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Crop Weed Identification System Based On Convolutional Neural Network

[1]K. Srinidhi Reddy, [2]Kaithapuram Sirichadana, [3]Sanganamoni Srivani, [4]Jakkula Varalaxmi
[1] Assistant Professor, Electronics and Communication Engineering, BRECW
[2,3,4]B.Tech Students, Department of Electronics and Communication Engineering, BRECW

ABSTRACT

Crop and weed classification is a critical task in precision agriculture, aiding in the efficient management of crops and reducing herbicide use. Traditional methods of classification rely heavily on manual labor and are often time-consuming and subjective. In recent years, deep learning neural networks have emerged as powerful tools for automating classification tasks in various domains. In this study, we explore the application of deep learning neural networks for crop and weed classification using image data.

We propose a novel approach that leverages convolutional neural networks (CNNs) to automatically extract features from images of crops and weeds. We train the CNN on a large dataset of annotated images, enabling it to learn discriminative features that distinguish between different crop and weed species. Additionally, we employ data augmentation techniques to enhance the model's generalization capabilities and improve its performance on unseen data.

Experimental results demonstrate the effectiveness of our approach in accurately classifying crops and weeds across different environmental conditions and growth stages. The proposed deep learning-based system offers several advantages over traditional methods, including scalability, adaptability, and automation. Moreover, it has the potential to significantly reduce the time and resources required for crop and weed classification, thereby facilitating more sustainable and environmentally friendly agricultural practice

INTRODUCTION

Crop production is an important component of the agriculture system and is responsible for global food management. Therefore, it is imperative to invent new trends and scientific methods to properly plan and manage them. As per recent studies, it has been found that weed growth and density strongly impact the agriculture system which results in crop yield loss. Weed is the undesirable plant in a particular situation or "a plant in the wrong place". In the entire world out of 2, 50,000 plant species, 250 weed family species are prominent in the agricultural and non- agricultural systems. Owing to different conditions and factors around the world about 30,000 species are grouped as weeds and categorized in different families . In general, weeds compete for the nutrients, water, sunlight, and space for their growth. Weed as well as the crop requires nutrients such as nitrogen, phosphorus, and potassium for their growth. As there is an increase in weed growth, it shows a negative impact on crop yield.

LITRATURE REVIEW

Jin, Che & Chen (2021) have discussed the different types of weed categories in rabi crops. Authors have used 3716 multi-class weed images. They resized the image using the pre- processing technique. Further, the authors used the segmentation technique for object detection. They have used 3 different classifiers such as ResNet -152 V2, VGG-19, and EfficientNet B2. After comparing the come Efficient B2 model has achieved 96% accuracy.This section has discussed weed detection, growth, density, and crop yield loss estimation using deep learning techniques. This review includes identification, detection, and density estimation of weed based on machine learning and a deep learning approach.

Kaur & Gautam (2021) have discussed the monocot dicot crop leaves identification and detection using Inception V3 architecture achieving 90.79% accuracy. They have worked with five different leaf stress such as “Target_Spot”, “Leaf_mold”, “Bacterial_spot”, “Early_blight”, and “Early_blight” classified on cucumber leaves. The author has compared different CNN models such as ResNet-151, VGG-19, and Inception V3 pre-trained CNN models for disease identification and detection. After comparison, the authors have achieved 96% accuracy [86].

Kropff (2021) has suggested the scattering transformation for texture classification of weed images; it also includes Gary Level Co-occurrence Matrix (GLCM) and binary patterns. This pattern doesn’t include combined steps for wavelet decomposition of weed image. The scattering transform has been further trained for synthetic data and proved to achieve 85% accuracy. This technique does not introduce overlapped weeds/crop images in different crops; it has worked only for the synthetic dataset [88].

Wu et al. (2021) have discussed K-Mean combined with CNN multilayer fine-tuning of various parameters using a proposed algorithm. They have also discussed weed identification and detection on soya bean plants associated with different CNN parameters. The authors have collected the visual texture and morphological features of weed leaves. They extract the GLCM techniques for textures were extracted from images.

Misra, Crispim & Tougne (2020) have discussed the nutrients deficiency in the soil and estimated the compound nutrients such as carbon (OC), Phosphorus pentoxide (P2O5), Manganese (Mn), and Iron (Fe), soil pH worth, and types, soil supplements nitrous oxide (N2O) existed in soil. Other supplements such as P2O5 and Potassium Oxide (K2O) also estimated the prediction based on crop yield loss using various Supervised Machine Learning algorithms.

