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RESEARCH ARTICLE

Revolutionizing Agriculture: Machine and Deep Learning Solutions for Enhanced Crop Quality and Weed Control

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ABSTRACT Agricultural systems are being revolutionized due to emerging technologies that aim to make improvements in the traditional agriculture system. The major goal is not just to enhance agricultural output per hectare but also to enhance crop quality while protecting the natural environment. Weeds pose a significant threat to crops as they consume nutrients, water, and light, thereby reducing crop productivity. Spraying the entire field uniformly to control weeds not only incurs high costs but also has adverse environmental effects. To address the limitations of conventional weed control methods, in this research, Machine Learning (ML) and Deep Learning (DL) based techniques are proposed to identify and categorize weeds in crops. For ML-based techniques, several statistical and texture-based features are extracted, including central image and Hu moments, mean absolute deviation, Shannon entropy, gray level co-occurrence matrix (GLCM) and local binary patterns (LBP), contrast, energy, homogeneity, dissimilarity, correlation, and summarized local binary pattern histogram. YOLOv8m is employed to identify weeds and for weed classification, features extracted from two standard benchmark datasets, CottonWeedID15 and Earlycrop-weed are fed to Support Vector Machine (SVM), Random Forest, and Artificial Neural Network (ANN) while employing Synthetic Minority Oversampling Technique (SMOTE) to balance the classes. In addition to ML-based techniques, Deep learners such as VGG16, VGG19, Xception, DenseNet121, DenseNet169, DenseNet201, and ConvNeXtBase are trained on raw data with balanced classes for automated feature extraction and classification. Among the ML-based techniques, SVM with a polynomial kernel achieves 99.5% accuracy on the early crop weed dataset, and Artificial neural network attains 89% accuracy on the Cottonweedid15 dataset. Meanwhile, the combined employment of ConvNeXt and Random Forest results in the highest accuracy among DLs, specifically 98% on the early crop weed dataset and 90% on the Cottonweedid15 dataset. The high accuracy achieved underscores the practical viability of these methods, offering a sustainable and cost-effective solution for modern agriculture.

INDEX TERMS ConvNeXtBase, DenseNet, generative AI, smart agriculture, VGG, Xception, YOLOv8.

I. INTRODUCTION

Every year, the world's population is growing at a rate of 1.09%. By 2050, it is projected that the global population will reach 9 billion. Due to the increase in the population, the demand of food is also increasing. To meet this demand, agricultural production needs to be increased by 70% [1]. However, the agricultural sector faces many challenges, such as lack of cultivable land, saline land, barren land, climate change, water scarcity, as well as weeds in crops. Artificial

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intelligence can play crucial role in mitigating these issues in agriculture with the aid of computer vision, machine learning, and deep learnings [2]. According to their leaf shape, weeds are divided into three primary groups: broad-leaf weeds, grasses, and sedges. Weeds are non-essential plants that are found in different parts of the crop. These weeds not only damage the crop but also provide shelter and breeding grounds for various pests. As per European Crop Protection (ECPA), weeds and pests cause about a 40% loss in crop yields. Therefore, many methods have been devised to eliminate weeds from the crop to avoid damage. One of these methods is to remove weeds from the crop by hand [3]. This method demands lots of hard work and time. Another method is to remove weeds with the help of specially designed mechanical devices. These devices are moved between the rows of crops. however, these devices are not workable on crops that are not grown in rows. One approach to eliminating weeds in crops is to use chemical sprays. Our farmers spray uniformly across the entire field to keep weeds at bay. Spraying in fields uniformly raises production costs and has negative environmental consequences. Fig 1 shows the conventional weed-control techniques. Artificial intelligence is able to make a weed control system with the help of computer vision, deep learning, and machine learning. Artificial intelligence has both economic and environmental benefits. The first stage in building an automated weed removal system is to correctly detect and recognize weeds by the automated weed removal system [4]. Weed classification and detection in crops are challenging problems because most of the time, weeds and crops have the same color and texture. It is difficult to differentiate between them. Due to different sun angles, lighting varies on the surface of weeds and crops, producing illumination and shadow, which creates more difficulty in detection and classification. Image capture, pre-processing of pictures, feature extraction, and weed detection and classification are the four main phases of a typical weed detection system [5]. In recent years, with the advancement of science, Technology, and artificial intelligence, both have experienced rapid growth. For solving classification and detection problems, many new computer vision, machine learning, and deep learning algorithms have been introduced which are only able to work due to the graphics processing unit. Deep learning models, such as deep neural networks, demand high computation. But with the help of transfer learning, we are able to reduce computation. In transfer learning, we use already learned weights that are transferred from another problem-related domain. Transfer learning (also known as transferring deep learning model's weights) solely entails fine-tuning model parameters using additional datasets in the target domain. Transfer learning is really helpful in achieving good results with less computation. The authors of [6] discovered that optimizing DL models on agricultural datasets helps decrease training epochs while enhancing model accuracy. On the early-crop-weeds Dataset [6] and the Plant Seedlings Dataset, they enhanced the classification accuracy by 0.51% to 0.89% by fine-tuning four DL models [7].

Major Research Contributions: Our research addresses the challenges in weed detection and classification by focusing on the features that can produce upstanding ML and DL-based models. The research makes significant contributions to the smart agriculture field by introducing novel feature-based approaches and generating a comparative insight into the effectiveness of features for weed identification and classification, and proposing solutions for removing weeds.

- A meticulous effort has been made to annotate the "CottonWeedID15" dataset. The dataset contains images of various weeds commonly found in cotton fields. These images are scrupulously annotated with rectangular regions of interest (ROI) markings and are released with this research [8]. By providing this annotated dataset, the research serves as a valuable resource for the research community for future investigations in the field of weed identification and control.
- Our research makes a significant contribution by thoroughly investigating the efficacy of various statistical and texture features, encompassing simple moments, Hu moments, GLCM (Gray-Level Co-occurrence Matrix), and LBP (Local Binary Pattern), in addition to exploring the potential of deep learning features. This exploration of diverse feature sets is crucial for advancing the understanding of feature extraction methods and computation in the context of weed detection.Models and feature sets yielded results of more than 88% on the testing set of both datasets.
- U2Net is used in a novel way to remove the background from the images and a rigorous comparison is made to evaluate the performance of the learners on images with a background and without a background.
- Our research contributes by disseminating a vital awareness message to the world's population, highlighting the transformative potential of deep learning technology in agriculture. By emphasizing the benefits of adopting deep learning techniques, we aim to inspire and educate farmers about the potential improvements in crop yield and overall prosperity that can be achieved through the integration of advanced technologies. This awareness initiative is a proactive step toward bridging the gap between technological advancements and practical implementation in the agricultural sector, fostering a more informed and tech-savvy farming community in the world.

The remaining sections of the article are structured as follows: Section II probes into related work and explores existing approaches relevant to the topic while section III outlines the proposed methodology with Fig 2, detailing the techniques. Section IV discusses the experimental setup along with results obtained from the multiple experiments. Finally, the findings and implications of the research are thoroughly discussed in section V, and the conclusion is presented in Section VI.

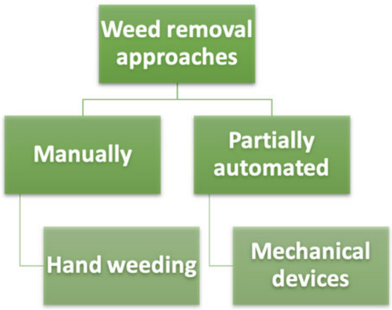

FIGURE 1. Weed removal approaches.

