International Journal of Chemical and Biochemical Sciences
(ISSN 2226-9614)
Journal Home page:www.iscientific.org/Journal.html


# Using Image Analysis and Artificial Intelligence to Differentiate Between Crops and Weeds

***Abhilash Kumar Saxena[1], Esha Rami[2], Kiran KS[3], Preeti Naval[4]***

[1]*College of Computing Science and Information Technology, Teerthanker Mahaveer University, Moradabad, Uttar Pradesh, India*

[2]*Department of Biotechnology, Parul University, PO Limda, Vadodara, Gujarat, India*

[3]*Department of Physics, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Bangalore, India*

[4]*Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh, India*

**Abstract**

A recurring problem in agriculture is the coexistence of weeds with farmed crops, which affects productivity and resource use. Traditional weed control techniques depend on the manual effort and the careless application of pesticides, which raises expenses and raises environmental issues. A more accurate and effective method for distinguishing the weeds from crops in real-time is needed so that we focused interventions and sustainable agricultural methods can be implemented. In this study, we investigate the use of imagery analysis and artificial intelligence (AI) for differentiating the weeds and crops throughout farming environments as a remedy to these difficulties. To improve the decision-making process, we present novel barnacles mating-tuned Adaboost (BM-AB) strategy in this work. The suggested approach was assessed using a dataset that included a variety of photos of weeds and crops. Gabor filter is performed to obtain major attributes and BM optimization methodology is utilized to boost the AB's effectiveness in crop-weed distinction. The study is conducted using the Python language to analyse the effectiveness of the suggested BM-AB approach. According to the study's outcomes, the BM-AB architecture is a solid option for computerized crop-weed discrimination that can be advantageous for weed prevention tactics, optimizing resources and farming precision.

**Keywords:** Agriculture, crop-weed discrimination, sustainability, imagery analysis, AI, barnacles mating-tuned Adaboost (BM-AB)

**Full-length article** **Corresponding Author*, e-mail: abhilashkumar21@gmail.com

## 1. Introduction

Crops and weeds are two different plant families that have important agricultural significance. Cultivated plants produced for human food, animal feed, or industrial usage are referred to as crops. To maximize quality and productivity, these plants are chosen and cared to enhance quality and yield. Selective breeding is used on crops to improve desired characteristics including yield, disease, insect resistance and environmental adaptation [1, 2]. Weeds, on the other hand, compete for resources with crops, which results in reduced the agricultural output. Invasive and hardy, weeds can thrive in a variety of environments. They are not purposefully planted, in contrast to crops and they can reduce agricultural output via water, nutrients and sunshine. Additionally, weeds can harbour pests and illnesses, endangering the health of farmed crops even more [3, 4]. A number of traits, like as shape, growth patterns and effects on agricultural ecosystems, are used to distinguish between crops and weeds. Generally speaking, crops are well-managed, grow consistently and support the general goals of farming. On the other hand, weeds exhibit traits that set them apart from cultivated plants, making them easy to identify. They can grow quickly and uncontrollably [5].

As modern agricultural research has shown, efficient crop-weed discrimination is necessary for implementing specific weed control techniques including the application of cutting-edge technology like machine vision and artificial intelligence. While minimizing the detrimental effects of weeds on crop health and productivity, accurate identification enables targeted treatments, optimal resource allocation and the promotion of sustainable farming methods [6, 7]. Moreover, weeds are adaptable, evolving resistance to traditional control methods. This adaptability stems from their prolific seed production and diverse reproductive strategies, allowing them to colonize and spread in agricultural fields. Additionally, weeds can serve as hosts for pests and diseases, further jeopardizing the well-being of crops. The ecological impact of unchecked weed growth extends beyond individual fields, affecting surrounding ecosystems and biodiversity [8]. Farmers use a mix of mechanical, chemical and cultural techniques to control weed infestations in response to these difficulties. Crop rotation and cover crops interrupt weed development cycles in a culturally relevant way. Mechanical methods eradicate weeds physically by using tillage and precision agricultural tools. Herbicides are used in chemical control to target certain weed species and minimize damage to crops. For sustainable agriculture to flourish, it is important to strike a balance between these techniques since relying too much on one might exacerbate environmental problems or breed weed populations that are resistant to herbicides [9, 10].

The research [11] used two meta-heuristic algorithms and artificial neural networks (ANNs) to build a system of stereo vision that can differentiate between weeds and rice plants, as well as further discriminated between two kinds of weeds in rice field. The results suggested the promise of the proposed stereo vision technology, which included integrated artificial neural network bee algorithm (ANN-BA) classifier for improved classification accuracy and calculating the average of the matching points across many channels. The aim of research [12] was to use machine learning and approaches for image processing to identify weeds in crop. They examined the effectiveness of various machine learning techniques, including random forest (RF), support vector machine (SVM) and k-nearest neighbours (KNN), in these identification of weeds through the analysis of Unmanned aerial vehicle (UAV) photos obtained from a chilli crop field. The results of the experiment show that RF was more effective than various classifiers in terms of performance metrics and accuracy. The research [13] analysed a plant and weed identification tool using artificial deep neural networks was developed, tested and trained to weed the inter-row space in agricultural areas. To address the issue of weed growth in agricultural systems, high-level weeding robot design was developed and proposed. When compared to other approaches, the outcome illustrates that this methodology reduces the amount of computation.