3-MATERIALS AND METHODS

The datasets involved in weed detection, classification, weed/crop growth, and density estimate are described in this chapter. Firstly, we provide information regarding the dataset, pre- processing, and segmentation techniques. The different types of CNN models are also explained in this chapter. The data has been collected from a standard data repository as Crop Weed Field Image Dataset (CWFID). There are eleven different types of data in this category. A separate part describes the characteristics of the dataset obtained for the research gap. The quality of data is maintained by removing noise, and enhancement using pre-processing. Further enhanced and normalized to attain the optimal performance when using the Deep Learning technique. Fig 3.1 shows the steps involved in the detection and classification of weeds.

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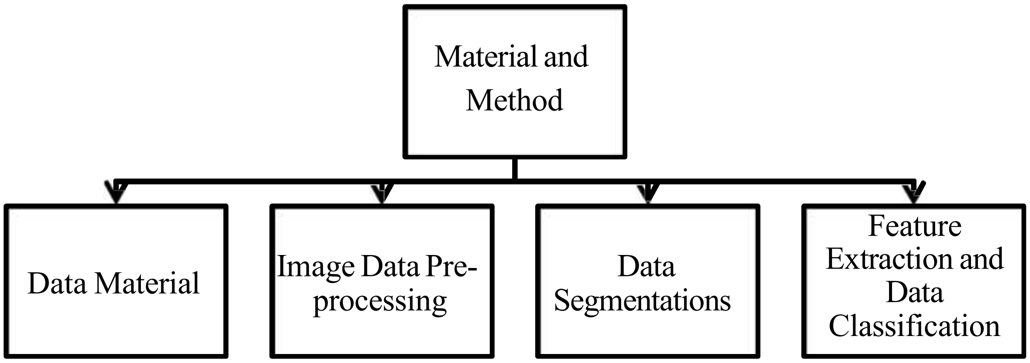

Fig 3.1 Steps involved in the classification and detection of weed image.

Data Material

The weed image data has been collected from different and secondary resources. This data has provided information about the discrimination of crop and weed data in the soya bean crop field.. This research has used standard datasets, i.e. Crop Weed Field Image Dataset (CWFID) in the soya bean crop.

The complete dataset provides information about the weeds and crops based on images of soya bean crops. The dataset of CWFID of soya bean crops has publicly available on https://github.com/cwfid/dataset. CWFID is a benchmark standard for crop and weed identification in single plant phenotyping and other precision agriculture computer vision tasks. This dataset includes 332 weed species from 160 different crops, including soybean, rice, carrots, and wheat. All photos are self-contained and provide ground truth images.

Proposed Methodology

This section has been describing the System structure and proposed methodology for weed growth and density estimation in the soya bean plant.

4-Hybrid Deep Learning Model for Weed Growth and Density Rate Estimation

In India, agriculture is the main source of income for the Indian economy. It is believed that agriculture can become a support for the economy in the coming times. Recently released data has revealed that agriculture has been the only sector that has grown throughout the year. The weeds within the crops will absorb macronutrients such as nitrogen (N), Phosphorus (P), and Potassium (K) are major nutrients that are important for crop growth, but it has been absorbed that weeds and affects crop yield production. The complete flow of the algorithm is given in fig 4.1.The proposed Crop Yield Loss Estimation due to Weed (CYLEW) has achieved a complete result of crop yield loss due to weeds. As many authors have also worked regarding weed detection, growth estimation, plant disease identification, etc., the major contributions in this work are:

5-RESULT AND ANALYSIS

This chapter discussed weed and crop growth comparison and weed density estimation. The comparative analyses of a proposed model from the existing model are discussed in the next section. This chapter also gives detailed information on the outcomes, results, and performance of all algorithms that have been used for building growth and density system.

5.1.1 Training and Testing Dataset

For training images used window size 336 × 320 × 3. Weed images containing multiclass weed species have been considered for observation. The training and testing of image classification have been performed using 8400 data images. The distribution of data among the model has depicted in fig 5.1.