II. RELATED WORK

Machine learning and deep learning techniques are used in the detection and recognition of weeds in crops, producing astonishing results in precision farming. Reference [3] proposed two techniques for classification based on weed density. They used three classes, with each class representing weed density. In their first technique, after creating a density-based dataset, they converted each image to grayscale, then reduced the image size to reduce computing time. Grey level co-occurences matrix is calculated from the reduced-size images, and features like correlation, contrast, homogeneity, and energy are extracted from each grey level co-occurences matrix. They trained a support vector machine model with a radial basis kernel and achieved a 10-fold cross-validation accuracy of 72.73%. They also conducted a comparison of radial bases and linear kernels. The highest accuracy achieved with a linear kernel is 51.52%, which is comparatively lower than a radial base kernel. Random forest achieved a 69.70% cross validation accuracy after a 10 fold cross-validation with GLCM features. In their second method, they extracted the green channel from the RGB image of a density-based dataset. Then they calculated Mean, variance, kurtosis, and skew. They trained a support vector machine model with a radial basis kernel and achieved a 10-fold cross-validation accuracy of 84.85%.

To address dataset issues, the generative adversarial techniques of deep learning are critical for creating synthetic images [9] They generate synthetic images with traditional augmentation as well as with a deep convolutional generative adversarial network. In their work, they use transfer learning to set the weights of a neural network. They took a neural network with ImageNet weights. In their experiment with DCGAN, they used the PlantVillage dataset. The best FID score was achieved after 46,000 iterations, and the FID was 86.93% for synthetic tomato images, and for synthetic black nightshade images, the FID score is 146.85, which was achieved by DCGAN after 29,500 iterations. In a noisy test set, the performance of inception-resnet was 89.06%. With real and synthetic images, the inception F1 score was 98.63, and in a noisy test set, the performance of inception was 87.05%.

Many researchers used image processing techniques for weed identification. Reference [10] provided a review of image processing techniques. After collecting the dataset, then researchers apply preprocessing on the dataset, and after preprocessing, image enhancement algorithms are used. On enhanced images segmentation algorithms are used, which are threshold-based or learning-based. Then researchers extract features from the binary image. Feature extraction is based on morphology, spectral property, visual texture, and spatial context. Then these features are fed in machine learning or deep learning models and classified the weed images. Deep learning models such as GANS and CNN were also discussed. Agriculture's massive dataset challenges require deep learning to solve.

Turf grass is used in athletics grounds, lawns, golf courses, and many other areas. So [11] proposed methods to avoid weeds in turf grass. They used a Sony DSC-HX1 camera for dataset collection. They took images from multiple golf courses (Riverview, Sun City, Tampa, and Miami). Hydrocotyle spp., Hedyotis cormybosa, and Richardia scabra were the weeds used in their datasets. They did training with one weed and with turf grass and also with multiple weeds with turf grass. For training, they used VGGnet, Googlenet, and Detectnet architectures.The F1 score values of VGGnet and Googlenet for Hydrocotyle spp. are 0.9990 and 0.667 on validation dataset. The F1 score values of VGGnet and Googlenet for Hedyotis cormybosa are 0.9950 and 0.7091 on validation dataset. The F1 score values of VGGnet and Googlenet for Richardia scabra are 0.9911 and 0.6667 on the validation dataset. For multiple species Googlenet F1 score was 0.72667 and VGGnet F1 score was 96.33 on the validation dataset. Many classification and detection experiments have been conducted in agriculture as a result of the advent of deep learning algorithms. Reference [12] did a survey of deep learning techniques. They conducted a survey of existing deep learning algorithms for weed identification and classification in various crops. Deep learning architectures used in research papers are VGGNet, modified Xception, Inception-ResNet, MobileNet, DensNet, ResNet-50, VGG-16, VGG-19, Inception v3, SegNet-512, SegNet-256, YOLO-v3, tiny YOLO-v3, single-shot detector, convolutional neural network, segnet, alexnet, deeplab-v3, U-net, artificial neural network, VGG-F, VGG-vd-16, AlexNet, U-Net, SegNet, hybrid network, faster R-CNN, ESNet, Joint unsupervised learning deep cluster, LeNET, etc. Various crops and weeds are used with various deep learning models. Furthermore, they discussed how GANS and synthetic data can also play an important role in catering to the problems of complex patterns in agriculture. For weed removal applications, High precision is required, But achieving high precision in agriculture is still a challenging problem. [13], they did work with sugar beet fields and four species of weeds, which are named as Pig-weed, Lambsquarters, Hare's-ear mustard, and turnip weed (scientifically known as. Amaranthus chlorostachys, Chenopodium album,Conringia orientalis and Rapistrumrugosum). They used fourier transform and moment features with SVM and ANN. The ANN achieved a 99.50% accurate classification of weed. The ANN exhibited an overall accuracy rate of 92.92%. On the other hand, SVM overall accuracy was 95. 93.33% SVM correctly classified 93.33% of weeds.

In [6], they generated Early-crop-weed dataset, which includes tomato and cotton crops along with two weed species (black nightshade and velvetleaf). They combined fine-tuned pre-trained convolutional networks (Inception-Resnet, Densenet, Xception, VGNets, and Mobilenet) with ''traditional'' machine learning classifiers (Logistic Regression, Support Vector Machine and XGBoost). They used transfer learning for training. Their results showed that the fine-tuned Densenet with Support Vector Machine combination achieved a micro F1 score of 99.29%. Other architectures also achieved more than 95% accuracy. In [14] they purposed several experimented approaches and explained how to fine-tune parameters and extract deep features using deep learning, combining them with machine learning algorithms. They used four public datasets in their work named as flavia, swedish leaf, UCI leaf and plantvillage. They extracted features with deep neural networks (AlexNet and VGG-16) and after extracting features, they applied classic machine learning classifiers (LDA and SVM) for classification. In their last experiment, they produced features with AlexNet and VGG 16. Then they combined the features which are produced by AlexNet and VGG16. Then they used end-to-end RNN on these featues, and after training, produced classification results on test data. All their experiment produced more than 90% classification accuracy.

Broadleaf crops and weeds that also have broadleaf make it more difficult to identify broadleaf weeds inside broadleaf crops [15]. They used wheat and weed species (cleavers, crickweed, and shepherds purse). For weed detection, they used CenterNet2, Faster R-CNN, TridentNet, VFNet, and YOLO version 3. For weed classification, they used Alexnet, DenseNet, ResNet, and VGGNet. On weed detection, YOLO v3 achieved the highest F1 score on validation as compared to other models, which is 0.65. VGGNet and DenseNet F1 scores are 1, which is higher than as compared to other models. In another work [16], they did a comparative performance analysis of 3 image classification models that were trained for classifying various species of weed, as well as the detection model performance developed to detect and classifying weed species. The dataset contain 462 RGB photos of early season weeds commonly found in corn and soybean crops (redroot pigweed, gigantic ragweed, foxtail, and cocklebur). There are 181 images of redroot pigweed, 173 images of gigantic ragweed,73 images of foxtail, and 35 photographs of cocklebur. They used models named Resnet50, VGG16, and inception for image classification. With an accuracy of 98.90, VGG16 was the best performing classification model. In their research work [17] they presented a new dataset which had 5187 coloured images, captured under different natural light conditions, that contained images of 15 different weed classes (Morning Glory, Carpetweed, Palmer Amaranth, Waterhemp,Purslane, Nutsedge, Eclipta, Sicklepod, Spotted Spurge, Ragweed, Goosegrass, Prickly Sida, Crabgrass, Swinecress, and Spurred Anoda). This study also evaluates 35 state-of-the-art deep learning models for multi-class weed identification. In total 35 models are trained and among all these models the top 5 models that performed the best were ResNeXt101, RepVGG-B1, RepVGG-B2, ResNeXt50, and RepVGG-A2.

