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“CROP AND WEED CLASSIFICATION BASED ON MACHINE LEARNING TECHNIQUES”

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ABSTRACT

The agriculture sector is undergoing significant transformation due to technological advancements and the rise of precision agriculture, which utilizes data analytics for various applications. A crucial application of precision agriculture is crop-weed detection using machine learning and deep learning algorithms. A major challenge for these automated detection algorithms is the noise and disturbances in images captured by unmanned aerial vehicles (UAVs). This paper analyzes feature extraction followed by machine learning for crop weed detection, incorporating noise removal and feature extraction to improve the training process. Additionally, an attention-based deep learning model has been developed to identify critical information from large datasets, enhancing training efficiency. A comparative analysis of both approaches regarding classification accuracy is presented. The experimental results demonstrate that the proposed approach surpasses contemporary deep learning algorithms such as CNN, ResNet, YOLO, and RCNN in terms of classification accuracy.

Key Words: Precision Agriculture, Crop-Weed Detection, Feature Extraction, Deep Bayes Net, Regularization, Classification Accuracy.

I. INTRODUCTION

Precision agriculture is one of the emerging technologies that is causing a rapid transformation in the agricultural sector. Precision agriculture is a contemporary agricultural technique that maximizes crop yield and boosts efficiency via the use of cutting-edge technology and data analysis. It makes the optimum use of resources like water, fertilizer, and seeds to maximize yields while minimizing waste and environmental damage are the core objective of precision agriculture. Among the principal uses of precision agriculture are [1]:

Soil mapping: Precision agriculture begins with a thorough analysis of soil type, composition, and fertility, enabling farmers to make informed decisions about crop selection and management. Variable-rate planting: This technique allows farmers to plant seeds at different rates based on specific field conditions, optimizing yields and reducing waste. Precision irrigation: By utilizing data and analysis to monitor soil moisture levels, farmers can make informed decisions about when and how much to water their crops, conserving water and minimizing waste. Crop monitoring: Precision agriculture enables real-time monitoring of crop growth and health, helping farmers identify and address potential issues before they escalate.

Yield mapping: This approach allows farmers to accurately map yields and pinpoint underperforming areas in the field, guiding future planting decisions and optimizing production. Weed and pest management: Image processing and machine learning techniques automate and expedite the task of crop weed classification, enhancing system productivity..

All things considered, precision agriculture is a significant advancement towards the creation of efficient and sustainable farming methods and has the potential to completely change how food is produced and cultivated

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worldwide. Although precision agriculture may be applied in many different contexts, one of the most prevalent but significant applications is the categorization of crop weeds. It is vitally essential because, if not found and removed in its early phases, weeds will harm the primary crop. [3].

Crop weed categorization is based on the identification and separation of weeds from crops in agricultural settings. In precision agriculture, this is an essential duty that helps farmers control weed infestations, use fewer herbicides, and produce more crops. In order to automate the process of classifying weeds, machine learning techniques have become increasingly popular in recent years. With the use of machine learning and sophisticated image processing techniques, automated crop-weed categorization has become more popular. The practice of sorting crops in an agricultural field from weeds is known as crop weed classification. A branch of artificial intelligence known as "machine learning" makes use of statistical models and algorithms to teach computers how to analyze and forecast data.

Computers can learn from data and generate predictions using statistical models and algorithms, which are used in machine learning, a branch of artificial intelligence. Using tagged data, machine learning algorithms may be trained to discriminate between crops and weeds in the context of crop weed classification.

Various methods are employed in machine learning for crop weed classification, including supervised learning, unsupervised learning, and deep learning. Supervised learning algorithms, like decision trees and support vector machines, utilize labeled data to learn and distinguish between crops and weeds. Unsupervised learning algorithms, such as clustering, detect patterns and relationships in the data without labeled examples. Deep learning algorithms, such as convolutional neural networks, analyze complex image data to identify crops and weeds.



Figure 1: An example of weed infestation

The effectiveness of machine learning-based crop weed classification depends on various factors, including the quality of the training and testing data, the selection of algorithms and features, and the presence of noise and variability in the data. Despite these challenges, research has demonstrated that machine learning can be highly effective in crop weed classification, offering potential improvements in efficiency and accuracy.