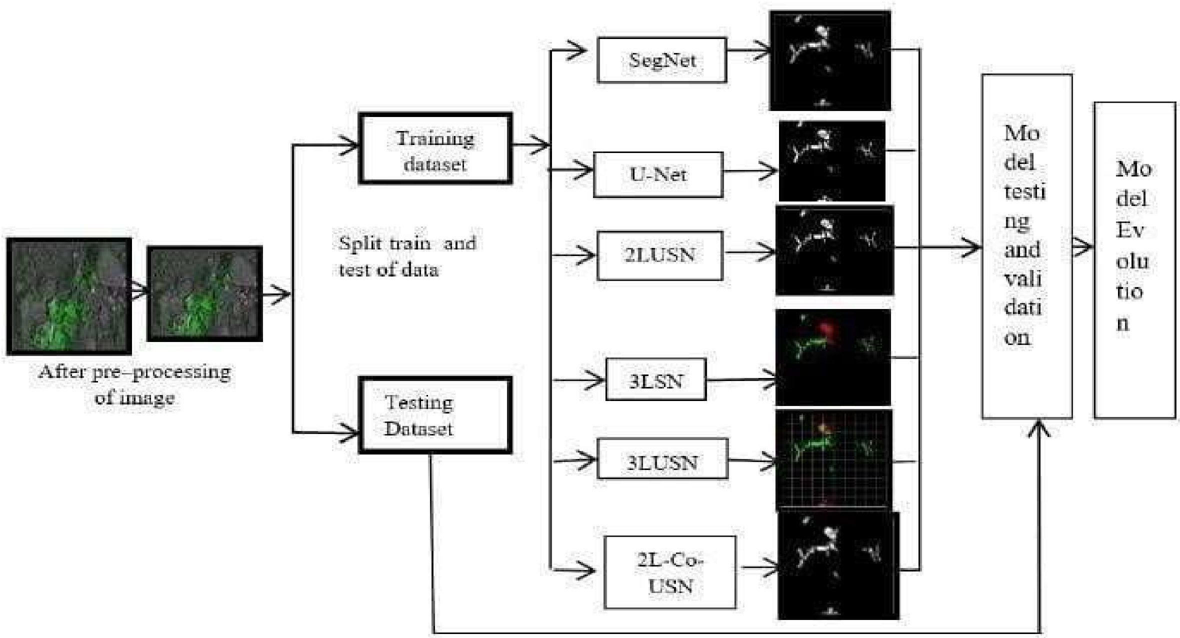

Fig 5.1. Distribution of data among the model.

5.1.2 Weed Growth Estimation

This work has estimated the weed growth and density estimation in the soya bean crop plant. The complete steps of the weed growth plant (Chenopodium Album) are depicted in fig 5.2. This image is shown in the seeding stage, V1 first node of leaf, V2 second node of leaf, V3 is the third node and remaining stages are R1 as the flowering stage, R2 is beginning of pod stages and finally shown S1 stage of leaf fall.

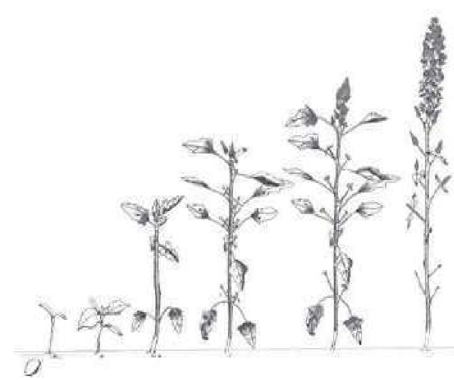

Fig 5.2. Growth stages of weeds („ChenopodiumAlbum").

The leaf count and coverage area are important factors to reduce the yield loss. This observation has been done using vegetation segmentation.