An improved YOLOv5 Convolutional Neural Network is constructued for Solanum rostratum Dunal detection [18]. Solanum rostratum Dunal weed is classified as one of the most harmful weeds in the US and China. Total 413 images of Solanum rostratum Dunal at different stages of growth were obtained using different devices. YOLOv5 is combined with the Convolutional Block Attention Module (CBAM) to increase the extraction of relevant features while suppressing others. This combination is known as YOLO-CBAM. YOLO-CBAM is made up of four parts: input, backbone, neck, and prediction. The model results in a precision of 0.9036, recall of 0.9012 and an average precision of 0.9272. This research [19] was carried out to identify weeds in the fields of bell pepper. During preprocessing, lighting variations and noise were removed, and data augmentation was applied to enhance quality and avoid overfitting. AlexNet, GoogLeNet, InceptionV3 and Xception are those Convolutional Neural Network architectures that were applied during this research. All the models provided results with 94.5% - 97.7% of accuracy. Overall, InceptionV3 provided the highest accuracy of 97.7%. In weed identification tasks, speed, computation time, accuracy, and memory are very noticeable things [20]. In their work, they focused on such things and used lightweight, deep learning models for weed identification. Using the SLIC super pixel technique, images were divided into 15336 segments: 3249 for soil, 7376 for soybeans, 3520 for grass, and 1191 for broadleaf weeds. For weed identification, they used mobilenetv2, resnet50, and three custom models. The 5-layer CNN design has the lowest latency and memory utilisation (1.78 GB and 22.245 ms, respectively), as well as the highest detection accuracy 97.7%.

In this research [21] optimization algorithms(Adagrad, AdaDelta, Adaptive Moment Estimation (Adam), and Stochastic Gradient Descent (SGD)) were used with deep convolution neural networks (AlexNet, GoogLeNet, VGGNet, and ResNet). VGGNet is particularly designed for small convolution kernels to limit the number of neurons and number of parameters. ResNet (Residual Network) is used to fix the degradation problem for deep networks by using residual learning to train the deeper networks. For the best performing input image size, the classification accuracy hierarchy, from lowest one to highest one, was VGGNet, GoogLeNet, AlexNet ResNet. The study [22] shows how we can use Siamese neural networks to solve large dataset problems. The Siamese neural network with convolutional layers was used for training. The support dataset contains 1,5,10,15, and 20 images of each type, while the query contains 40 images of each. Support datasets were used to fine tune the SNN. Then it was evaluated on a testing set, and further enhancement in accuracy was observed as the accuracy jumped to 70.1% and 70.0% from 67.5% and 66.6% for the validation and testing data sets, respectively.

In this paper [23], the main purpose was to train Deep Convolutional Neural Networks (DCNNs). Four DCNNs (GoogLeNet, ShuffleNet, MobileNet, and VGGNet) were assessed to find and differentiate weeds that are growing in bermudagrass turf. Both VGGNet and ShuffleNet demonstrated exceptional overall accuracy in the validation process, with values equal to or greater than 0.999. SE-YOLOv5x was first time tested on lettuce crops and weeds dataset [24]. The dataset they used in their work had five kinds of weeds and one lettuce crop. For classification, SVM, SE-YOLOv5x surpassed YOLOv5x, SSD (VGG), SSD (Mobilenetv2), Faster-RCNN (Resnet50), and Faster-RCNN (VGG) are used. SE-YOLOv5x demonstrates superior performance in the classification of lettuce and weeds. The aim of [25] was to recognize plants in UAV images using the transformer's architecture. The dataset was divided into 5 classes: weed, beet, off-type beet, parsley, and spinach. Each class contains 3200 to 4000 images, except off-type beets, which only have 653 samples. Random rotations and flips were performed so the total dataset contains 19265 images. EfficientNet B0, EfficientNet B1 and ResNet 50 were the conventional neural networks that were applied to the dataset and provided a F1-score of 98.7%, 98.9% and 99.2% respectively. A deep learning model named the original generative adversarial network designed by Ian Goodfellow [26] is proposed. In their network, they used two learning models: one called the generator, and the other called the discriminator. They trained them in an adversarial process. Generators try to fool discriminators, and discriminators try to classify fake and real data. Finding a discriminator with the highest classification efficiency and a generator that confuses the discriminator the most is the method for training a GAN model. This first architecture of the GAN model is the next step towards augmentation [27]. This paper provides an overview of GAN's architectural evolution and its application in agriculture. They evaluate how GAN's architecture plays a role in weed detection, postharvest detection of fruit defects, plant phenotyping, plant health conditions, animal farming, and aquaculture. Handcrafted features are used with machine learning and automated features through deep learning [28]. For knowing which features produce better results. For handcrafted features, they used a local binary pattern and a grey level co-occurrence matrix. From the grey level co-occurrence matrix, they extract features like contrast, energy, dissimilarity, area second moment (ASM) and correlation. Distance, angle, and a number of levels were the parameters used in the grey level co-occurrence matrix for feature extraction. Points and radius were the parameters that were used in the local binary pattern. They experimented with different numbers of features, and SVM produced the best results with 90% accuracy, on 55 features (LBP8-1; 5 LBP162; 14 LBP24-3; 15 contrast; 15 dissimilarity; and 4 correlation).

Various models and algorithms exhibit distinct accuracies when applied to diverse datasets, each necessitating varying computational resources. It is imperative to delve into the intricacies of these models and algorithms, meticulously analyzing their features to gauge the requisite computational power. Developing methodologies to address weed-related challenges with efficient computations is paramount. Existing studies often overlook the nuanced impact of background areas on the accuracy of weed and crop identification under varying lighting conditions. A notable research gap lies in understanding how the background area influences the performance of different models. A comprehensive exploration of this aspect is essential for advancing the precision and applicability of weed detection methodologies Overcoming variations in lighting conditions, diverse weed species, and the demand for expansive annotated datasets is pivotal. Particularly in countries, where traditional agricultural approaches persist, there is a pressing need to raise awareness about modern technologies. This not only promises increased yields and profitability but also advocates for environmentally sustainable practices by discouraging the excessive use of herbicides. Bridging this awareness gap would contribute significantly to advancing agricultural practices in the world.

III. PROPOSED METHODOLOGY

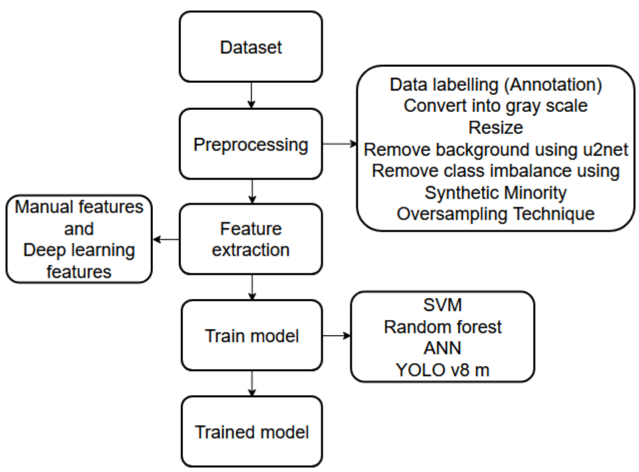

FIGURE 2. High level methodology diagram.

A. DATASETS

We are using two datasets in our work: one called early-crop-weed [6] and the other CottonWeedID15 [17]. early-crop-weed datasets have two weeds (velvet leaf and black night shade) and two crops (cotton and tomato), whereas CottonWeedID15 has fifteen weeds (carpetweeds, crabgrass, eclipta, goosegrass, morningglory, nutsedge, palmeramaranth, prickly sida, purslane, ragweed, sicklepod, spotted spurge, spurred anoda, swinecress, and waterhemp).Fig 3 and 4 shows both datasets are unbalanced.