On use of machine learning models for crop weed classification, several critical factors must be considered. These include the size and quality of the training data, the selection of features to represent the images, and the evaluation metrics used to measure model performance. Attention to these factors can enhance the model's accuracy and effectiveness in classifying crop weeds. Machine learning models have demonstrated their potential to significantly improve the management of weed infestations in agricultural fields. By selecting the appropriate model and carefully

considering these factors, it is possible to achieve superior performance and accuracy in crop weed classification.[6]. The area of image classification has greatly advanced with machine learning, enabling automatic picture detection and classification. The technique of automatically classifying images into several groups or classes according to the visual content of the image is known as image classification. Applications of image classification, including medical imaging, object recognition, and facial recognition, have made use of machine learning models, wherein a major area today happens to be precision agriculture.

II. METHODOLOGY

Data collection is the initial stage in the machine learning categorization of agricultural weeds. To identify the crops and weeds that are present in the field, this entails gathering photos of agricultural fields and manually annotating the photos. Then, to classify agricultural weeds, the annotated photos are used to train machine learning algorithms such as convolutional neural networks (CNNs), support vector machines (SVMs), or BaileysNet [11]. After it has been trained, the machine learning model may be used to recognize the crops and weeds in new photos of agricultural fields and categorise them. The accuracy of the machine learning model may be assessed using measures such as precision, recall, and F1-score. The following are some of the difficulties in applying machine learning to the categorization of crop weeds: [12]

Data imbalance: This issue arises because there are frequently much less weed samples than agricultural samples in the training dataset. As a result, the machine learning system may perform poorly on the weed data and over fit to the crop ones.

2. Variation in weed appearance standards: Machine learning algorithms have a hard time correctly classifying weeds due to their diverse range of sizes, shapes, and colors.

3. Variability in field conditions: It can be challenging to create machine learning models that can effectively generalize to fresh photos of agricultural fields since variables like lighting, soil moisture, and development stage can all have an impact on how crops and weeds appear.

Notwithstanding these difficulties, machine learning has demonstrated promise in the categorization of crop weeds and holds the potential to completely transform how farmers handle weed infestations in their fields. In order to automate the process of recognizing weeds in agricultural fields and separating them from crops, machine learning models are commonly utilised in crop weed classification. To accomplish the objective of classifying crop weeds, a number of machine learning techniques have been suggested and used in this sector [13].

2.1 Pre Processing

Before extracting features and classifying crops and weeds, data pre-processing is essential. The initial step involves identifying potential weed sections in the composite image and performing segmentation.

Segmentation: This process can be implemented by detecting sudden changes in the image's gradient values, which indicate new data classes. Image segmentation involves computing the maximum gradient as follows:

$$g_{max} = \max \left[\frac{\partial}{\partial r} \oint_{r=x_0, y_0}^{r=x_f, y_f} \frac{I(x, y)}{2\pi r} ds \right] \quad (1)$$

Here,

g_{max} is the maximal gradient

r is the radius

ds is the infinitesimal change in area

I is the image in spatial domain

The separation of the concerned area is followed by noise removal stage. The noise removal stage employs the discrete wavelet transform which is defined as:

Discrete Wavelet Transform: The Discrete Wavelet Transform, often known as the DWT, is a mathematical technique that is employed in signal processing and data filtering. It is a representation of time and frequency that enables the study of pictures and signals at various scales. In order to identify and remove undesired elements, such as

noise or background information, DWT divides a signal or picture into several frequency sub-bands. The goal is to eliminate noise effects by keeping the approximate co-efficient values and deleting the detailed co-efficient values, expressed as:

$$X(t) \xrightarrow{S,W} Co - \text{efficients (Approx, Detailed)} \quad (2)$$

Here,

Approx. represents the approximate co-efficient values

Detailed represents the detailed co-efficient values

S and W are the scaling and wavelet filters of the DWT

X is the time domain samples of the data.