There are five different parameters such as growth

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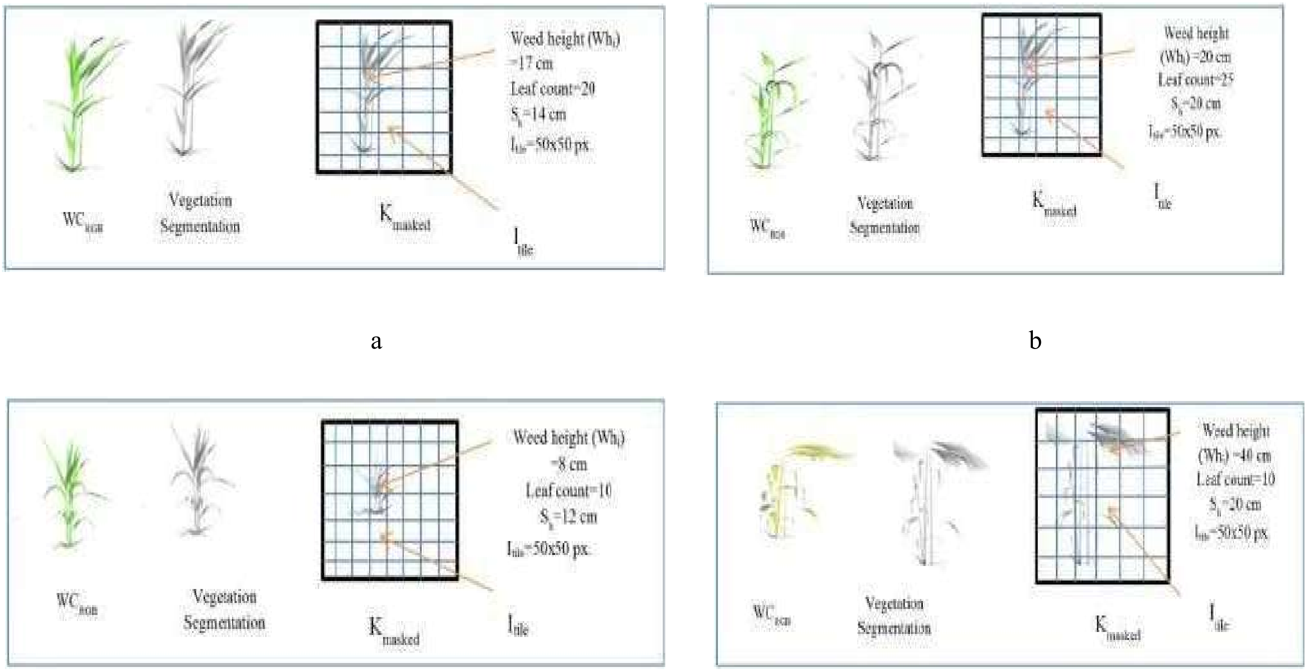
stages, predicted height and no of leaves, miss classified weed plants, incorrect vegetation segmentation, and overlapped plant using vegetation segmentation. Descriptions of weed plant height based on tile classification are given in fig 5.3



a b

c d

Fig 5.3. Growth analysis of weeds in different stages such as a, b, c, d.

The seeding stages of the weed plant are uncountable and the remaining V1, V2, V3, R1, R2, and S1 stages are given in Table 5.1.The heights of weed and vegetation coverage area ofimage data are classified using $WStile$ in the "Chenopodium Album" plant. In this study, the "Chenopodium murale", "Melilotus albus" and "Avena fatua" weeds have more effect on crop plants which has 40 cm has crop growth.

Growth stages of weed	**Predicted height (WS_h) and no leaf in a plant (WL_c)**	**Misclassifie d weeds plant (%)**	**Incorrect vegetation segmentation (%)**	**Overlapped plant using vegetation segmentation (%)**
V1 first Node	WS_h= 2, WL_c= 7	5.23	42.12	2
V2 Second Node	WS_h=12, WL_c = 8	52.12	45.74	2
V3 third	WS_h 17,	57.25	40.52	2

Node	WL_c = 20			
R1 begins to flower and the pod	WS_h=20, WL_c = 25	48.18	46.74	3
R2 begins to flower and the pod	WS_h=30, WL_c = 25	58.25	39.81	1
S1 start leaf fall	WS_h=40, WL_c = 12	57.10	40.41	2

Table 5.1. Summary of different parameters related to vegetation segmentation of weeds

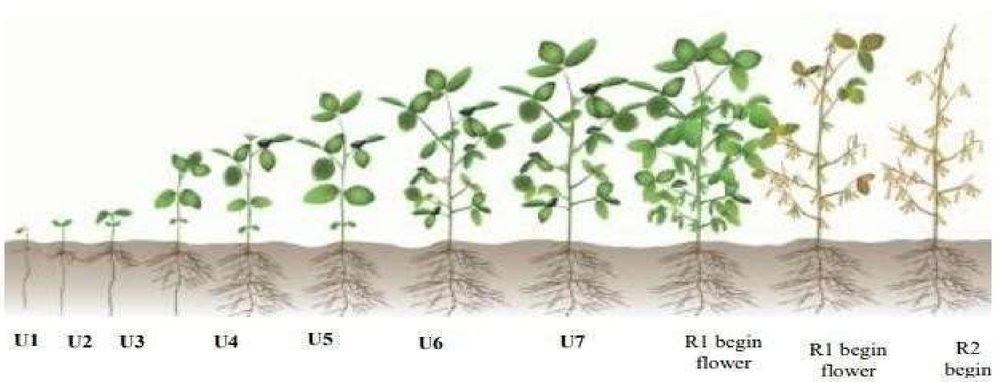
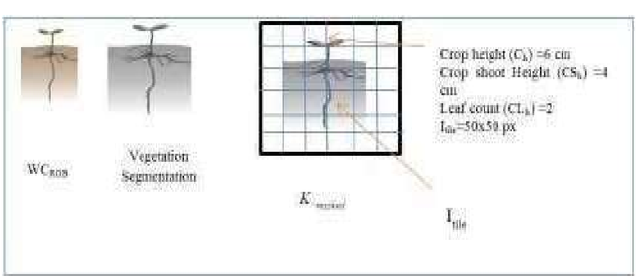