The study [14] examined the early weed identification during cultivation was critical for identifying and controlling the plant illnesses as well as avoiding large-scale crop losses. However, traditional techniques of weed detection are labor-intensive and costly. In order to achieve those objectives, software was suggested for agricultural pest detection that makes use of the YOLOv5 neural network, together with traditional K-Nearest Neighbors, Random Forest and Decision Tree algorithms. Results from actual data show that the proposed approach can recognize weeds in low-resolution photos. The article [15] investigated different aspects of the algorithms and techniques utilized by researchers in computer vision and machine learning to create artificial intelligence models that removed weeds from agricultural areas. The most effective outcomes are obtained with tiny datasets using algorithms such as KNN rather than using SVM, which was known to produce superior results with binary classification issues, if the dataset has more than one class. The research [16] analysed three deep learning image processing-based lettuce weed estimation algorithms with professional eye evaluations. Support vector machines employed HOGs as feature descriptors. The second method identified objects using the robust YOLOV3 (you only look once V3) technique, while the third segmented each instance using a Mask R-CNN. The findings show that, in comparison with more conventional techniques, these complex algorithms improve weed coverage estimations by increased accuracy and lowered subjectivity.

The paper [17] examined crop categorization and weed analysis utilizing weed identification which helps in automating the weed elimination process. They examined the effectiveness of classifiers based on SVM, ANN and CNN. The potential of CNN's deep learning to extract relevant characteristics from images was considered to provide superior performance than that of SVM and ANN. The article [18] described the use of (RGB) Red Green Blue cameras (UAVs) unmanned aerial vehicles application and with the (SLIC) algorithm simple linear iterative clustering and the (RF) random forest classifier to distinguish between upland rice fields: crops and weeds. Based on the result, consumer-grade UAV images can distinguish rice and weeds with enough precision even in the early phase of rice plant development addressing the needs of (SSWM) site-specific weed management system. The development of the SLIC-RF algorithm makes it possible. The research [19] aimed to evaluate and create an affordable smart system for targeted Artificial intelligence (AI) in weed control. The strategy included combining AI algorithms for weed identification and categorization. The technology's ability to improved precise weed control techniques was shown by the findings, which highlighted the technology's potential for successful and sustainable agricultural uses.

The study [20] investigated advanced deep neural networks for weed detection. Inception-V3, Inception-ResNet-v2, MobileNetV2, VGG16 and ResNet-50 are a few examples. They examined transfer learning by employing crop and weed dataset images to modify the pre-trained weights for feature extraction. On the massive pooled dataset, ResNet-50 beat other deep networks, although VGG16 outperformed others on small datasets. Traditional methods are laborious and slow, yet it reduced agricultural yield. Therefore crop management involves image analysis and artificial intelligence to discriminate weeds and crop. This method uses advanced technologies to improve precision farming and enable focused treatments.

## 2. Methodology

This article presents a new barnacle's mating-tuned Adaboost (BM-AB) method to improve crop-weed discrimination. The suggested method is validated using a large dataset of weed and crop images. The Gabor filter separates important elements in the image and the BM optimization approach improves the Adaboost algorithm's crop-weed detection.

### *2.1. Dataset*

The dataset we used for our data analysis was obtained from the Kaggle website https://www.kaggle.com/code/databeru/plant-seedlings classifier- grad-cam-acc-95. There are 5,539 images in this collection that show crop and weed seedlings at different stages of growth. The images have been divided into twelve distinct groups. These classifications reflect common plant species in Danish agriculture. RGB photos of plants in various stages of growth constituents of each class. Images come in different kinds of sizes and they are in PNG format. The gathered data is split into two types such as training (80%) and testing (20%). Fig. 1 illustrate examples of sample image of weeds and crops discrimination.