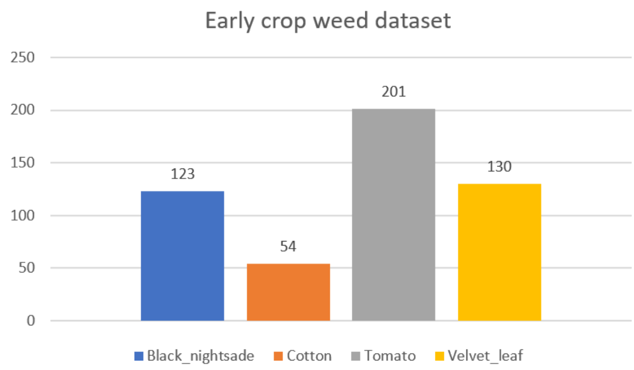

FIGURE 3. Early-crop-weed dataset class imbalance.

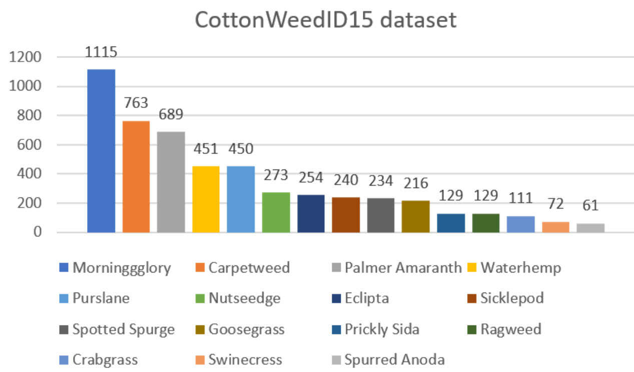

FIGURE 4. CottonWeedID15 dataset class imbalance.

B. PREPROCESSING

1) ANNOTATION

For YOLO training, an annotated dataset is required; therefore, we annotated using LabelImg. We concentrated on creating bounding boxes only around the areas where weed's leaves are present. We made sure to maximize the weed's leaf coverage while minimizing the soil area. The objective of our bounding box was to minimize the inclusion of soil and maximize the area covered by weed's leaves.This approach also helps in reducing land pollution since the spray was intended for leaves and not for the soil. Fig 5 shows annotation of purslane class image.

2) GRAYSCALE AND RESIZE

To reduce computation, we converted the color images to grayscale. This allowed us to process only one channel image. Since the dataset images had large dimensions, we resized them to 224 by 224. By reducing the image size, we were able to significantly reduce the computation time required for further processing.

FIGURE 5. Annotation of purslane class image from cottonweed dataset.

3) REMOVE BACKGROUND USING U2-NET

The U2-Net model is a deep learning model developed by researchers from Hefei University of Technology in China. It consists of 23 layers and is an improved version of the U-Net model. The U2-Net architecture is specifically designed to capture multi-scale contextual information and accurately detect salient objects in images. In U2-Net, the image is passed through an encoder. The encoder includes multiple convolutional layers that extract features and reduce the image dimensions. The encoded features are then passed to the decoder layer, which consists of upsample layers. These layers gradually increase the spatial dimensions while preserving the learned features.U2-Net also utilizes skip connections between the encoder and decoder, which help in achieving accurate image segmentation. The output of the decoder is a saliency map, which is a binary mask. The saliency map helps in segmenting the image by highlighting the regions of interest. Fig 6 shows background removed through U2-Net.

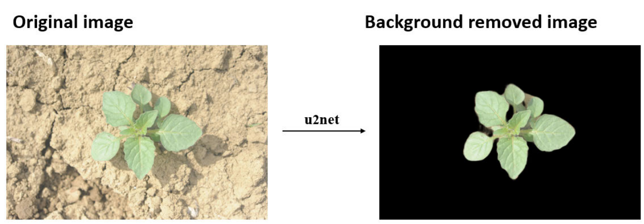

FIGURE 6. Background removed through U2-Net.

4) SMOTE SYNTHETIC MINORITY OVER-SAMPLING TECHNIQUE

SMOTE is a data upsampling technique that is helpful in addressing class imbalances. SMOTE aims to create synthetic samples that lie along the line segment connecting the original minority class sample and its nearest neighbor. SMOTE selects a random sample image from the minority class and examines the most closely similar images using k nearest neighbors. Then, using interpolation, SMOTE generates a new image, and this process continues until all classes are not balanced.

C. MANUAL FEATURES

In our first experiment which named as manual features with background and without background, we used the pretrained U2Net to remove the background from the images. This process helped isolate the interest area in the images Next, we converted the color images to grayscale. For reducing computational complexity, we resized the images to a dimension of 224 pixels. For feature extraction, we utilized the Grey Level Co-occurrence Matrix (GLCM) approach. We calculated the GLCM using different angles (0°, 90°, 45°, and 135°) and considered neighboring pixel distances of 1, 3, and 5. These settings allowed us to capture various texture patterns and spatial relationships in the images.From the GLCMs, we derived several texture features including energy, correlation, dissimilarity, homogeneity, contrast, and entropy. And the summation of the local binary uniform pattern histogram from local binary pattern. Additionally, we computed statistical features such as mean, standard deviation, variance, mean absolute deviation, contrast, skewness, kurtosis, entropy, and image moments. Furthermore, we calculated seven Hu moments [29]. Which are invariant image moments representing shape and geometric properties.To account for edges and finer details in the images, we performed the calculation of image moments and Hu moments twice. The first calculation was carried out on the original grayscale images, while for the second calculation, we applied the Prewitt filter to extract edge gradient before computing the image moments and Hu moments. We performed this experiment without background removal too for knowing the importance of background.Normalization is applied to these features before being fed into classifiers. We utilized the Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance in the dataset.

$$\text{Energy} = \sum_{i=1}^{N}\sum_{j=1}^{N} \text{GLCM}(i,j)^2$$

$$\text{Correlation} = \sum_{i=1}^{N}\sum_{j=1}^{N} \frac{(i-\mu)(j-\mu)\text{GLCM}(i,j)}{\sigma^2}$$

$$\text{Disimilarity} = \sum_{i=1}^{N}\sum_{j=1}^{N} |i-j|\text{GLCM}(i,j)$$

$$\text{Homogeneity} = \sum_{i=1}^{N}\sum_{j=1}^{N} \frac{\text{GLCM}(i,j)}{1+|i-j|}$$

$$\text{Contrast} = \sum_{i=1}^{N}\sum_{j=1}^{N} (i-j)^2\text{GLCM}(i,j)$$

$$\text{Mean} = \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

$$\text{Standard deviation}$$
$$= s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2}$$

$$\text{Variance} = s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2$$

$$\text{Mean absolute deviation}$$
$$= MAD = \frac{1}{n}\sum_{i=1}^{n}|x_i-\bar{x}|$$

$$\text{Mean squared deviation}$$
$$= MSD = \frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2$$

$$\text{skew} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{\frac{3}{2}}}$$

$$\text{kurt} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^{2}} - 3$$

$$\text{Entropy} = H = -\sum_{i=1}^{n} P(x_i)\log_2 P(x_i)$$

$$\text{Summation of local binary pattern histogram}$$
$$= \sum_{i=1}^{n} h_i$$

$$\text{Image moment} = m_{p,q} = \sum_x\sum_y x^p y^q \cdot I(x,y)$$

$$\text{Central moment} = \mu_{p,q} = \sum_x\sum_y (x-\bar{x})^p(y-\bar{y})^q \cdot I(x,y)$$

$$\text{Prewitt Filter in xy direction :}$$
$$\begin{bmatrix}-1 & 0 & 1\\ -1 & 0 & 1\\ -1 & 0 & 1\end{bmatrix}\begin{bmatrix}-1 & -1 & -1\\ 0 & 0 & 0\\ 1 & 1 & 1\end{bmatrix}$$

$$\text{Edge Gradient} = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2}$$