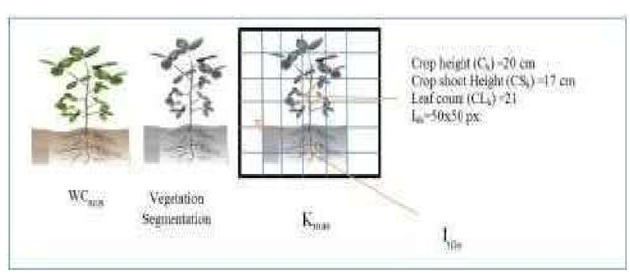
Fig 5.4. Complete growth stages of soya bean plant

The crop (Soya bean) growth has been categorized as U1 as the seeding stage, U2 as the first node of the leaf, V3 as a third node, and the remaining stages are U4, U5, U6, and U7 are growing stages.

The R1, R2, and R3 are bringing of flower, pod, and seed stages respectively, and finally S1 stage of leaf fall. The complete crop (soya bean) growth stages and segmented analysis are directed in fig 5.5.



a



b

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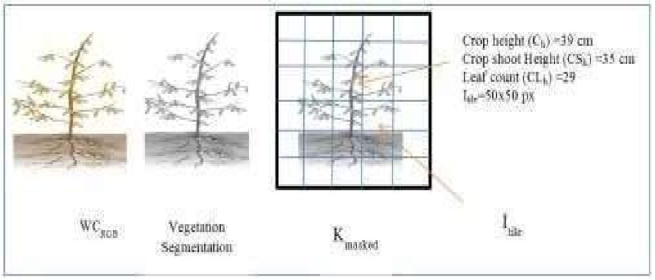
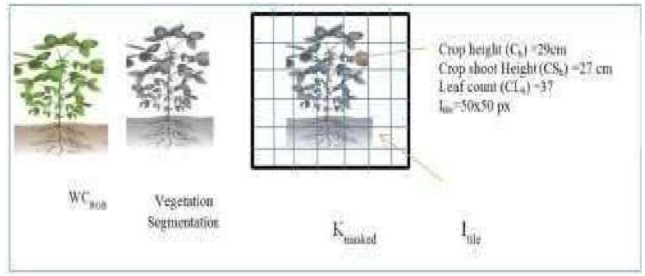
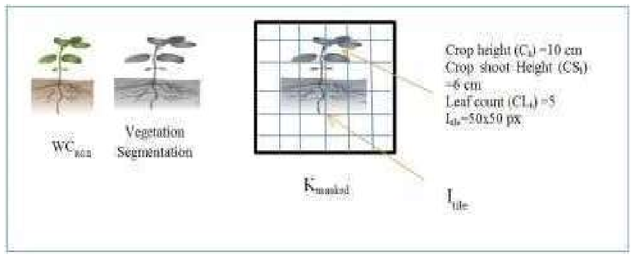


c



d



e

Fig 5.5. Crop growth estimation is based on different growth stages such as a, b, c, d, and e.

The height of crops and vegetation coverage area of image data has been predicted the soya bean plant growth stages are given in Table 5.2. The heights of weed and vegetation coverage area of image data are classified using $WStile$ in soya bean plant.

Based upon the observation maximum WSh is 40cm and WSh for a crop is 35 cm which has more growth compared to crop growth [126]. The comparative analysis of weed and crop growth is depicted. The proposed work has been analyzed based upon a few parameters such as weed shoot height (WSh), leaf count (CSh), weed coverage, miss classified crop leaf, incorrect leaf count, and overlapped leaf classification. Based upon the observation maximum WSh is 40cm and WSh for a crop is 35 cm which has more growth compared to crop growth [126]. The comparative analysis of weed and crop growth is depicted.