### *2.2. Feature selection using Discrete wavelet transformation*

Discrete Wavelet Transformation (DWT) is emerging as an effective technique in agricultural applications for weed and crop discrimination. DWT improves the precision of discriminating between crops and unwanted plants in images data by evaluating frequency components, enabling more effective and focused agricultural management activities. In digital signal processing, seismic wave analysis and hyperspectral image processing, the wavelet transform is utilized and other domains for noise reduction, data compression and information extraction.The following formula can be used to calculate a function's DWT, $\mathbf{e}(\boldsymbol{\lambda})$ as shown in Equation (1-5)

$$\boldsymbol{w}_{\boldsymbol{e}(\boldsymbol{\lambda})}(\boldsymbol{l},\boldsymbol{s}) = <\boldsymbol{f}(\boldsymbol{\lambda}), \emptyset_{\boldsymbol{l},\boldsymbol{s}}, (\boldsymbol{\lambda})>, \qquad (1)$$

Its $\boldsymbol{l^{th}}$ scale signal energy is expressed as follows:

$$\boldsymbol{F_l} = \sqrt{\frac{1}{S}\sum_{S=1}^{S}\boldsymbol{W}_{\boldsymbol{e}(\boldsymbol{\lambda})}(\boldsymbol{l},\boldsymbol{s})} \qquad (2)$$

$w_{e(\lambda)}(l,s)$ Denotes the $S^{th}$ coefficient of the level j decomposition, the discrete wavelet function is denoted by $\emptyset_{l,s}, (\lambda)$, $F_l$ is the wavelet's energy coefficient and that level's entirety of correlationsldecomposition is denoted by s. The wavelet transform can be used to deconstruct hyperspectral data and achieve dimensionality reduction and information extraction. Wavelet transform is based on the mother wavelet to a great extent. The wavelet function of Daubechies has been discovered to perform well, hence it is employed in this analysis. The wavelet transform was implemented in this study to reduce the number of dimensions in data from spectral imaging and extract features and the use of wavelet coefficients as classification features. A step-wise regression approach was applied to choose a subsection of wavelet coefficients with a high classification performance.

### *2.3. Barnacles Mating-Tuned Adaboost (BM-AB)*

The novel Barnacles Mating-Tuned Adaboost (BM-AB) combines marine mating behaviour insights with Adaboost for enhanced weed and crop detection. This novel technique employs nature-inspired algorithms to improve precision in agricultural imaging systems for more effective weed management and crop identification.

#### *2.3.1. Barnacles Mating optimization (BMO)*

A barnacle is a kind of marine invertebrate found in shallow and coastal regions. They grow on the hard surfaces of the water and they are present throughout the sea. Barnacle larvae were dispersed in the sea after hatching eggs to discover and attach to the hard surface. In fact, hard surfaces hide barnacle bodies and improve the plates made of shells. They must achieve a balance of managing last longer erections and finishing more companions in a chaotic flow. Based on these behaviours, a novel optimization approach known as BMO approach, or Barnacles Mating Optimizer has been introduced.

The solution's initial barnacle population can be identified as follows:

$$X = \begin{Bmatrix} \chi_1^1 & \chi_1^N \\ \vdots & \vdots \\ \chi_n^1 & \chi_n^N \end{Bmatrix} \qquad (3)$$

where $n$ signifies the number of candidates and $N$ denotes the number of decision factors according to lower and upper limits:

$$l_b = [l_b^1 \cdots l_b^1] \qquad (4)$$

$$u_b = [u_b^1 \cdots u_b^1] \qquad (5)$$

The variables $i$ represented by the expressions $ub$ and $lb$. At the first iteration, better to worst outcomes are saved and sorted by determining the objective function for each candidate. The approach offered consists of exploration and exploitation. As an example, the sperm cast process can be used to generate offspring in Equation (6-7):

$$b_D = rand(n) \qquad (6)$$

$$b_M = rand(n) \qquad (7)$$

where $b_D$ and $b_M$ are the mated parents.

The BMO method, which simulates the reproduction process by taking into consideration The genotype frequencies of the parents and the inheritance of behaviours in the offspring generation in Equation (8-9)

$$X_t^{N_{new}} = pX_{b_D}^N + qX_{b_M}^N \qquad (8)$$

Now, $qX_{b_M}^N$ and $X_{b_D}^N$ represent the Mum and Dad candidates factors, respectively, where $p$ is a pseudo-random number in the range of 0 to 1, or (1p). When the selection of candidates for mating is superior first, $pl$ quantity is considered, the following exploration term might take place:

$$X_t^{N_{new}} = rand \times X_{b_M}^n \qquad (9)$$

In Equation (9) $rand$ denotes a random number between zero and one. Mum's candidate can create the lately produced offspring for exploration. To increase the candidate dimension's solution matrices, the offspring will be considered and compared with the parents. As a result, a strategy for organizing individual dimension was used to choose fifty percent top alternatives and the wrong answer was removed. By combining self-population-based initialization, the Modified Barnacles Mating Optimization (MBMO) approach expands the core Barnacles Mating Optimization (BMO) algorithm. BMO, like further metaheuristic models, uses an optimization method based on population that starts with initialization at random. To calculate population size, a control variable is necessary. It is valuable highlighting that population size selection to address case concerns is difficult. The populace that can adapt to it will control population size at every instance. A population that is capable of self-adaptation can reach the initial size in the first iteration in Equation (10-11).

$$PopSize = d \times 10 \qquad (10)$$

where $d$ stands for the dimension of the problem and it is as follows:

$$PopSize_{new} = \max(d, round(PopSize + r \times PopSize)) \qquad (11)$$

Where $r$ denotes a random number between $-0.5$ and 0.5.