$$\begin{aligned}
\text{Hue moment}_1 &= \text{ῆτ}\alpha e_{20} + \text{ῆτα}_{02},\\
\text{Hue moment}_2 &= (\text{ῆτα}_{20} - \text{ῆτα}_{02})^2 + 4\text{ῆτα}_{11}^2,\\
\text{Hue moment}_3 &= (\text{ῆτα}_{30} - 3\text{ῆτα}_{12})^2 + (3\text{ῆτα}_{21} - \text{ῆτα}_{03})^2,\\
\text{Hue moment}_4 &= (\text{ῆτα}_{30} + \text{ῆτα}_{12})^2 + (\text{ῆτα}_{21} + \text{ῆτα}_{03})^2,\\
\text{Hue moments}_5 &= (\text{ῆτα}_{30} - 3\text{ῆτα}_{12})(\text{ῆτα}_{30} + \text{ῆτα}_{12})\\
&\quad \times [(\text{ῆτα}_{30}+\text{ῆτα}_{12})^2 - 3(\text{ῆτα}_{21}+\text{ῆτα}_{03})^2]\\
&\quad + (3\text{ῆτα}_{21} - \text{ῆτα}_{03})(\text{ῆτα}_{21} + \text{ῆτα}_{03})\\
&\quad \times [3(\text{ῆτα}_{30}+\text{ῆτα}_{12})^2 - (\text{ῆτα}_{21}+\text{ῆτα}_{03})^2],\\
\text{Hue moment}_6 &= (\text{ῆτα}_{20} - \text{ῆτα}_{02})[(\text{ῆτα}_{30} + \text{ῆτα}_{12})^2\\
&\quad - (\text{ῆτα}_{21} + \text{ῆτα}_{03})^2] + 4\text{ῆτα}_{11}\\
&\quad \times (\text{ῆτα}_{30} + \text{ῆτα}_{12})(\text{ῆτα}_{21} + \text{ῆτα}_{03}),\\
\text{Hue moment}_7 &= (3\text{ῆτα}_{21} - \text{ῆτα}_{03})(\text{ῆτα}_{30} + \text{ῆτα}_{12})\\
&\quad \times [(\text{ῆτα}_{30}+\text{ῆτα}_{12})^2 - 3(\text{ῆτα}_{21}+\text{ῆτα}_{03})^2]
\end{aligned}$$

$$- (\tilde{\eta}\tau\alpha_{30} - 3\tilde{\eta}\tau\alpha_{12})(\tilde{\eta}\tau\alpha_{21} + \tilde{\eta}\tau\alpha_{03})$$
$$\times [3(\tilde{\eta}\tau\alpha_{30}+\tilde{\eta}\tau\alpha_{12})^2-(\tilde{\eta}\tau\alpha_{21}+\tilde{\eta}\tau\alpha_{03})^2].$$

where:

- $\tilde{\eta}\tau\alpha_{ij}$ denotes the central moment of order (i, j),
- The central moments are calculated using the formulas mentioned earlier for central moments.

D. DEEP LEARNING FEATURES

Deep learning features from images are extracted through CNNs (Convolutional Neural Networks). The early layers of CNNs extract features like corners, textures, and edges. Deeper layers of CNNs extract higher-level features, such as shapes, objects, and semantic representations. To address class imbalance, we applied synthetic minority oversampling technique (SMOTE). After balancing the classes, we used transfer learning and utilized the ImageNet weights with some famous cnns models for feature extraction. Fig 7 and 8 show the results of applying SMOTE on the early-crop-weed and CottonWeedID15 datasets, respectively.

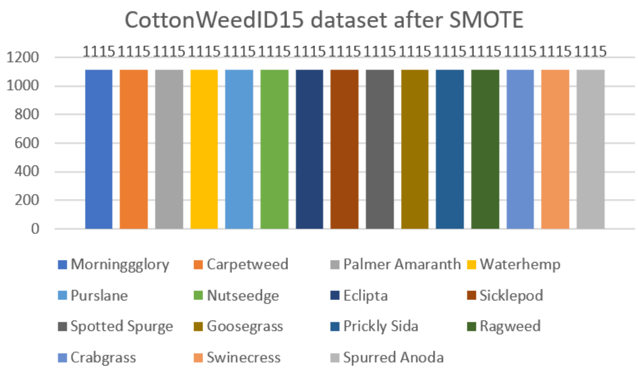

FIGURE 7. Class imbalance removed from the CottonWeedID15 dataset using SMOTE.

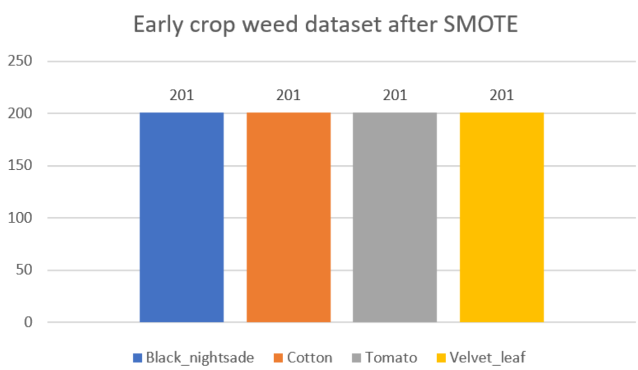

FIGURE 8. Class imbalance removed from the early-crop-weed dataset using SMOTE.

IV. EXPERIMENTS AND RESULTS

1) MANUAL FEATURES AND CLASSIFIERS

After extracting the manual features, we divided them into three ratios. The training dataset ratio was 65%, 20% was for validation and 15%was for testing. These ratios were used to train and evaluate our classifiers: SVM, random forest, and ANN. Among these classifiers, the ANN (Artificial Neural Network) showed superior performance compared to SVM and random forest. The testing accuracy achieved by the Artificial Neural Network was 89.26 on CottonWeedID15 dataset, and on early-crop-weed dataset SVM showed superior performance compared to ANN and random forest. The testing accuracy achieved by the SVM with polynomial kernel was 99 on early-crop weed dataset. We utilized Autokeras for the artificial neural network. Autokeras tests 100 different architectures and selects the best architecture based on validation accuracy.Fig 13 shows the validation and trainning loss. The SVM model's optimal parameters were determined using grid search. After evaluating various options for C, gamma, and degree, the grid search identified the best combination as C = 0.1, degree = 3, gamma = 0.4, and kernel = 'poly'. These parameters were chosen from a range of possibilities: C values included 0.1, 0.2, 0.3, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 10, and 100; gamma values included 0.1, 0.2, 0.3, 0.5, 0.6, 0.7, 0.8, and 0.9; and degree values included 1, 2, 3, 4, 5, and 6. In random forest, we start training with 2 trees and incrementally add 1 tree until we reach a total of 300 trees. Then, we select the tree that achieves the highest validation score and train the random forest using that specific number of trees. Table 1 shows the experiment and results on early-crop-weed dataset of manual features with Artificial neural network classifiers. Table 2 shows the experiment and results on CottonWeedID15 datset of manual features with Artificial neural network classifiers. Fig 9 shows the comparative analysis of classifiers on both dataset. Table 3 shows the experiment and results on early-crop-weed dataset of manual features with SVM and Rndom forest classifiers.

TABLE 1. Experiment and results on early-crop-weed dataset of manual features with Artificial neural network classifiers.

Classes	Experiment 1 ECW+ANN+SMOTE minmax normalization	Experiment 2 SEG+ECW+ANN+SMOTE minmax normalization
Blacknightsade F1 score	0.97	0.79
Cotton F1 score	1	0.95
Tomato F1 score	0.98	0.98
Velvetleaf F1 score	1	0.8

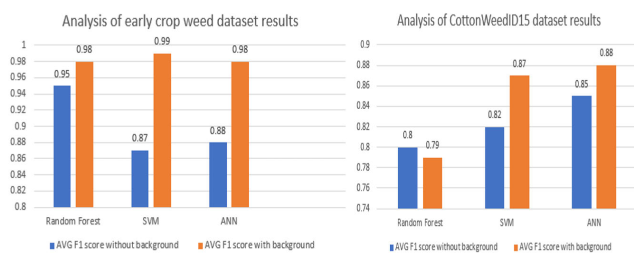

FIGURE 9. Experiment and results on the CottonWeedID15 dataset and early-crop-weed dataset of manual features.