Growth stage of crop	**Predicted Height and no leaf in plant**	**Misclassified crops plant leaf (%)**	**Incorrect vegetation segmentation (%)**	**Overlapped plant using vegetation segmentation (%)**
Seeding	WLc=1and WSh=4cm	55.28	42.72	2

Beginning of First Node(U1)	WLc=2and WS=6cm	52.28	45.72	2
Beginning of the second and third Node(U2,U3a nd)	WLc=5and WSh=10cm	57.28	40.72	2
Growing Stage(V4toU7)	WLc=21 and WSh=20cm	57.28	46.72	3
Flowering, Pod and seed stage(R1,R2,R3)	WLc=37 and WSh=29cm	48.28	39.72	1

Table 5.2. Summary of different parameters related to vegetation segmentation of crops

Weed density Estimation

Measure the number of weed species in a unit area called weed density. For a site-specific weed management system, it is a crucial task to estimate weed density. These density estimates are not for specific weed plant species; rather density includes different functionality of leaf factors. After identifying the weed-infested area calculate the weed density estimation. The next step is to identify weed covered in the field for weed density. Vegetation Cluster Rate (VCR) is used to calibrate the weed image that is defined as follows.

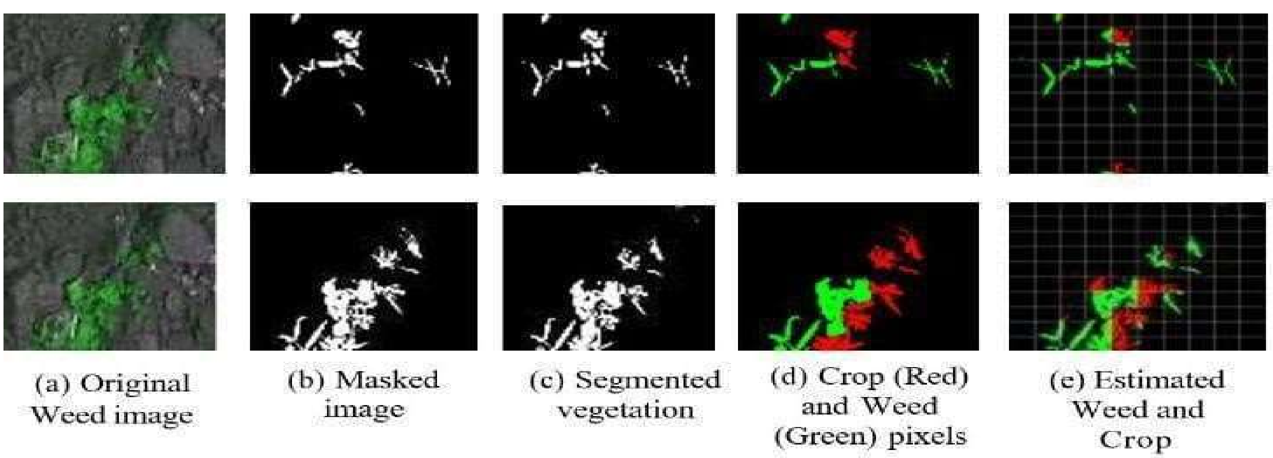


fig 5.6. Weed density Estimation

Table 5.3. Time consumption of tile processing

Length of tile size	25 × 25 px	50 × 50 px	100 × 100 px
Computation time	4.97	0.89	0.99

Model	**Dataset**	**mIoU**
SegNet	CWFID	0.89
U-Net		0.90
3LSN		0.90
3L-USN		0.91
2L-USN		0.92
2L-Conv-USN		0.93

Table 5.4. Quantitative evolution for vegetation segmentation

The next is vegetation cluster rate using ground-truth value has estimated using Ground truth vegetation coverage ($CoverageGT$) predicted vegetation coverage ($Coveragepred$) are compared using mIoU merit. The vegetation cluster rate evolutions are given in table 5.5. The weed density for each tile is measured by cluster rate. The estimated cluster rate ($CRest$) is compared against cluster rate in ground truth pixel-wise annotation. ($CRgt$). A comparison of the estimated clustered cluster rate for the weed-infested region with the ground truth value is presented in Table 5.6.