Thus he

for ($i=1$: levels of decomposition)

{

Compute C_A and C_D values

Retain C_A values and discard C_D

}

2.2 Feature Extraction

Because UAVs are used to collect the photos for precision agricultural applications, there may be a significant amount of pixel similarity between weeded and non-weeded photographs, which results in low accuracy. Therefore, it is necessary to compute picture characteristics that may be used to differentiate between weeded and non-weeded groups [16]. In this study, the statistical characteristics that were calculated using the pixel values are:

The features computed in the proposed work are:

1. Mean or first moment: It is the average value or first moment computed as:

$$\text{Mean } (\mu) = \frac{1}{N} \sum_i^N f_i X_i \quad (3)$$

2. Standard Deviation: It is a measure of the difference between the instantaneous value and the mean, and is given by:

$$\text{Standard Deviation } (\sigma) = \sqrt{\frac{1}{N} \sum_i^N (X_i - \mu)^2} \quad (4)$$

3. Variance: It is the square of the standard deviation and is defined as:

$$\text{var} = \sigma^2 \quad (5)$$

4. Skewness: It denotes the amount of asymmetry of the probability distribution curve with respect to the y-axis of the curve.

$$\text{skewness} = \frac{\sum_i^N (X_i - \mu)^3}{(N-1)\sigma^3} \quad (6)$$

5. Kurtosis: The kurtosis is also termed as the fourth standard moment and is mathematically computed as:

$$\text{Kurtosis} = E\left[\left(\frac{X-\mu}{\sigma}\right)^4\right] \quad (7)$$

6. Energy: The energy is also termed as the angular secondary moment and is defined as:

$$Energy = \sum_{i,j}^N |p_{i,j}|^2 \quad (8)$$

7. Contrast: It is the degree of difference among the average and differential change in illuminance and is mathematically given by:

$$Contrast = \sqrt{\frac{1}{mn} \sum_{i,j}^{m,n} [X(i,j) - Mean(i,j)]^2} \quad (9)$$

8. Entropy: It is the average information content associated with a random variable having a probability function P , and is computed as:

$$E = -P(I_{x,y}) \log_2 I_{x,y} \quad (10)$$

9. Homogeneity: It is a statistical measure pertaining to the similarity of distributed values of a random variable, and is mathematically defined as:

$$H = \sum_{i,j}^{m,n} \frac{P_{i,j}}{1 + |i-j|^2} \quad (11)$$

10. Correlation: It is a measure of the amount of similarity among the pixel values

$$Corr_{i,j} = \sum_{i,j}^{m,n} \frac{(i-\mu_x)(j-\mu_y)P_{i,j}}{\sigma_x \sigma_y} \quad (12)$$

11. Inverse difference moment: It is defined as:

$$IDM = \sum_{i,j}^{m,n} \frac{1}{1 + (i-j)^2} p_{i,j} \quad (13)$$

The GLCM normalizing factor is computed as:

$$N = \frac{X_{i,j}}{\sum_{i=0}^{m-1} \sum_{j=0}^{n-1} X_{i,j}} \quad (14)$$

12. Root Mean Square Value (rms): It is often computed as metric corresponding to squared averages or means. It is computed as:

$$rms = \sqrt{\frac{\sum_{i=1}^n X_i}{n}} \quad (15)$$

Here,

X_i denotes the instantaneous value of the random variable X

$I_{x,y}$ denotes an image which is a function of spatial co-ordinates (x, y)

m, n denote the pixels along x and y axes

$mean$ denotes the average illuminance of the image

X denote the distinct values in the set

f demotes the frequency distribution of the values

N denotes the total number of levels in the normalized GLCM matrix

$p_{i,j}$ denotes the normalized GLCM matrix

P_j denotes joint probability

P denotes probability

A fresh image is classified using the same attributes that were used to train the machine learning model. As a result, the training dataset will be prepared using two distinct kinds of data:

- 1) Plants with weed infestation.
- 2) Plants not infested by weeds.