### *2.3.2. AdaBoost*

An integrated learning method is called AdaBoost. It shows effectiveness in distinguishing between weeds and crops. It improves accuracy by building a robust model by combining many weak classifiers. The iterative training process of AdaBoost improves discriminating in crop-weed classification tasks by highlighting misclassified occurrences. The AdaBoost algorithm was utilized to build a strong classifier Using the training strategy (also known as weak learning). The objective of identifying the weak learning the weakest classifier might differentiate negative and positive samples. The weak learning method determined the each feature's threshold value, to ensure a small percentage of samples were incorrectly categorized. Eq. (12) describes a weak classifier in Equation (12-18).

$$h_t(\chi_j) = \begin{cases} 1, \chi_j < \theta_t \\ -1, otherwise \end{cases} \quad (12)$$

In which $h_t(\chi_j)$ is the weakest classifier, $\chi_j$ is the definite value of the $j^{th}$ feature, $t$ is a dynamic index indicating iterative processes and $\theta_t$ is the threshold determined by applying Eq. (13).

$$\theta_t = \arg min_{\varepsilon_t} \quad 13)$$

where the error rate of the $t^{th}$ iterative iteration is denoted by $\varepsilon_t$. The total of the weights of features that were incorrectly categorized is the error rate, or $\varepsilon_t$

$$\varepsilon_t = \sum_{j=1}^{M} D_t(j)[y_j \neq h_t(\chi_j)] \quad (14)$$

$D_t(j)$ is the $j^{th}$ misclassified feature's weight, $y_j$ is the $jth$ feature's reference value, which has a value of 1 or 1 and the sample count is denoted by $M$.

$$D_{t+1}(j+1) = D_t(j)\exp(-a_t y_j \theta_t)/Z_t (15)$$

where $Z_t$, The normalizing factor is discovered using Eq.(15).

$$Z_t = \sum_{j=1}^{M} D_t(j) \quad (16)$$

The error rates were clearly reduced by weak learning processing. In fact, no one weak classifier could execute low-error classification task. To create a strong classifier, these weak classifiers double their weights and join them linearly Eq. (16) defines the most robust classifier.

$$H(\chi) = \begin{cases} 1, \sum_{t=1}^{T} a_t . h_t(\chi) \geq \frac{1}{2}\sum_{t=1}^{T} a_t \\ -1, + \quad otherwise \end{cases} \quad (17)$$

In which $H(\chi)$ and $h_t(\chi)$ are the functions of the strong and weak classifiers. The number of weak features or classifiers is $T$. and $a$ is the weight of the weak classifier, which is updated between iteration rounds. The update rule of $a$ is,

$$\frac{a_t = \frac{1}{2} l_n(1-\varepsilon_t)}{\varepsilon_t} \quad (18)$$

Barnacles Mating-Tuned Adaboost (BM-AB) is an innovative technique to weed and crop identification that incorporates knowledge from barnacle mating behaviour into the AdaBoost algorithm. This hybrid model uses nature-inspired algorithms to improve precision in agricultural imaging systems, allowing for better crop and weed detection. Algorithm 1 shows a Barnacles Mating-Tuned Adaboost (BM-AB).

***Algorithm 1: Process of BM-AB***

```
function BM_AB_Adaboost(X_train, y_train, T):
N = number of samples
M = number of features
initialize_weights(D, N)
strong_classifier = 0
for t in range(T):
weak_classifier = train_weak_classifier(X_train, y_train, D)
predictions = weak_classifier.predict(X_train)
error = calculate_error(predictions, y_train, D)
alpha = 0.5 * ln((1 - error) / error)
update_weights(D, alpha, predictions, y_train)
strong_classifier += alpha * weak_classifier
return strong_classifier
function train_weak_classifier(X_train, y_train, weights):
function calculate_error(predictions, true_labels, weights):
function update_weights(weights, alpha, predictions, true_labels):
function predict(strong_classifier, X_test):
```

## 3. Experimental result

Training was conducted on a PC equipped with a 8-fundamental Xeon CPU, 16 GB of RAM, and a GTX 1060 six-GB graphics card. Method one utilized C++, method two used the 3 method uses Python alongside the Tensor Flow package for assessments and a dark-net structure for learning. The effectiveness of the proposed and current methodologies was evaluated in terms of (accuracy, precision, F1 score and recall). Non-Calibrated SVM, Non-Calibrated RF, Calibrated SVM, Calibrated RF [21] were existing method compared to proposed method.

