ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 02 (2024)

IMPROVED CAT SWARM OPTIMIZATION WITH ENSEMBLE LEARNING FOR EFFICIENT CROP AND WEED CLASSIFICATION

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Abstract

In recent days, Image processing has been extensively utilized in several fields; its applications appear in agriculture and clinical fields. To classify the weed still physical power is employed in various parts of the world. Physical power has been applied for weed identification in several parts of the world. After that, several approaches for detecting weeds without human intervention appeared and they could not reach the public because of shortage in accuracy. The large space requirements and higher computation time are considered issues in the current system. It also has issues in the feature selection mechanism for attaining superior features to progress the performance of learning. To deal with the issues of the current system mentioned above in the proposed system, the Improved Cat Swarm Optimization (ICSO) with EL-MCNN, Weighted Support Vector Machine (WSVM), and Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithms are introduced. The proposed system includes main phases like pre-processing, image sharpening, feature extraction, feature selection, and classification. In the pre-processing step, the dynamically weighted median filtering algorithm is introduced to take off the noise produced in images efficiently. Image sharpening is done by using a piecewise regression model which has been utilized to increase the quality of images. Feature extraction is performed using quad histogram and Gray Level Co-occurrence Matrix (GLCM) for the utilization of extracting the Edge Orientation Histogram (EOH) feature and shape features effectively. The feature selection is completed by using the ICSO algorithm through the local search optimum and average inertia weight values. Then the EL-MCNN, WSVM, and ANFIS algorithms are proposed to classify the samples into crop, weed, and background accurately. The performance metrics are considered in terms of precision, recall, specificity and, f-measure which are evaluated using existing ensemble MCNN and proposed EL- MCNN, WSVM and, ANFIS algorithms.

Keywords: Improved Cat Swarm Optimization (ICSO), EL-MCNN, Weighted Support Vector Machine (WSVM), and Adaptive Neuro-Fuzzy Inference System (ANFIS)

1. INTRODUCTION

Image processing is a method aimed at improving the quality of raw images obtained by the cameras or sensors located on satellites, space probes, and aircraft or images taken in daily life for various applications. Many methods have been developed for image processing over the past four to five decades. The demand for food quantity and quality is increased because the growing and better-informed population creates challenges and opens up opportunities for agriculture. Amongst difficulties in reducing the negative background affected through the intensive production. One method of achieving this is for the clear precision processing of crops and fields through modern machinery such as Precision Agriculture (PA) [1]. Observing the production areas through the utilization of Unmanned Aerial Vehicles (UAVs)is considered an instance of PA. Data can be employed for adjusting the herbicide distribution models and fertilizer. Automated plant-specific processing and ground vehicles can be utilized through the supplementation of targeted methods [2]. These vehicles must can distinguish among plant species, or at least among the weed and crop to employ the appropriate action.

Diversity in plant species has been accomplished through the utilization of Computer Vision (CV) and Machine Learning (ML). CV is a method that analyzes a digital image thus an action could be associated with it. By using ML, digital image analysis can be automated because algorithms learn what to look for in image data. The information accessibility with consistent annotations, both in quantity and quality considered as the difficulties in this annotation. Two datasets of interest have been released in recent years: the 2015 Crop/Weed Field Imagery Dataset (CWFID) [3] and the 2016 Road Beet Dataset [4].

Following [8], an algorithm was developed that estimates the angular intensity of the cross-section of an image and categorizes the image into wide and narrow classes. But, it cannot be categorized accurately for many weeds. Weed removal through image processing recognition and weed classification is of economic and technical

ISSN:2731-538X | E-ISSN:2731-5398
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importance in the agricultural industry [8]. Weeds are removed from images by image processing, and defined by their color, shape, and size features. These features have been used for categorizing the weeds and similar crop species.

To solve these problems, the proposed systems use MCNN, WSVM, and ANFIS algorithms based on the EL to classify crops and weeds. From this suggested work, texture, color, shape features, and Edge Orientation Histogram (EOH) are removed through preprocessed images. The ICSO algorithm is utilized for feature selection to attain greater classification accuracy. EL-MCNN, WSVM, and ANFIS algorithms based on optimal feature selection will classify images into crop, weed, and background types. Its contributions to this study are preprocessing, image sharpening, feature extraction, feature selection, and classification of NIR and Red image datasets. The suggested ICSO by MCNN, WSVM, and ANFIS algorithms based on the EL method offers better classification outcomes.

The research study is ordered as follows: Section II reviews the weed classification and identification methods. Section III explains the suggested system procedure. Section IV provides the result and discussion, and Section V deals with the conclusion and framework.