III. MODELING AND ANALYSIS

The major aim of this research work is to classify weeded and non-weeded crops with high accuracy. This is however a non-trivial problem to address as the pixel values of both classes happen to overlap. The hypothesis of any designed algorithm lies in the classification of partially overlapping datasets based on the deep probabilistic classifiers. The major challenge in this aspect is the similarity among infested and non-infested plants, hence accurate decision making is challenging for overlapping data samples. The intersection of sets overlapping sets makes the decision making challenging and hence a probabilistic classification is needed. The Bayes Net performs based on the conditional probability model wherein the training dataset is considered to be true as the apriori probability. The classification is done based on the maximum probability of the sample belonging to a particular class. The network is based on the assumption that the weights of the network are random variables and would change based on the data set used to train the network. The Bayesian Network is particularly useful for classification problems which exhibit close similarity among feature values of multiple classes, or overlapping feature values [30]. This is typically true in case of brain tumor classification as the region of the tumor and the composite image exhibit varying levels of fuzziness in the boundary depending upon the tumor case. The weight of the network are to be chosen in such a way that it maximizes the conditional probability of a data belonging to a particular class. The probability function can be computed as:

$$P\left(\frac{X}{X_i, k_1, k_2, M}\right) = \frac{P\left(\frac{X_i}{X, k_2, M}\right)P\left(\frac{X_i}{k_1, M}\right)}{P\left(\frac{X}{k_1, k_2, M}\right)} \quad (16)$$

Here,

P denotes probability

X_i denotes the set of weight and bias

X denotes the training data set

M denotes the network architecture in terms of the hidden layers and neurons

k_1 and k_2 are the regularization parameters for the network

Generally, the term $\rho = \frac{k_1}{k_2}$ is called the regularization ratio [31]. The regularization parameter is adopted in this case to limit the variations in the weights by introducing a penalty factor to the learning algorithm's cost function or objective function J . The regularization is different from early stopping or convergence in the sense that the earlier truncates the iterations prior to convergence to a minimum value of J whereas the latter tries to restrict the values of weights and number of parameters by modifying the cost function. Thus, regularization allows a much steeper decrease in the cost

function and eventually lesser values as compared to early stopping. This significantly helps to reduce the time complexity of the algorithm. The regularization parameter is responsible for the number of iterations needed to reach convergence and typically shows an inverse relationship with the number of iterations n . The number of hidden layers in the network have been taken as 20, with the activation function being the sigmoid function. The Deep Bayesian Network is typically a deep neural network trained using the Bayesian Rule.

The training algorithm adopted in this work is given by:

Step.1: Initialize weights (w) randomly.

Step.2: Fix the maximum number of iterations (n) and compute $\rho = \frac{k_1}{k_2}$

Step.3: Update weights using gradient descent with an aim to minimize the objective function J given by:

$$J = \frac{1}{m} \sum_{i=1}^m (v_i - v'_i)^2 \quad (17)$$

Step.4: Compute the Jacobian Matrix J given by:

$$J = \begin{bmatrix} \frac{\partial^2 e_1}{\partial w_1^2} & \dots & \frac{\partial^2 e_1}{\partial w_m^2} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 e_n}{\partial w_1^2} & \dots & \frac{\partial^2 e_n}{\partial w_m^2} \end{bmatrix} \quad (20)$$

Here,

The error for iteration 'i' designated by e_i is computed as:

$$e_i = (y_i - y'_i) \quad (21)$$

Here

y_i is the actual value

y'_i is the predicted value

Step.5: Iterate steps (1-4) till the cost function J stabilizes or the maximum number of iterations set in step 2 are reached, whichever occurs earlier.

The accuracy of the proposed classifier is computed based on the true positive (TP), true negative (TN), false positive (FP) and false negative (FN), mathematically:

$$Ac = \frac{TP+TN}{TP+TN+FP+FN} \quad (22)$$

Aiming for high classification accuracy values and other related characteristics is the goal of every planned strategy. The system's computational complexity, which is frequently assessed in terms of the quantity of training iterations and execution time, is another crucial factor that determines whether an algorithm will be useful in practice on devices with limited hardware. One kind of supervised learning is attention-based multi-instance learning. The learner receives a collection of labelled bags, each containing several instances, as opposed to a set of instances that are individually labelled.

If every instance in a bag is negative, then in the basic situation of multiple-instance binary classification, the bag may be classified as negative. Conversely, if a bag has at least one positive case, it is labelled positive. The learner attempts to either (i) induce a concept from a set of labelled bags that will properly label individual instances, or (ii) learn how to label bags without inducing the concept.