2) DEEP LEARNING FEATURES AND CLASSIFIER

Various CNN architectures, including VGG16, VGG19, Xception, DenseNet-121, DenseNet-169, DenseNet-210, and

TABLE 2. Experiment and results on CottonWeedID15 dataset of manual features with ANN.

Classes	Experiment 1 CWID15+ANN +SMOTE +Manual features	Experiment 2 SCWID15+ANN +SMOTE +Manual features
Carpetweed F1 score	0.79	0.94
Crabgrass F1 score	0.97	0.96
Eclipta F1 score	0.87	0.86
Goosegrass F1 score	0.95	0.92
Morningglory F1 score	0.54	0.55
Nutsedge F1 score	0.95	0.89
Palmer Amaranth F1 score	0.76	0.7
Prickly Sida F1 score	0.96	0.93
Purslane F1 score	0.86	0.87
Ragweed F1 score	0.97	0.93
Sicklepod F1 score	0.91	0.94
Spotted Spurge F1 score	0.91	0.89
Spurred Anoda F1 score	0.98	0.97
Swinecress F1 score	0.99	0.96
Waterhemp F1 score	0.86	0.79

ConvNeXt, were utilized for automated feature extraction. These architectures were initialized with pre-trained weights from the ImageNet dataset. Following the extraction of automated features, a random forest algorithm was employed for classification. Notably, the features obtained from the ConvNeXt architecture outperformed both manual features and features extracted from other CNNs when used with random forest. On the early-crop weed dataset, the random forest model with ConvNeXt achieved a testing accuracy of 98%, while on the CottonWeedID15 dataset, the accuracy reached 89%. In Fig 10 and 11, a comparative analysis is presented, examining the performance of automated features across various architectures when combined with the random forest. table 4 and 5 shows experiments and results on erarly crop weed and segmenter early-crop-weed dataset of deep learning features with random forest classifiers.Table 6 and 7 shows experiments and results on CottonWeedID15 and segmented CottonWeedID15 dataset of deep learning features with random forest classifiers. In random forest, we start training with 30 trees and incrementally add 30 tree until we reach a total of 300 trees. Then, we select the tree that achieves the highest validation score and train the random forest on cotton weed id 15 dataset using that specific number of trees. And on early-crop-weed dataset, we start training with 10 trees and incrementally add 10 tree until we reach a total of 300 trees. Then, we select the tree that achieves the highest validation score and train the random forest on early-crop-weed dataset using that specific number of trees.

3) YOLO V8

YOLOv8, belongs to You Only Look Once (YOLO) family, represents a real-time object detection algorithm that has demonstrated substantial advancements compared to its previous versions. YOLOv8 has a Backbone consists of convolutional layers that extract features from the input image. YOLO v8 also utilizes SPPF layer and convolution

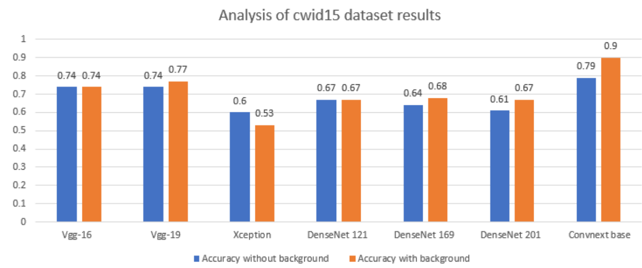

FIGURE 10. Analysis of CottonWeedID15 dataset results.

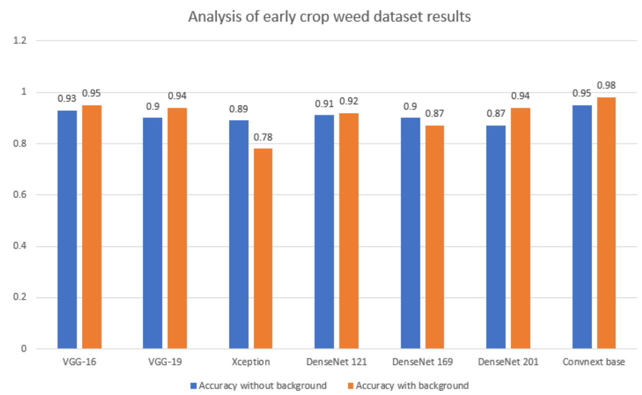

FIGURE 11. Analysis of early-crop-weed dataset results.

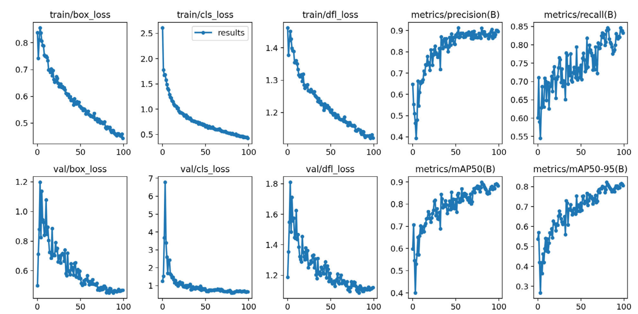

FIGURE 12. YOLOv8 training and validation loss.

layers, YOLO v8 processes features at different scales. The Upsample layers enhanced the feature resolutions. For enhacing detection accuracy, YOLO v8 used C2f module for the integration of contextual information and feature.The Detection module utilizes convolution layers and linear layers for bounding boxes and object classes. We utilized YOLOv8-M for object detection. We initialize the learning rate to 0.01 and used stochastic gradient optimizer with a batch size of 1. Additionally, we initialize weight decay with 0.0005 to prevent the model from becoming overly complex and momentum with 0.9.After 100 epochs, utilizing YOLOv8-M, achieved an overall mean average precision of 89.Table 8 shows analysis of YOLOv8 results. Fig 12 shows YOLOv8 validation and training loss. Fig 14 shows the YOLOv8 confussion matrix on cotton weedid 15 dataset. Fig 15 shows precision recall curve. Fig 16 shows detetection of weed.

TABLE 3. Experiment and results on early-crop-weed dataset of manual features with SVM and Random forest classifiers.

classes	Experiment 1 ECW+RF+SMOTE minmax normalization	Experiment 2 SEG+ECW+RF+SMOTE minmax normalization	Experiment 3 ECW+SVM+SMOTE minmax normalization	Experiment 4 SEG+ECW+SVM+SMOTE minmax normalization
Blacknightsade F1 score	0.96	0.94	1	0.83
Cotton F1 score	1	0.95	0.99	0.92
Tomato F1 score	0.98	0.98	1	0.95
Velvetleaf F1 score	0.99	0.93	0.99	0.79
Best Parameters	19 trees	35 trees	C=0.1 gamma=0.4, kernel=poly degree 3	C=0.3 gamma=0.3, kernel=poly degree 4

TABLE 4. Experiment and results on early-crop-weed dataset of deep learning features with Random forest classifiers.