Dataset Name	**Mean Accuracy (MA) in %**	**Mean Absolute Error (MAE) in %**	**Root Mean Square Error (RMSE) in %**
CWFID	83.56	1.72%	3.12
Ground Truth dataset	86.93	1.89	3.20

Table 5.5. Accuracy of weed/crop density estimation

Comparison of different CNN models with a base model

The calculation was compared with state-of-the-art strategies such as Accuracy, F1 score, Intersection over union, Precession, and Recall given below in table 5.8. The semantic and vegetation segmentation, color texture, and shape are described using the proposed HDS-CNN model.

Segmentation Methods	IoU (%)	Accuracy (%)	Precision (%)	Recall (%)	ST (ms)
SegNet	87.43	90.69	75.64	79.43	79.21
U-Net	92.33	95.62	87.43	82.55	46.24
3LUSN	94.40	94.84	93.33	92.85	39.90
3LSN	95.40	97.02	84.43	91.85	40.09

Table 5.6. Comparison of HDS-CNN model from SegNet and U-Net CNN models.

The proposed model has been compared from SegNet, U-Net, 3LSN, 3LUSN, 2LUSN, and 2L- Conv-USN CNN models. The 2L-Conv-USN have been achieved the maximum data accuracy of 98.95% which is given in fig 5.10. The existing SegNet and U-Net models achieved the maximum data accuracy was 90.69% and

95.62% respectively. The 3LSN, 3L-USN, and 2L-USN models have achieved 97.02%, 98.84%, and 98.05% data accuracy which is better than SegNet and U-Net models. The 2L-Conv-USN models have achieved 98.95% data accuracy Further, WDE and WGE algorithms provide the complete data after processing for training and testing. The weed image data has been divided into 80:20 for training and testing. The proposed model has achieved 98.95% data accuracy

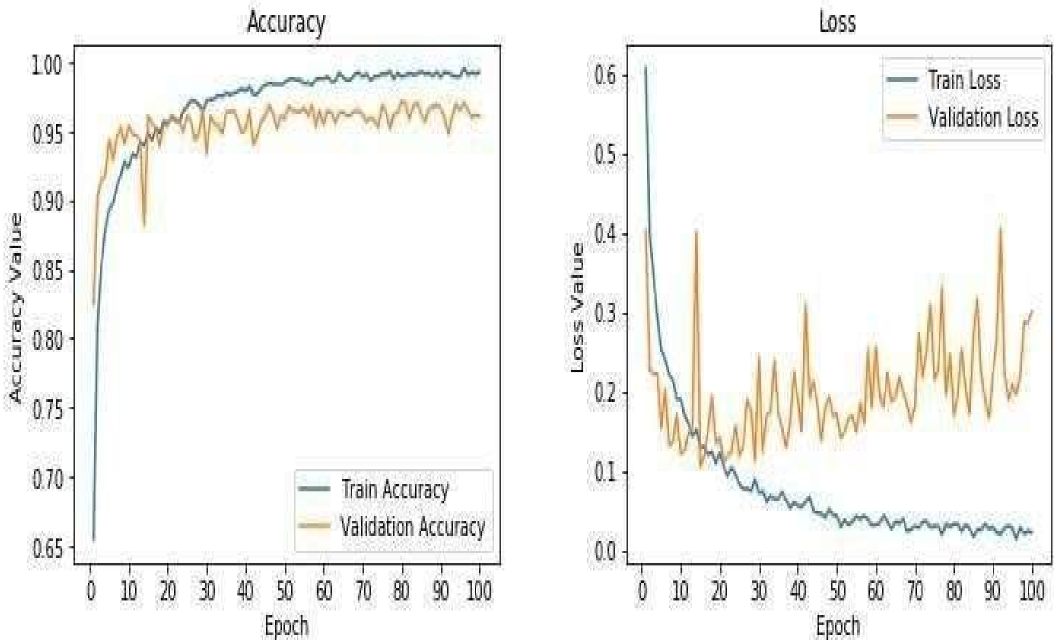
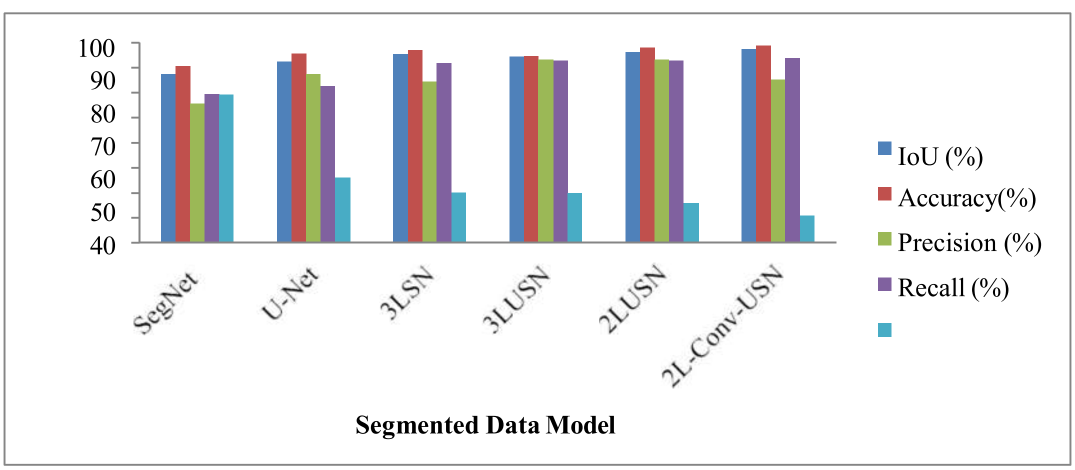