IV. RESULT AND DISCUSSION

The simulations are carried out on Matlab (Matrix Laboratory) with the image processing, statistical, neural network and deep learning toolboxes (libraries). A machine with Intel i5 Processor, with 16BG of RAM has been used.

The first step towards classification happens to be the data acquisition, processing and feature extraction. An experimental setup for the same has been explained in brevity in this section. A dataset of 1300 images have been obtained from CFID datasets whose details are presented in table 1.. Images have been labelled to create an exhaustive dataset comprising of images of two categories, which are:

- 1) Weed infested.
- 2) Weed non-infested

The sequential implementation is presented next.

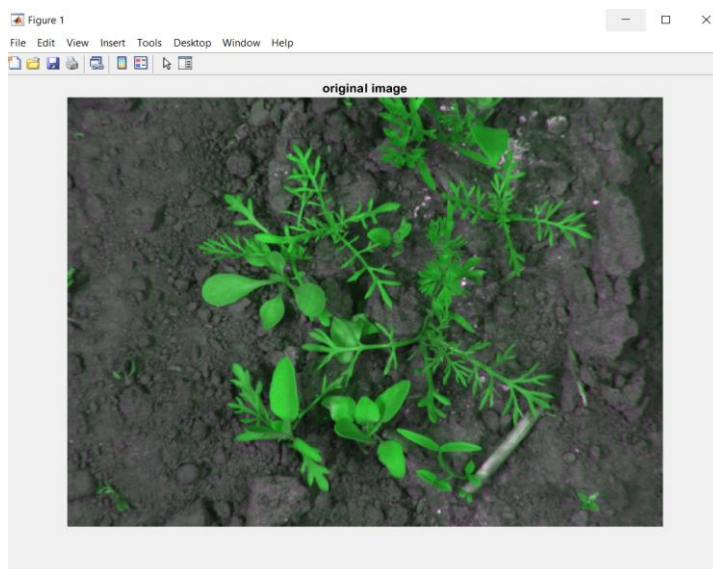


Figure 2: Original Image

Figure 2 depicts the original image under interest.

In the next step, the RGB to grayscale conversion is done to facilitate the computation process from 3 channels to single channel analysis.



Figure 3: Illumination Enhancement

Figure 3 depicts the illumination enhancement performed on the grayscale image. A subsequent processing of the image can be done using the 2-dimensional discrete wavelet transform (DWT). The wavelet decomposition has been done using the Haarlet family at level 4. The decomposition and subsequent synthesis of the image from the co-

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efficients has been depicted in figure 4.