2. RELATED WORK

A fuzzy classification method is suggested by Bress an et al (2009) in [10] for weed invasion risk in agricultural areas that takes into account weed variability. The inputs to the system are infection features removed through maps of estimates of weed seed production and weed cover as well as inferred competitive potential for narrow-leaved weeds and broad-leaved weeds. This method offers greater accuracy and a low efficiency level.

Discussion of weed classification by Shahbudinet al (2010), which is essential to recognize weed species to control. Several classification systems have been used to classify weeds depending on images. Many methods measure only accuracy percentage and the totality of classifier parameters are not analyzed or discussed. The effects are discussed and shown with clear generalized concepts to demonstrate the performance of the SVM classifier. On the other hand, it has a dimensionality problem.

Patch-based weed identification with hyper spectral imaging is examined by Farooqet al (2018) in [13]. For this purpose, Convolutional Neural Networks (CNNs) are assessed and then linked with Histograms of Oriented Gradients(HOG), the appropriate patch size is examined and limitations of RGB images are verified. Investigation al out comes specify the total accuracy of weed classification with CNN increases by expanding the usage of bands. The accuracy is greater but the computational load of CNN increases slightly as the number of bands increases.

Six meta-heuristic systems were introduced by Seifiet al (2020) in [14],This system forecasts the (GWL) Ground Water Level by combining the Artificial Neural Network (ANN), ANFIS, and SVM, also estimating the uncertainty and spatial variation analysis. It consists of the krill algorithm (KA),CSO, Weed Algorithm (WA),Grasshopper Optimization Algorithm (GOA),Particle Swarm Optimization (PSO), and Genetic Algorithm (GA)have been employed for hybridization as well as enhancing the performance of the SVM, ANFIS, and ANN models. Finally, GOA improved the accuracy of the ANN, SVM, and ANFIS models, but it had problems with convergence speed.

3. PROPOSED METHODOLOGY

From this suggested work, the ICSO algorithm with EL-MCNN, WSVM, and ANFIS algorithms is introduced for accurate crop and weed classification.

3.1 Dataset Acquisition

Sequoia multispectral sensors have been utilized for image acquisition which have features with four fine band global shutter imagers (1.2MP), and one rolling shutter RGB camera (16MP).

From this proposed study, 40m x 40m is considered for the weed testing area. Now apply some levels of herbicide in the field; max, mid, and min, corresponding to left (yellow), middle (red), and right (blue). The images of the field from left to right contain only crops, crops/weeds, and weeds, respectively. Then, extraction of the NDVI from the left and right patch images was obtained by the utilization of fundamental automatic image processing methods. Images of crop weeds can only be illustrated manually on the advice of crop science experts. It takes an average of about 60 minutes per photo. Every test image includes NIR, (Near InfraRed-790 nm), NDVI images, and red channel (660 nm).By the NIR and Red images, NDVI extraction takes place, given as NDVI = $\frac{((NIR-Red)}{(NIR+Red)}$ where the difference between the soil and vegetation is indicated.

ISSN:2731-538X | E-ISSN:2731-5398
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3.2 Pre-Processing

3.2.1 Image alignment:

To compute the indices, they carry out the fundamental image processing for NIR and Red images through un distortion image, geometric transformation assessment makes use of image correlation and clipping trim so that the processing time of this process is minimal because adaptation is essential for estimated only once for cameras that are inflexibly fixed relative to each other. Fig.1 represents the overall block diagram of the proposed work.