Accuracy: An indicator of a deep learning model's accuracy is the percentage of outcomes that were predicted. Better performance is indicated by higher values. Loss: A metric used to quantify the prediction error of a model while training and validation with the goal of reducing the difference among predicted and actual values. The training graph tracks these metrics over epochs, aiming for high accuracy and low loss as shown in Fig 2.

### *3.1. Accuracy*

Accuracy in binary classification measures how accurate the model's predictions are in general, such as when differentiating between weeds and crops. The formula below is used for calculation in Equation (19):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (19)$$

Where,

- The quantity of weeds that are anticipated is called as True Positives (TP).
- The quantity of crops that are accurately anticipated is called as True Negatives (TN).
- The number of occurrences that were wrongly identified as weeds but were actually crops is called a false positive (FP).

The number of occurrences that were wrongly identified as crops but were actually weeds is called a false negative (FN).

**Figure 1.** Sample of weeds and crops [Source: https://www.kaggle.com/code/databeru/plant-seedlings-classifier-grad-cam-acc-95]

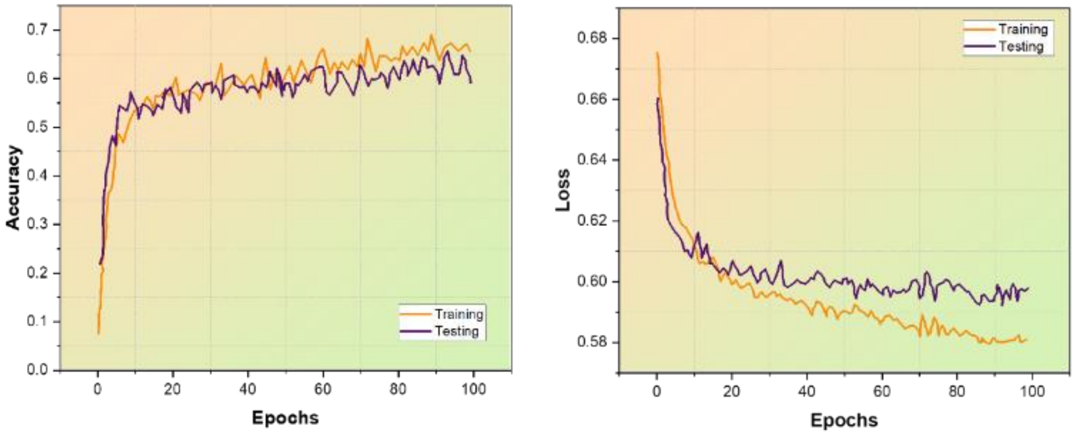


**Figure 2.** Outcome of accuracy and loss (Source: Author)

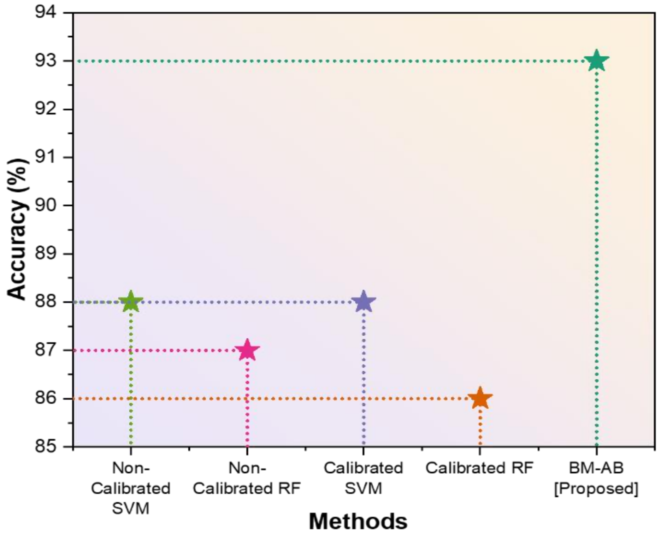


**Figure 3.** Result of accuracy (Source: Author)

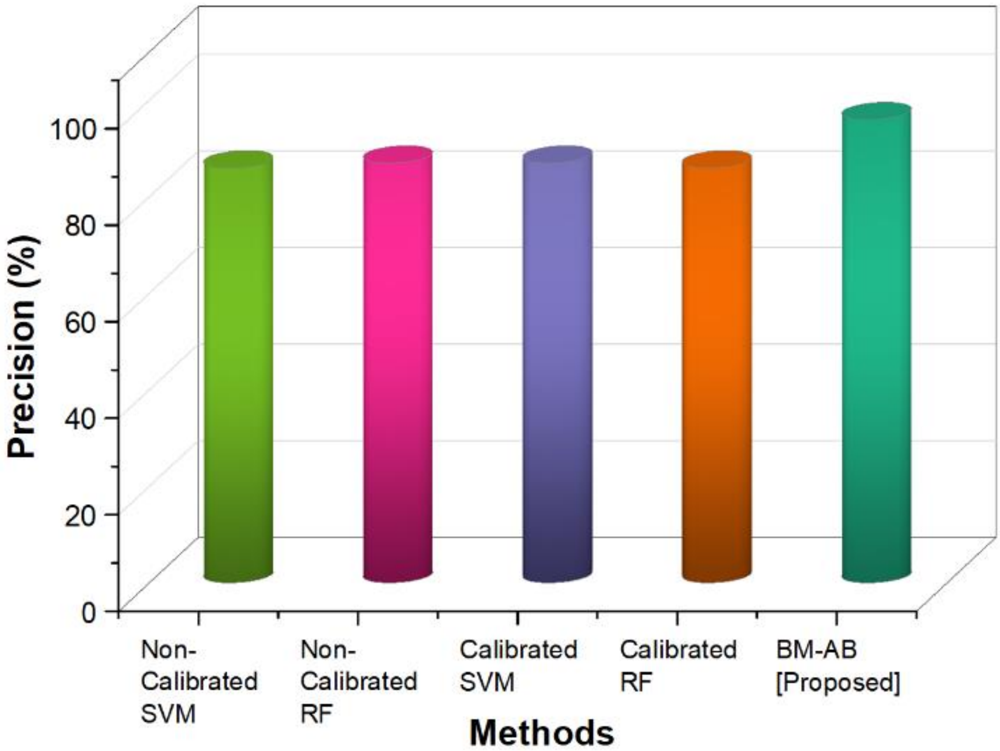


**Figure 4.** Result of precision (Source: Author)

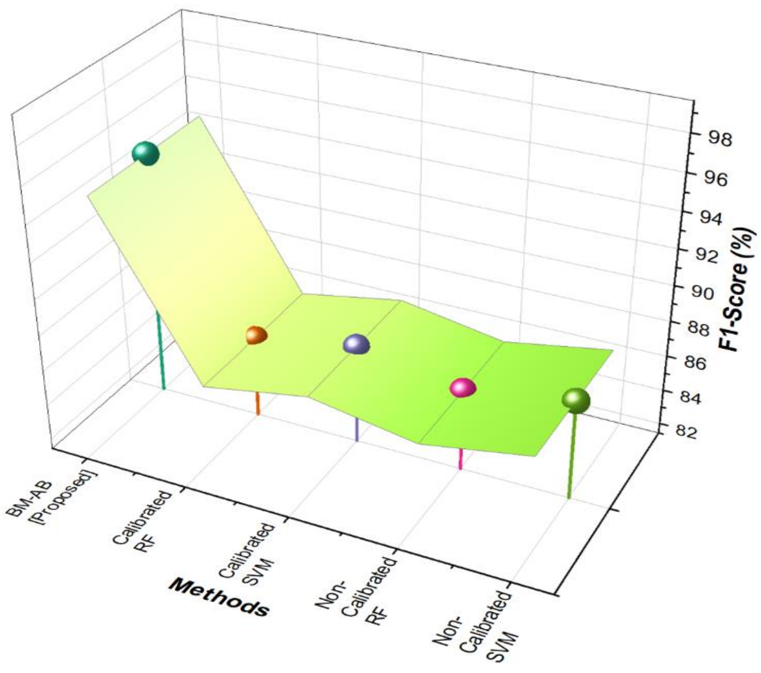


**Figure 5.** Result of F1score (Source: Author)

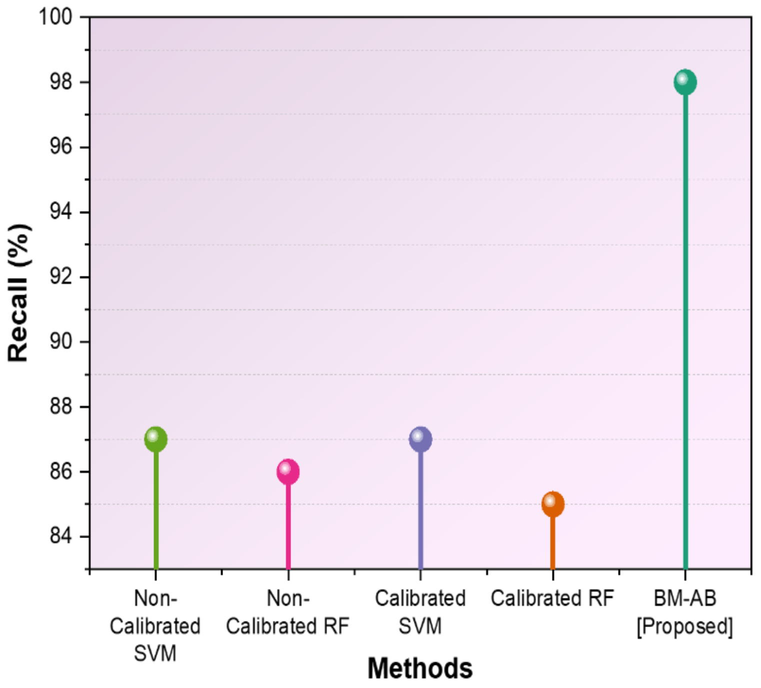


**Figure 6.** Result of Recall (Source: Author)

**Table 1.** Result of precision and accuracy (Source: Author)

| Method | Accuracy | precision |
|---|---|---|
| Non-Calibrated SVM | 88% | 86% |
| Non-Calibrated RF | 87% | 87% |
| Calibrated SVM | 88% | 87% |
| Calibrated RF | 86% | 86% |
| BM-AB [Proposed] | 93% | 96% |

