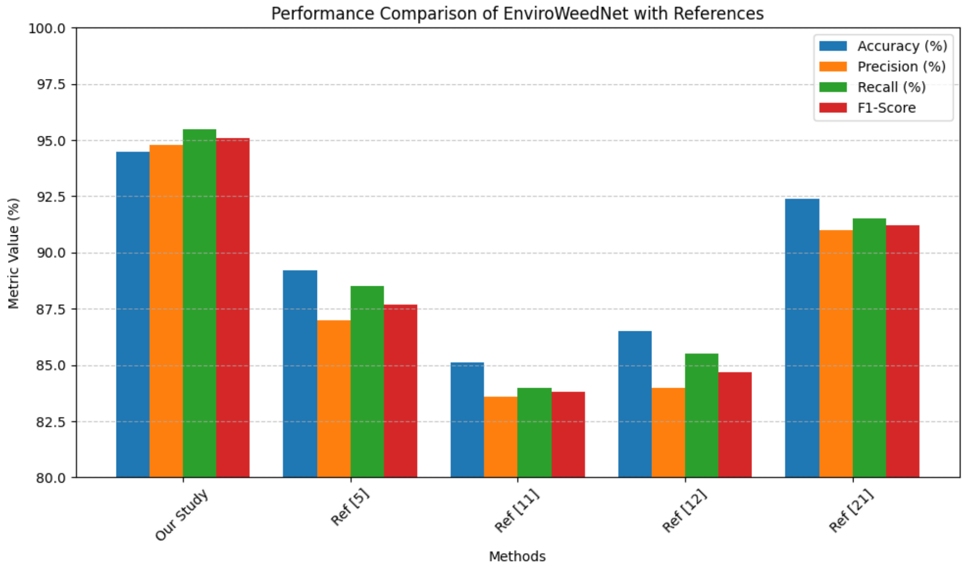

Figure 9. Comparative analysis of the proposed model

5. CONCLUSION

The proposed EnviroWeedNet algorithm was developed to address the limitations of current weed and crop classification models. Through this hybrid approach, the model successfully differentiates between crops and weeds with significantly improved accuracy, precision, recall, and F1-score when compared to traditional machine learning models such as SVM, RF, and ResNet-50. The evaluation results show that the proposed work achieved an accuracy of 94.5%, which is higher than many state-of-the-art models. Additionally, with a precision of 94.8% and a recall of 95.5%, the model demonstrates an excellent balance between identifying true positives (actual weeds) and minimizing false positives, which is critical in agricultural settings. The high F1-score of 95.1% highlights the model's robust performance, ensuring that it is effective in both detection and classification under varying field conditions. When compared to existing studies, the proposed algorithm consistently outperforms these models in every key performance metric. Future work could explore the model's adaptability to other agricultural environments and broader datasets.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest regarding the publication of this paper.

DATA AVAILABILITY

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

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