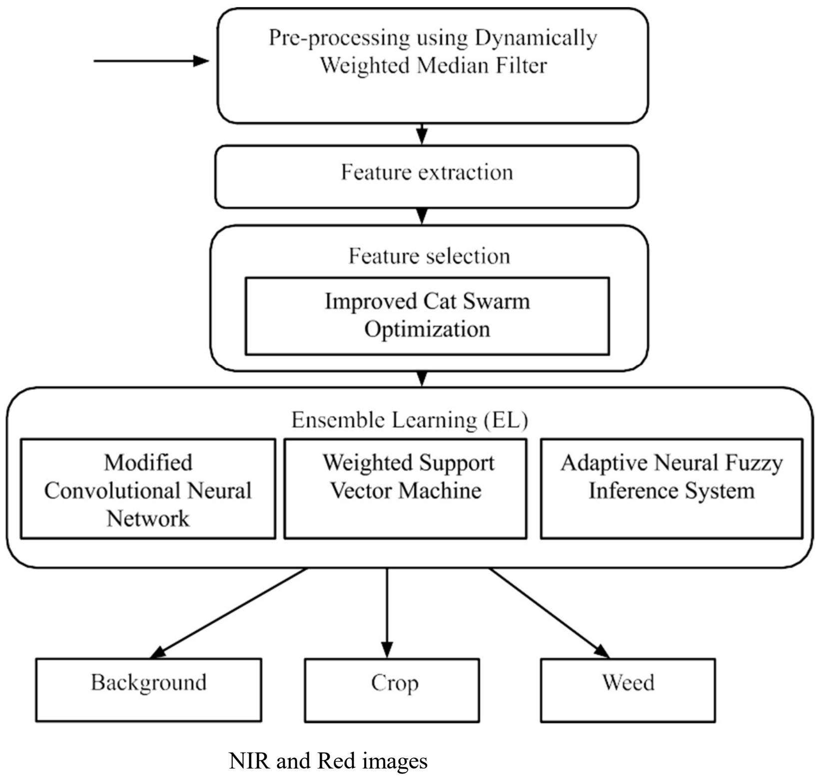

Fig1.Block Diagram of the proposed Algorithm

3.2.2 Dynamically Weighted Median Filtering (DWMF) algorithm

DWMF is employed for the preprocessing in this proposed system and inputs that are given in this algorithm are noisy image I and binary image I_b.Through the proposed noise detection algorithm, the I_b can be attained. For the patches, W*W, all the noisy pixels in the I and the I_b can be detected by selecting W_b and W_n. The size W*W of W_{weights} is computed, though the Location of (W_{weights})Weightage window is detached when W_b has value 1 with a condition that all entries of the W_b have value 1, then for avoid deviation W_{weights} is displaced by the W_b. In this way, zero weightage can be acquired through the detection of noisy pixels. The weights assigned in the W_{weights} will be shifted as a deviation in the W-weights is detected for the exclusion of elements in noisy positions. For, if every element corresponding to a weightage 4 can benoticed as noisy pixels, then the weight of 4 will be detached from the W_{weights}. Therefore, a jump of 2 is detected when changing the weightage from 3 to 5 at W_{weights}. In this case, the weights are reallocated to reduce the number of iterations. The altered window is summed and the weight of the highest one is improved if the sum is even. The odd sum condition is executed to avoid an average value of two pixels according to DWMF. The final weightage window W_R is generated after checking the odd sum of the iterated window and the iteration table A_R is created. Noisy pixels are displaced by the median value of A_R.

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3.3 Image sharpening procedure by piecewise regression model

Gaussian blur is employed for aligned images (threshold = 1.2), followed by a refining method to remove fine responses (e.g., shadows, small debris) in this work. It is used to select a threshold on the acquired image and final blob recognition is performed with a minimum of 300 connected pixels.

Image sharpening is performed through a piecewise regression model to improve image quality [15]. Each pixel in the research field, except constraint pixels, was employed to evaluate the regression parameters. The formula can be expressed as follows:

$$T^*_{g.f} = a_{g.c} . NDVI_{g.f} + b_{g.c} + \epsilon_{g.c} \quad (1)$$

Where the constants are $a_{g.c}$ and $b_{g.c}$ (i.e., slope and intercept) are assessed for the coarse spatial resolution pixel group (NDVIg,c) given the NDVI value of group g. ($NDVI_{g.f}$)denotes the group of pixels with decreasing fine spatial resolution within g.

3.4 Feature extraction

This method is a way of identifying the collection of features to effectively represent data for analysis and categorization. Color, texture, shape, and edge features are removed to categorize crops, weeds, and backgrounds.

3.4.1 Color feature extraction by Quad Histogram

The color feature extraction is performed based on a Quad Histogram in this research work.

The quadtree disintegration is employed to the imageries and homogenous blocks with various sizes are identified.

The histogram adds up the number of pixels for each type and can be quickly produced by reading every pixel in the image one at a time thus raising the appropriate bin. Quad-tree decomposition depends on sequentially segregating the image block into quadrants on the difficulty of the block. If a sub-image is not a homogeneous block, it is further divided into four sub-images of equal size until all sub-images form a homogeneous block. A sub-image is called a homogeneous block with a condition that the highest value of the elements in the block minus the least value of the elements in the block is superior to its corresponding threshold.

3.4.2 Texture feature extraction by Gray Level Co-occurrence Matrix (GLCM)

A significant feature is employed to detect areas of interest in an image called texture. GLCM is widely utilized in several texture studies and it is significant for the feature extraction approach. It is a technique of recording the pictorial content of an image for indexing and retrieval and is also helpful for indicating relevant data to solve an algorithmmic work associated with a given application.