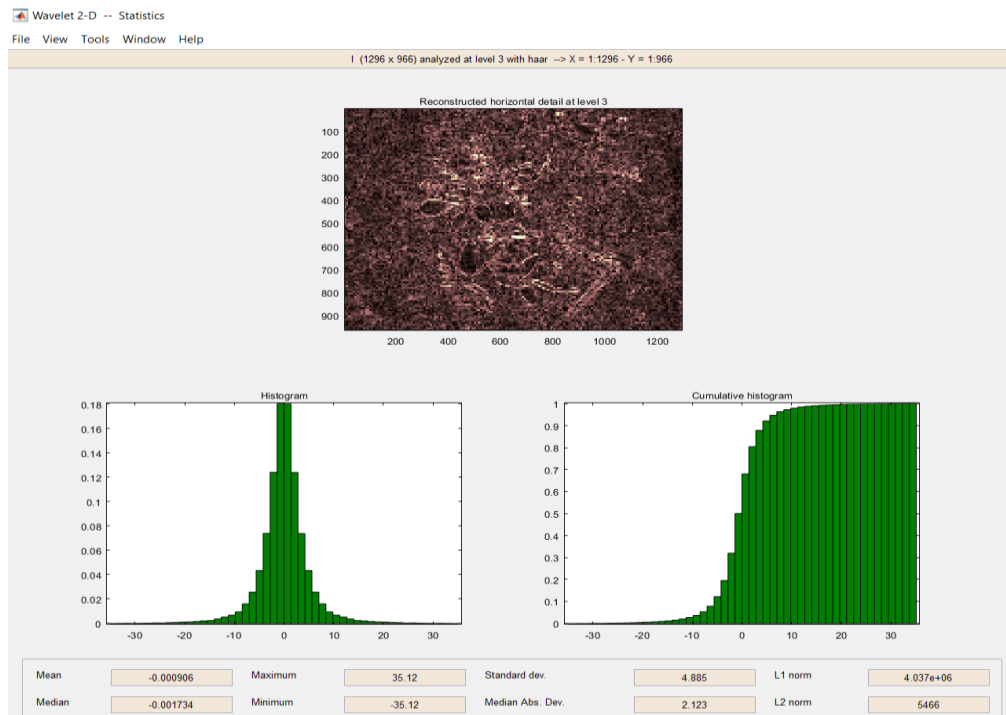


Figure 4: Wavelet Decomposition and Histogram Analysis

Figure 4 depicts the histogram analysis of the details using co-efficient values at

An analysis of the histograms of the actual image, approximations and details yield the fact that approximations contain the maximum information while the details contain noise effects which can be filtered to remove effects of noise and disturbance. The classification of the proposed work has been done based on the Deep BayesNet with the sigmoid activation function. The back propagation training rule has been used for weight update. The classification accuracy can be visualized using the confusion matrix.

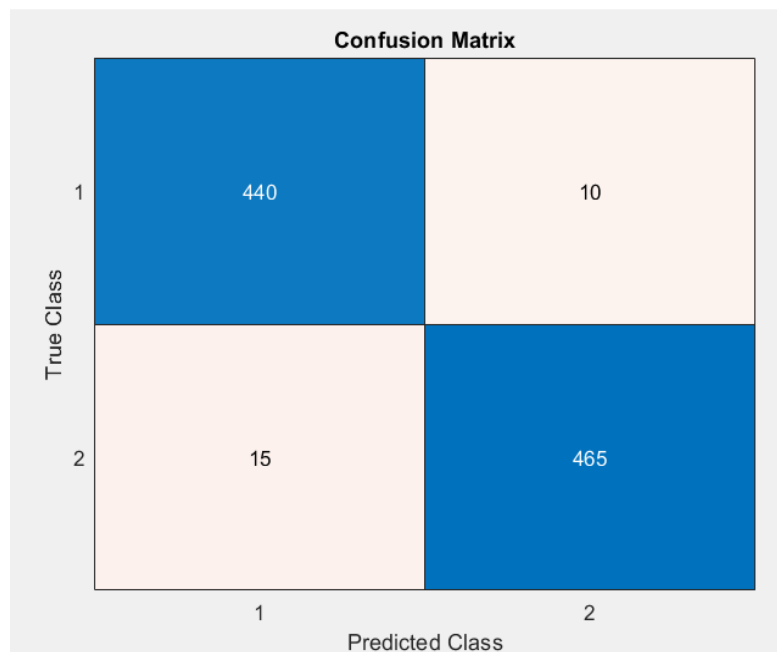


Fig. 6 Confusion Matrix

The accuracy of the proposed system is computed as:

$$Ac = \frac{440 + 465}{440 + 465 + 15 + 10} = 97.31\%$$

Thus for the used dataset, the proposed system attains an accuracy of 97.31% which outperforms baseline techniques in terms of classification accuracy. A summary of results is provided in table 1 for ready reference.

Table. 1 Summary of Results

S.No.	Parameter	Value
1	Dataset Set	GitHub: https://github.com/cwfid/dataset
2	Image Type	jpg
3	Pre-Processing	DWT
4	Segmentation Method	Max gradient
5	Features	12: stochastic
6	Classifier	Deep BayesNet
7	Custom CNN (500 X 500)	94.7
8	Custom CNN (250 X 250)	90.6
9	Custom CNN (125 X 125)	89.7
10	ResNet 18	94.8
11	ResNet 50	95.7
12	DenseNet 128	90.1
13	VGG Net	91
14	Faster RCNN	67
15	YOLO	95
16	Accuracy (proposed work)	97.31%

It can be observed that the proposed technique comprising of image pre-processing, segmentation followed by classification through the Deep Bayes Net can outperforms baseline techniques in terms of classification accuracy.