**Table 2.** Result of F1score and Recall (Source: Author)

| Method | Recall | F1score |
|---|---|---|
| Non-Calibrated SVM | 87% | 87% |
| Non-Calibrated RF | 86% | 86% |
| Calibrated SVM | 87% | 87% |
| Calibrated RF | 85% | 86% |
| BM-AB [proposed] | 95% | 98% |

Fig. 3 and Table 1 illustrate the accuracy result. When comparing our proposed method (BM-AB - 93%) with the existing method (Non-Calibrated SVM - 88%, Non-Calibrated RF- 87%, Calibrated SVM - 88%, Calibrated RF - 86%), our proposed method shows a higher value than the existing method and it shows that our proposed method is effective to identify the difference between weeds and crop.

### *3.2. Precision*

Precision is defined as the percentage of true positive predictions to total positive predictions generated by the model in the context of binary classification discriminating between weeds and crops. The following is the formula for precision in Equation (20):

$$\text{Precision} = \frac{TP}{TP+FP} \tag{20}$$

Fig. 4 and Table 1 illustrate the precision result. When comparing our proposed method (BM-AB - 96%) with the existing method (Non-Calibrated SVM - 86%, Non-Calibrated RF - 87%, Calibrated SVM - 87%, Calibrated RF - 86%), our proposed method shows a higher value than the existing method as well as it shows that our proposed method is superior to identify the difference between weeds and crop.

### *3.3. F1 score*

The F1 score is a statistical measure that provide an accurate evaluation of a classification performance of the model by combining recall and accuracy. An imbalance between the two groups makes the F1 score particularly useful for differentiating between weeds and crops. The F1 score is calculated using the following Equation (21):

$$\text{F1 score} = (2 \times \text{Precision} \times \text{Recall})/(\text{Precision}+\text{Recall}) \tag{21}$$

Fig. 5 and Table 2 illustrate the F1 score result. When comparing our proposed method (BM-AB - 98%) with the existing method (Non-Calibrated SVM - 87%, Non-Calibrated RF - 86%, Calibrated SVM - 87%, Calibrated RF - 86%), our proposed method shows a higher value than the existing method as well as it shows that our proposed method is better to identify the difference between weeds and crop.

### *3.4. Recall*

Recall, known as Sensitivity or True Positive Rate, is a statistic that evaluates a classification model's ability to catch the positive events. Recall refers to the percentage of actual weeds that the model correctly identifies while attempting to distinguish between weeds and crops. The recall formula is as follows in Equation (22):

$$\text{Recall} = \frac{TP}{TP+FN} \tag{22}$$

Fig. 6 and Table 2 illustrate the recall result. When comparing our proposed method (BM-AB - 95%) with the existing method (Non-Calibrated SVM - 87%, Non-Calibrated RF - 86%, Calibrated SVM - 87%, Calibrated RF - 85%), our proposed method shows a higher value than the existing method, this shows that our proposed method is superior to identify the difference between weeds and crop.

## 4. Conclusions

In order to solve the continuing problem of weeds coexisting with crops in agriculture, this study investigates a new approach based on image analysis and artificial intelligence. The barnacles’ mating-tuned Adaboost (BM-AB) technique is introduced in the study and its efficacy in real-time crop-weed discrimination is demonstrated, providing a promising path for sustainable farming activities. The Barnacles Mating-tuned Adaboost (BM-AB) method for weed-crop discriminating. A dataset is used in the approach including a variety of images of crops coupled with weeds and it applies BM optimization to increase the efficacy of Adaboost while using Gabor filter for feature extraction. Implementation and assessment are done with Python. The results show that the suggested BM-AB architecture provides an effective way of automated crop-weed discrimination accuracy, precision, f1score and recall of 93%, 96%, 98% and 95% respectively. In support of sustainable agriculture, this strategy has the potential to advance weed prevention techniques, maximize the resource usage and improve agricultural accuracy.

## References


[1] B.M. McKay. (2022). Between the mine and the farm: livelihood diversification and social differentiation in the Bolivian highlands. The Journal of Peasant Studies.1-19.

[2] R. Sapkota. (2023). Harnessing the Power of AI based Image Generation Model DALLE 2 in Agricultural Settings. arXiv preprint arXiv. 2307.08789.