The matrix GLCM, in which the number of rows and columns equals the number of gray levels G in the image. The relative frequency obtained by the matrix element $P\ (i,\ j\ |\ \Delta x,\ \Delta y)$ at two pixels, detached through a pixel distance $(\Delta x, \Delta y)$, appears in a certain neighborhood, one pixel having intensity 'i' and the other will be 'j'. The quadratic statistical probability values for modifications among gray levels 'i' and 'j' at a particular displacement distance d and a particular angle (ɵ) can be obtained from the $P\ (i,\ j\ |\ d,\ ɵ)$. By using a large number of intensity levels G, provides allocation for storing temporary information. i.e. For each combination of $(\Delta x,\ \Delta y) or\ (d,\ ɵ)$ to a $G \times G$ matrix. This method is very sensitive to the texture sample's dimension by which they are assessed [16], because of their high dimensionality. Therefore, the gray level's amount is frequently diminished. The matrix signifies the reference pixel (i) and neighbor pixel (j) relationship.

Energy: A measure of the amount of repeating pixel pairs can be termed Energy (E). It estimates the uniformity of an image. Its value will be large when similar pixels arrive. It is expressed as,

ISSN:2731-538X | E-ISSN:2731-5398
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$$E = \sum_{i,j=0}^{N-1} p_{i,j}^{2} \tag{2}$$

The number of the GLCM is p.

Entropy: A statistical measure of randomness utilized for describing the texture of an input image.

$$\text{Entropy}= - \sum\sum p(i,j) \log log\, p(i,j) \tag{3}$$

Contrast: Measuring local variations in the GLCM and also computing the intensity contrast among one pixel and its neighboring pixels for the entire image. A constant image has 0 contrast.

$$\text{Contrast} = \sum\sum (i-j)^{2} p(i,j) \tag{4}$$

Where p(i,j) = pixel at location (i,j)

Correlation: Measures the common probability of occurrence of specified pairs of pixels.

$$\text{Correlation} = \frac{\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \left(i-\mu_i\right)\left(j-\mu_j\right)p(i,j)}{\sigma_i \sigma_j} \tag{5}$$

Homogeneity: Measures the proximity of the GLCM elements distribution to its diagonal.

$$\text{Homogeneity} = \sum_{i,j} \frac{P(i,j)}{1+|i-j|} \tag{6}$$

$$\text{Dissimilarity}= \sum_{i,j=0}^{N-1} P_{i,j} |i-j| \tag{7}$$

The first element represents the vertical coordinates and the second represents the horizontal coordinates in the above equation (7).

High discriminative power for differentiating two dissimilar images is offered by all those features. From this study, the GLCM second-order texture is built for extracting the features of statistical texture. The second orders have six measures homogeneity, entropy, correlation, energy, contrast, and dissimilarity are analyzed. Energy is a measure of the softness of an image. Contrast measures local-level variations that take lower values for low-contrast images and higher values for high-contrast images. Homogeneity measures the proximity of the elements distribution in the GLCM, the range is from 0 to 1 as well as its value is 1 for diagonal GLCM. Entropy gives a measure of chances. The difference between the two image features is effectively provided by dissimilarity.

3.4.3 Edge Orientation Histogram (EOH)

The EOH feature is removed from the image and represents the spatial gradient orientation in an image. Now, it involves determining the relationship among two specific orientations in an image region and also invariant to changes in global illumination.

3.4.4 **Shape feature extraction**

A collection of shape features as edge and frame features are evaluated for all the image patches of the NDVI image created in the preceding step. Shape feature extraction is evaluated through the Zernike moment function in this proposed work.

3.4.5 Feature selection using an ICSO algorithm

Selection of optimal features by the ICSO algorithm for enhancing the accuracy of weed classification. Depending on common cat behavior, the CSO algorithm was established. Cats spend maximum time relaxing as well as noticing their surroundings instead of chasing objects, which yields extreme energy resource utilization.

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Revealing the above two significant cat behavioral characteristics, the algorithm can be split into two sub-modes, and CSO appeals to these behavioral characteristics “seeking mode” and tracing mode”. The tracing mode simulates the behavior of cats after running towards a target while the seeking mode simulates the behavior of cats at rest and observing their surroundings [17].

3.5.1. Seeking Mode: Resting and Observing

The cat's ability to rest can be determined by the seeking node. Here the cat travels to different locations for space searching however it stays aware. This can be understood as a search for local solutions. The utilized symbols in this mode are given below.