Fig 5.7. Comparative data analysis of the proposed HDS-CNN model. a) The Proposed model‟s data accuracy b) Training and Validation loss of a model.



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The loss function of the HDS-CNN Model for CYLEW

In a convolutional neural network, the loss function is used to calculate the error rate of the model which has an estimate based on the prediction value of the confusion matrix. The minimum error rate has indicated certain recognition capability. In general, the loss function is mostly classifying the Binary cross-entropy.

Performance Rating

In this study, there are 5 quantities criteria were used to evaluate the segmentation network. The segmentation performance [40] is shown in terms of F1 Score, Precision, Recall, IoU, and Accuracy are discussed in equations 5.5, 5.6, 5.7, and 5.8 [51][129]. There are 6 weed families and 10 different weed species have been categorized. Positive represents all regions correctly assigned to any class

of weed leaf, True Negative represents those leaves that are efficaciously recognized as crop plants; False Positive represents a plant thatis incorrectly assigned to weed class that has shown false leaf image identification; False

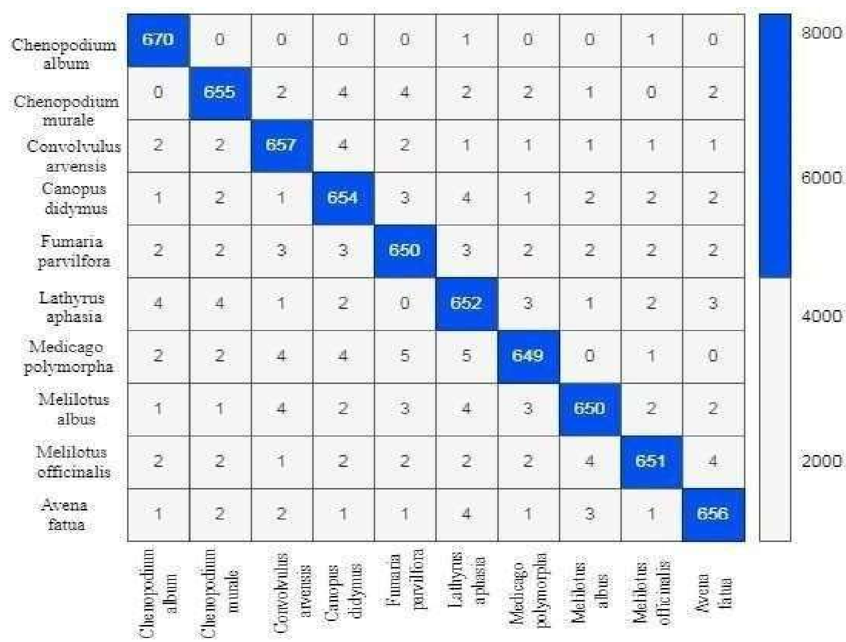

Fig 5.8. Confusion matrix of weed growth and density.

6-CONCLUSION

We proposed a novel scheme for spectrum sensing in MIMO-OFDM based Cognitive Radio system in this paper. Compared with traditional MIMO-OFDM system, where the signals received in each antenna are sampled by an individual analog-to-digital converter (ADC), our scheme can mix the received signals from multiple receiving antennas together and sample them signal through a single ADC by exploiting the sparsity model of the sub carriers allocated in transmission signals, which an lead to a signific an reduction of hardware cost.

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