classes	Experiment 1 ECW+RF +SMOTE VGG16	Experiment 2 ECW+RF +SMOTE VGG19	Experiment 3 ECW+RF +SMOTE Xception	Experiment 4 SEG+ECW+RF +SMOTE Densenet 121	Experiment 5 ECW+RF +SMOTE Densenet 169	Experiment 6 ECW+RF +SMOTE Densenet 201	Experiment 7 ECW+RF +SMOTE Convnext Base
Blacknightsade F1 score	0.96	0.91	0.7	0.86	0.85	0.9	0.97
Cotton F1 score	0.93	0.95	0.75	0.89	0.83	0.96	0.96
Tomato F1 score	1	1	0.91	1	0.97	1	1
Velvetleaf F1 score	0.9	0.9	0.73	0.94	0.86	0.89	0.99
Best Parameters	200 trees	100 trees	160 tree	70 tree	200 trees	90 trees	130 trees

TABLE 5. Experiment and results on segmented early-crop-weed dataset of deep learning features with Rndom forest classifiers.

classes	Experiment 1 SECW+RF +SMOTE VGG16	Experiment 2 SECW+RF +SMOTE VGG19	Experiment 3 SECW+RF +SMOTE Xception	Experiment 4 SECW+RF +SMOTE Densenet 121	Experiment 5 SECW+RF +SMOTE Densenet 169	Experiment 6 SECW+RF +SMOTE Densenet 201	Experiment 7 SECW+RF +SMOTE Convnext Base
Blacknightsade F1 score	0.94	0.92	0.88	0.94	0.95	0.0.84	0.95
Cotton F1 score	0.93	0.88	0.9	0.88	0.87	0.88	0.95
Tomato F1 score	0.95	0.91	0.9	0.97	0.96	0.95	0.96
Velvetleaf F1 score	0.91	0.92	0.88	0.88	0.82	0.99	0.95
Best Parameters	200 trees	100 trees	160 tree	70 tree	200 trees	90 trees	130 trees

TABLE 6. Experiment and results on CottonWeedID15 dataset of deep learning features with Random forest classifiers.

classes	Experiment 1 CWID15+RF +SMOTE VGG16	Experiment 2 CWID15+RF +SMOTE VGG19	Experiment 3 CWID15+RF +SMOTE Xception	Experiment 4 CWID15+RF +SMOTE Densenet 121	Experiment 5 CWID15+RF +SMOTE Densenet 169	Experiment 6 CWID15+RF +SMOTE Densenet 201	Experiment 7 CWID15+RF +SMOTE Convnext Base
Carpetweed F1 score	0.7	0.77	0.46	0.64	0.62	0.69	0.91
Crabgrass F1 score	0.86	0.88	0.57	0.76	0.78	0.72	0.93
Eclipta F1 score	0.63	0.68	0.45	0.55	0.59	0.57	0.81
Goosegrass F1 score	0.63	0.68	0.45	0.55	0.59	0.57	0.81
Morningglory F1 score	0.68	0.77	0.36	0.65	0.6	0.62	0.96
Nutsedge F1 score	0.84	0.87	0.54	0.67	0.65	0.66	0.91
palmer Amaranth F1 score	0.6	0.62	0.42	0.56	0.55	0.53	0.84
prickly sida F1 score	0.72	0.77	0.6	0.7	0.71	0.68	0.86
purslane F1 score	0.76	0.76	0.5	0.69	0.68	0.71	0.84
Ragweed F1 score	0.8	0.77	0.6	0.74	0.79	0.78	0.97
Sicklepod F1 score	0.63	0.73	0.46	0.58	0.67	0.6	0.86
Spotted spurge F1 score	0.7	0.73	0.5	0.65	0.64	0.63	0.86
Spurred Anoda F1 score	0.84	0.83	0.71	0.8	0.79	0.74	0.95
Swinecress F1 score	0.85	0.85	0.75	0.82	0.82	0.83	0.98
Waterhemp F1 score	0.62	0.73	0.47	0.6	0.58	0.63	0.84
Best Parameters	90 trees	190 trees	210 tree	210 tree	300 trees	240 trees	300 trees

TABLE 7. Experiment and results on Segmented CottonWeedID15 dataset of deep learning features with Random forest classifiers.

classes	Experiment 1 SCWID15+RF +SMOTE VGG16	Experiment 2 SCWID15+RF +SMOTE VGG19	Experiment 3 SCWID15+RF +SMOTE Xception	Experiment 4 SCWID15+RF +SMOTE Densenet 121	Experiment 5 SCWID15+RF +SMOTE Densenet 169	Experiment 6 SCWID15+RF +SMOTE Densenet 201	Experiment 7 SCWID15+RF +SMOTE Convnext Base
Carpetweed F1 score	0.61	0.61	0.41	0.59	0.55	0.52	0.73
Crabgrass F1 score	0.71	0.73	0.62	0.59	0.54	0.52	0.8
Eclipta F1 score	0.78	0.8	0.64	0.67	0.68	0.62	0.75
Goosegrass F1 score	0.71	0.74	0.49	0.65	0.62	0.61	0.8
Morningglory F1 score	0.74	0.69	0.62	0.67	0.65	0.63	0.68
Nutsedge F1 score	0.57	0.55	0.45	0.53	0.47	0.46	0.72
palmer Amaranth F1 score	0.78	0.75	0.64	0.7	0.64	0.61	0.84
prickly sida F1 score	0.67	0.67	0.56	0.58	0.57	0.5	0.77
purslane F1 score	0.79	0.78	0.73	0.73	0.75	0.75	0.78
Ragweed F1 score	0.71	0.76	0.55	0.58	0.52	0.54	0.85
Sicklepod F1 score	0.77	0.71	0.58	0.7	0.62	0.6	0.67
Spotted spurge F1 score	0.92	0.92	0.76	0.83	0.84	0.82	0.95
Spurred Anoda F1 score	0.92	0.88	0.78	0.83	0.77	0.74	0.79
Swinecress F1 score	0.58	0.53	0.4	0.54	0.41	0.4	0.74
Waterhemp F1 score	0.87	0.88	0.77	0.81	0.8	0.74	0.91
Best Parameters	90 trees	190 trees	210 tree	210 tree	300 trees	240 trees	300 trees

TABLE 8. Analysis of YOLO v8 reults.

Classes	images	instances	Box(P)	Recall(R)	map 50
All	1563	1770	0.911	0.839	0.822
Carpetweed	1563	328	0.83	0.686	0.664
Crabgrass	1563	56	0.97	0.586	0.587
Eclipta	1563	95	0.79	0.758	0.722
Goosegrass	1563	68	0.948	0.838	0.827
Morningglory	1563	367	0.909	0.874	0.865
Nutseedge	1563	84	0.867	0.94	0.704
Palmer Amaranth	1563	209	0.986	0.952	0.918
PricklySida	1563	42	0.922	0.85	0.868
Purslane	1563	154	0.916	0.916	0.912
Ragweed	1563	40	0.96	0.605	0.866
Sicklepod	1563	73	0.973	0.98	0.691
SpottedSpurge	1563	72	0.986	0.957	0.945
SpurredAnoda	1563	20	0.824	0.8	0.755
Swinecress	1563	22	0.875	0.909	0.864
Waterhemp	1563	140	0.914	0.936	0.877

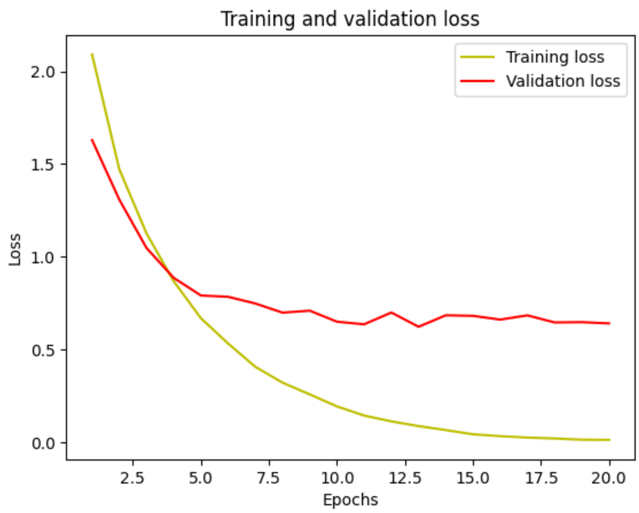

FIGURE 13. Training and validation loss of artificial neural network.