V. CONCLUSION

It can be concluded that AI and Machine Learning are making their presence felt in the domains of precision agriculture for attaining higher efficiency. This paper presents a combination of image enhancement, feature extraction and probabilistic classification. Important statistical features have been computed to accurately classify the weeded and non-weeded cases. The probabilistic BayesNet classifier has been explained with its salient features. This research presents a comparative analysis of the efforts and outcomes generated. The study's findings unequivocally demonstrate that the recommended strategy performs better than baseline methods in terms of classification accuracy and can accurately classify crop weeds, with a mean accuracy of 97.31% for the tested dataset.

Future directions of research may focus on transfer learning so as to use a trained model to be utilized for other datasets. Moreover, due to the down-sampling property of the DWT, the maximum overlap based DWT or MODWT can also be explored for raw data filtration.

REFERENCES

- [1] T Luo, J Zhao, Y Gu, S Zhang, X Qiao, W Tian, "Classification of weed seeds based on visual images and deep learning," *Information Processing in Agriculture*, Elsevier 2023, vol.10, no.1, pp.40-51.
- [2] ASMM Hasan, D Diepeveen, H Laga, MGK Jones, "Image patch-based deep learning approach for crop and weed recognition," *Ecological Informatics*, Elsevier 2023, vol. 78, 102361.
- [3] BK Hu, Z Wang, G Coleman, A Bender, T Yao, S Zeng, "Deep learning techniques for in-crop weed recognition in large-scale grain production systems: a review," *Precision Agriculture*, Springer Nature 2024, , vol. 25, pp. 1–29.
- [4] FH Juwono, WK Wong, S Verma, N Shekhawat, "Machine learning for weed–plant discrimination in agriculture 5.0: An in-depth review", "Artificial Intelligence in Agriculture, Elsevier, 2023, vol. 10, pp. 13-25.
- [5] H. L. Lee, C. L. Chang and C. C. Chang, "Precision Agriculture and Its Applications in Taiwan," in *IEEE Technology and Engineering Education (ITEE)*, 2016, pp. 200-205
- [6] D. Li, Z. Zhou and S. Li, "A Review of UAV Applications in Precision Agriculture," in *Journal of Sensors*, vol. 2017, pp. 1-13, 2017
- [7] J. R. Rosell-Polo, D. Sanz-Robinson and J. J. Vallés-Ros, "A Review of Methods and Applications of the Geometric Characterization of Tree Crops in Agriculture," in *Sensors*, vol. 15, no. 6, pp. 13035-13061, 2015.
- [8] A. Nayyar, J. Irvin and C. A. Grift, "A Review of UAV-Based Precision Agriculture and Its Contributions to Sustainability in Crop Production," in *Sustainability*, vol. 11, no. 17, pp. 4706-4722, 2019.
- [9] S. Arabi and S. G. McClure, "Integration of Unmanned Aerial Vehicles (UAVs) in Agriculture: A Review," in *Computers and Electronics in Agriculture*, vol. 144, pp. 49-61, 2017.
- [10] S. Bareth, M. Bolten and H. Gnyp, "Combined Spectral and Spatial Modeling of Crop Height Using Unmanned Aerial Vehicles," in *Remote Sensing*, vol. 7, no. 4, pp. 4213-4238, 2015.
- [11] D. Wang, Z. Gao, X. Wei and Z. Liu, "Crop-Weed Classification for Precision Agriculture Using a Deep Convolutional Neural Network," in *IEEE Access*, vol. 7, pp. 146471-146479, 2019
- [12] C. C. Ogbodo and B. J. Adeoye, "Crop-weed discrimination using machine learning techniques," in *IEEE International Conference on Electro/Information Technology (EIT)*, 2018, pp. 0919-0923
- [13] A. Singh, A. Dhaka and V. K. Banga, "Crop-Weed Classification using Machine Learning Techniques: A Review," in *IEEE International Conference on Computing, Communication and Automation (ICCCA)*, 2016, pp. 614-618
- [14] M. U. Anwar, H. Saeed and M. Riaz, "Crop-Weed Discrimination using Machine Learning Techniques: A Comparative Study," in *IEEE International Conference on Robotics and Automation Sciences (ICRAS)*, 2018, pp. 253-257
- [15] A. Raza, M. Rehman and F. Yasmin, "Crop and Weed Classification using Machine Learning Techniques," in *IEEE International Conference on Emerging Technologies (ICET)*, 2018, pp. 1-6
- [16] A. Zhang, X. Wei X. "A review on weed detection using ground-based machine vision and image processing techniques. *Computers and Electronics in Agriculture*", Elsevier 2019, 158, pp: 226-240
- [17] AM Anter, AE Hassenian, D Oliva, "An improved fast fuzzy c-means using crow search optimization algorithm for crop identification in agricultural", *Expert Systems with Applications*, Elsevier 2019, vol.118, pp.340-354.
- [18] A. Bakhshipour, A. Jafari A, S. Nassiri. D. Zare, "Weed segmentation using texture features extracted from wavelet sub-images", *Biosystems Engineering*, Elsevier 2017, vol.157, pp.1-12.
- [19] J Torres-Sospedra, P Nebot, "Two-stage procedure based on smoothed ensembles of neural networks applied to weed detection in orange groves", *Biosystems Engineering*, Elsevier 2014, vol.123, pp.40-55.
- [20] I Dasgupta, J Saha, P Venkatasubbu, "AI crop predictor and weed detector using wireless technologies: a smart application for farmers", *Arabian Journal for Science and Engineering*, Springer 2020, vol.45, pp.11115–11127.