[3] T. Singh A. Choudhary, S. Kaur. (2023). Weeds can help in biodiversity and soil conservation. Indian Journal of Weed Science (2023) 55(2): 133–140

[4] K. Fatema N.U. Mahmud, M.T. Islam. (2019). Beneficial effects of weed endophytic bacteria: diversity and potentials of their usage in sustainable agriculture. Agronomic Crops. 2: 349-364.

[5] Y. Fukano W. Guo, K. Uchida,Y. Tachiki. (2020). Contemporary adaptive divergence of plant competitive traits in urban and rural populations and its implication for weed management. Journal of Ecology. 108(6): 2521-2530.

[6] A.A. Adeniji, K.E. Jack, M.K. Idris, S.S. Oyewobi, H. Musa, A.O. Oyelami. (2023). Deployment of an Artificial Intelligent Robot for Weed Management in Legumes Farmland. ABUAD Journal of Engineering Research and Development. 6(2): 28-38.

[7] S.L. Young, J.V. Anderson, S.R. Baerson, J. Bajsa-Hirschel, D.M. Blumenthal, C.S. Boyd, C.D. Boyette, E.B. Brennan, C.L. Cantrell, W.S. Chao, J.C. Chee-Sanford. (2023). Agricultural Research Service Weed Science Research: Past, Present, and Future. Weed Science. 71(4): 312-327.

[8] M. Vasileiou L.S. Kyriakos C. Kleisiari G. Kleftodimos G. Vlontzos H. Belhouchette, P.M.

Pardalos. (2023). Transforming weed management in sustainable agriculture with artificial intelligence: A systematic literature review towards weed identification and deep learning. Crop Protection. 106522.

[9] M.I. Hussain Z. Abideen S. Danish, M.A. Asghar, K. Iqbal. (2021). Integrated weed management for sustainable agriculture. Sustainable Agriculture Reviews. 52: 367-393.

[10] C.N. Merfield. (2023). Integrated weed management in organic farming. In Advances in Resting-state Functional MRI. Woodhead publishing. 31-109.

[11] M. Dadashzadeh Y. Abbaspour-Gilandeh T. Mesri-Gundoshmian S. Sabzi J.L. Hernández-Hernández, M. Hernández-Hernández, J.I. Arribas. (2020). Weed classification for site-specific weed management using an automated stereo computer-vision machine-learning system in rice fields. Plants. 9(5): 559.

[12] N. Islam, M.M. Rashid, S. Wibowo, C.Y. Xu, A. Morshed, S.A. Wasimi, S. Moore, S.M. Rahman. (2021). Early weed detection using image processing and machine learning techniques in an Australian chilli farm. Agriculture. 11(5): 387.

[13] T.M. Shah D.P.B. Nasika, R. Otterpohl. (2021). Plant and weed identifier robot as an agroecological tool using artificial neural networks for image identification. Agriculture. 11(3): 222.

[14] B. Urmashev, Z. Buribayev, Z. Amirgaliyeva, A. Ataniyazova, M. Zhassuzak, A. Turegali. (2021). Development of a weed detection system using machine learning and neural network algorithms. Eastern-European Journal of Enterprise Technologies. 6(2): 114.

[15] R. Sohail Q. Nawaz I. Hamid S.M.M. Gilani I. Mumtaz, A. Mateen, J.N. Chauhdary. (2021). An analysis on machine vision and image processing techniques for weed detection in agricultural crops. Pakistan Journal of Agricultural Sciences. 58(1): 187-204.

[16] K. Osorio A. Puerto C. Pedraza D. Jamaica, L. Rodríguez. (2020). A deep learning approach for weed detection in lettuce crops using multispectral images. Agriculture Engineering. 2(3): 471-488.

[17] T. Sarvini T. Sneha S.G. Sushmitha, R. Kumaraswamy. (2019), April. Performance comparison of weed detection algorithms. In 2019 International Conference on Communication and Signal Processing. 0843-0847.

[18] K. Kawamura, H. Asai, T. Yasuda, P. Soisouvanh, S. Phongchanmixay. (2021). Discriminating crops/weeds in an upland rice field from UAV images with the SLIC-RF algorithm. Plant Production Science. 24(2): 198-215.

[19] V. Partel S.C. Kakarla, Y. Ampatzidis. (2019). Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. Computers and electronics in agriculture. 157: 339-350.

[20] A.M. Hasan, F. Sohel, D. Diepeveen, H. Laga, M.G. Jones. (2022). Weed recognition using deep learning techniques on class-imbalanced imagery. Crop and Pasture Science.

[21] J. Machleb, G.G. Peteinatos, M. Sökefeld, R. Gerhards. (2021). Sensor-based intrarow mechanical weed control in sugar beets with motorized finger weeders. Agronomy. 11(8): 1517.