V. DISCUSSION

Do deep learning features yield more accurate results compared to hand-extracted features? Yes, deep learning features indeed produce more accurate results than hand-extracted features, as demonstrated by our experiments. Despite the utilization of Prewitt filters for edge and fine detail enhancement, ConvNext still outperformed manual features in terms of accuracy. But with deep learning, we require high computation compared to using manual features with classifiers.

Is the synthetic minority oversampling technique (SMOTE) effective for weed classification problems? Yes, the synthetic minority oversampling technique (SMOTE) proves to be effective for weed classification problems, especially when dealing with unbalanced datasets. The use of Synthetic Minority Over-sampling Technique (SMOTE) addressed the class imbalance inherent in weed detection datasets. By generating synthetic samples for the minority class, the training set became balanced, preventing the model from being biased toward the majority class. This led to improved generalization and better performance on previously underrepresented weed instances. With the implementation of SMOTE, we were able to achieve 89% accuracy on the cotton weed ID 15 dataset and 99% accuracy on the early-crop-weed dataset. Both of these datasets were unbalanced, and SMOTE played a crucial role in attaining such high accuracy.

Does YOLOv8 perform well in agricultural problems?

Yes, YOLOv8 is an extremely powerful state-of-the-art object detection model. The model's ability to handle complex scenes and diverse weed types is a significant advantage, showcasing its suitability for agricultural applications. It performed exceptionally well in agricultural problems. The implementation of YOLO v8 for weed detection yielded promising results, achieving an overall mean average precision (mAP) of 89.

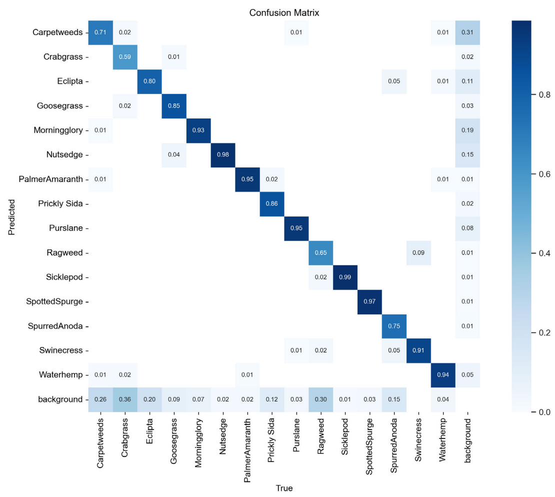

FIGURE 14. YOLO v8 confussion matrix on CottonWeedID15 dataset.

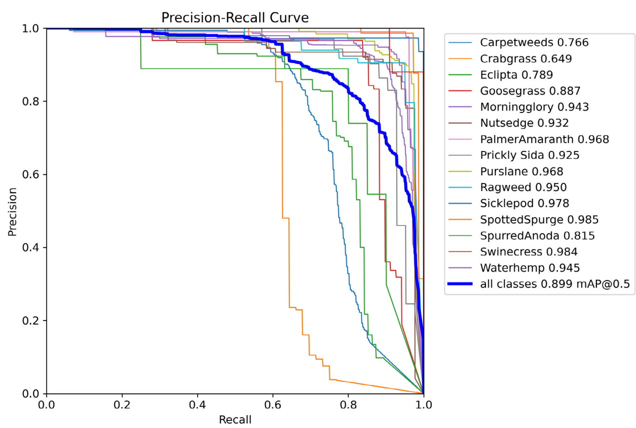

FIGURE 15. YOLO v8 Precision recall curve on CottonWeedID15 dataset.

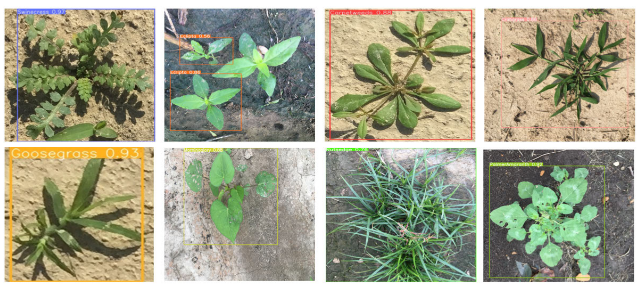

FIGURE 16. Detection of weed using YOLO v8.

IoT devices find application in agriculture, yielding positive outcomes. For secure operation of IoT devices in agriculture, an Intrusion Detection System (IDS) is essential [30]. The authors explored Machine Learning (ML) and Deep Learning (DL) techniques to enhance cybersecurity and prevent potential threats. Optimization algorithms enhance the learning capabilities of mathematical models [31]. In their work, the authors proposed an improved Chicken Swarm Intelligence (CSI) to optimize Support Vector Machine (SVM) learning parameters. They compared their proposed CSI with Particle Swarm Optimization (PSO) and Bat Algorithms. As observed, deep learning models are producing good results, but they still need improvement. To enhance deep learning models performance, [32] introduced marginal deep architectures, incorporating marginal Fisher analysis and introducing stacked feature learning modules. Their results show improvement, particularly in classification, and speech recognition problems.

Agricultural countries, with their predominantly agrarian economies, play a crucial role in the global agricultural landscape. The application of advanced technologies, such as deep learning, in the agricultural sector can have profound implications for improving productivity, sustainability, and crop yield. The integration of deep learning models, such as YOLOv8, into agricultural practices holds the potential to address challenges related to crop monitoring, pest control, and resource optimization.

To further advance weed detection in crops, future research could focus on refining the model's robustness to environmental factors and expanding the dataset to encompass a broader range of agricultural scenarios. Investigating transfer learning techniques and exploring the use of multi-sensor data for more accurate weed identification are potential avenues for improvement.Current research predominantly relies on RGB images for weed detection. Exploring the integration of multispectral data, such as infrared or hyperspectral imagery, could provide additional insights into weed characteristics and improve the model's accuracy, particularly in scenarios where visual cues alone may be insufficient.

VI. CONCLUSION

Agriculture is facing weed challenges, and automated weed control systems can assist farmers in crop production while also lowering production costs. A large image dataset is required for future work to meet the challenges of real time in agriculture. Moreover, deep convolutional generative adversarial networks should utilized for crop and weed augmentation. This approach allows us to enhance the agricultural dataset. Deep learning architectures produced great results, but room for improvement still exists. Deep learning algorithms are becoming a new step in improving crop yield and getting rid of these weeds more efficiently. People in agricultural countries are continuing to use traditional approaches due to lack of awareness of deep learning technologies. However, they should be directed toward modern technology to improve agriculture and crop yield. The key contributions of this research lie in advocating for the utilization of advanced technologies, particularly deep learning, to overcome traditional agricultural constraints. This shift has the potential to significantly impact the agricultural community by fostering increased awareness and adoption of modern techniques in the world, thereby elevating agricultural practices and crop yields. The study aims to catalyze a transformative impact within the community of practice and the relevant industry by promoting the integration of state-of-the-art technologies for sustainable and efficient weed management in agriculture.

DECLARATIONS

Data Availability: The dataset used in this research [8] is freely available.

Conflict of Interest: It is declared by the authors that there is no conflict of interest.

Code availability Code can be provided on request.

Authors' contributions Syed Mujtaba Hassan Rizvi worked on algorithm implementation and wrote the initial draft of the article. Asma Naseer floated the idea, supervised the implementation, contributed to the article write-up, and helped in implementation. Shafiq Ur Rehmanverified and analyzed the results and contributed to the article write-up. Sheeraz Akram improved the algorithm and the article write-up. Volker Gruhn funded the project and supervised it.

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