- [21] U. Shruthi, V. Nagaveni and B. K. Raghavendra, "A Review on Machine Learning Classification Techniques for Plant Disease Detection," 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS), 2019, pp. 281-284.
- [22] Y. Chen, Z. Wu, B. Zhao, C. Fan, S. Shi, "Weed and corn seedling detection in field based on multi feature fusion and support vector machine" Sensors, MDP1 2021, vol.21, no.12, pp.1-18.
- [23] X. Jin, J. Che and Y. Chen, "Weed Identification Using Deep Learning and Image Processing in Vegetable Plantation," in IEEE Access 2021, vol. 9, pp. 10940-10950.
- [24] S. Abouzahir, M. Sadik, E. Sabir, "Bag-of-visual-words-augmented Histogram of Oriented Gradients for efficient weed detection", Biosystems Engineering, Elsevier 2021, vol.202, pp. 179-194.
- [25] V. N. Thanh Le, G. Truong and K. Alameh, "Detecting weeds from crops under complex field environments based on Faster RCNN," 2020 IEEE Eighth International Conference on Communications and Electronics (ICCE), 2021, pp. 350-355.
- [26] V. N. Thanh Le, G. Truong and K. Alameh, "Detecting weeds from crops under complex field environments based on Faster RCNN," 2020 IEEE Eighth International Conference on Communications and Electronics (ICCE), 2021, pp. 350-355.
- [27] M. Alam, M. S. Alam, M. Roman, M. Tufail, M. U. Khan and M. T. Khan, "Real-Time Machine-Learning Based Crop/Weed Detection and Classification for Variable-Rate Spraying in Precision Agriculture," 2020 7th International Conference on Electrical and Electronics Engineering (ICEEE), 2020, pp. 273-280.
- [28] S. Sabzi, Y. Abbaspour-Gilandeh, "Using video processing to classify potato plant and three types of weed using hybrid of artificial neural network and particle swarm algorithm", Measurement, Elsevier 218, vol.126, pp.22-36.
- [29] Tin-Yau Kwok and Dit-Yan Yeung, "Constructive algorithms for structure learning in feedforward neural networks for regression problems," in IEEE Transactions on Neural Networks, vol. 8, no. 3, pp. 630-645.
- [30] F. Ahmed, Al-Mamun, A. Bari, E. Hossain, "Classification of crops and weeds from digital images. A support vector machine approach Journal of Crop Production", Elsevier 2013, vol.40, pp: 98-104.
- [31] S. S. Athani and C. Tejeshwar, "Support Vector Machine-Based Classification Scheme of Maize Crop," 2017 IEEE 7th International Advanced Computing Conference (IACC), 2017, pp. 84-88.