- Seeking Memory Pool (SMP): This parameter define show many copies of the cat are to be imitated.
- Seeking Range of Selected Dimension (SRD): It specifies the modification among new and old sizes of cats selected for mutation.
- Counts of Dimension to Change (CDC): It symbolizes the number of dimensions that the cat position has gone through to mutate.

The stages of the CSO algorithm seeking mode are given below.

1. Set the number of copies $(T)\, of\ i^{th}$ cat
2. According to CDC parameters, the following can be done
   a. Arbitrarily add or subtract SRD values from the current cat position
   b. Substitute the old values for each replicas
3. Estimate the fitness of each copies
4. Select the best candidate solution and arrange it at the position of ith cat.
5. The stages of the CSO algorithm search mode are given below.

3.5.2 Tracing mode

The cat's hunting skills are replicated by this mode. When the cat hunts, the cat's position and speed will be updated. Thus, there is a big difference between the cat's new and old positions. The position (P_i^c) and velocity (V_i^c) of the ith cat in space-C expressed by, $P_i^c = \{P_i^1, P_i^2, \ldots P_i^C\};\ V_i^c = \{V_i^1, V_i^2, \ldots V_i^C\}$.

$P_{best}^c = P_{best}^1,\ P_{best}^2, \ldots P_{best}^C$ symbolizes the best cat position.

Through (8) and (9), the velocity and position of the jth cat are evaluated.

$$V_{i\,new}^C = w * V_i^c + a * r * (P_{best}^c - P_i^c) \qquad (8)$$

The ith cat updated velocity in the cth dimension is indicated as $V_{i\,new}^C$, The jth cat old velocity is signified as V_i^c, weight factor w in the range from 0 and 1, the user-defined constant is referred toas a, random number$r$ in the range of 0 and 1, the jth cat best position in dth dimension can be signified as P_{best}^c, and the ith cat current position in the cth dimension denoted by P_i^c where $c = 1, 2, \ldots C$.

$$P_{i\,new}^C = P_i^c + V_i^c \qquad (9)$$

The ith cat updated position in the cth dimension is denoted by $P_{i\,new}^C$

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, the i^{th} cat current position in the c^{th} dimension is specified as P_i^c, and the i^{th} cat velocity is represented by V_i^c.

Issues found in the CSO algorithm

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The inertial weighting concept is presented [18] to overcome the premature convergence, because oflow diversity in the CSO algorithm. The position of the cats is updated through the current position and the speed of the cats is also stated in this system. At times, it fails to find an optimal solution because of a lack of information about the cat's best global position. Therefore, to solve these problems, the modifications are proposed in this algorithm are given below.

The ICSO algorithm

- To determine a favorable solution as well as enhance the convergence speed, the cat's best global position has been utilized to guide the cat's positions in tracking mode. Therefore, a new improved search equation is suggested for the tracking mode that includes the best overall position of the cat in the CSO algorithm.

$$P_{i\,new}^{C+1} = (1 - \alpha) * P_i^c + \alpha * X_g + V_i^c \quad (10)$$

- In tracking mode, the cat's previous position as well as the velocity vector for the cat's position updating were utilized by the CSO algorithm. The cat's updated position is affected only by the velocity vector. Therefore, for developing the CSO algorithm's diversity, particularly in tracking mode, a new update rate equation is proposed,

$$V_{i\,new}^{C+1} = V_i^c + \alpha(X_g - P_i^c) + \beta * \delta \quad (11)$$

A arbitrary vector uniformly distributed in the range [0, 1] isδ, acceleration parameters employed to manage the cat's position toward local and global best positions are α and β and the global best cat's position is represented by X_g.

To establish a balance among the process exploration as well as exploitation, two acceleration parameters α and β perform as control parameters. whereasβperforms as a decreasing function andα acts as an increasing function. Both values are flexible and equation (12) can be used for the estimation.

$$\beta(T) = \beta_{max} - \left(\frac{\beta_{max} - \beta_{min}}{T_{max}}\right) * T \quad (12)$$

The upper and lower bound can be represented byβ_{max} and β_{min} in equation (5), the greater number of iterations is denoted as T_{max},and the current number of iterations is T, Therefore, a step function whose value lies among the upper and lower limits is referred as $\beta(T)$. Larger values of α help exploration, while smaller values support exploitation. Controlling the process of the cat's explorations in the search space is considered as the main purpose of this parameter$\beta(T)$.

$$\alpha(T) = \alpha_{min} + (\alpha_{max} - \alpha_{min})\sin\left(\frac{\rho T}{T_{max}}\right) \quad (13)$$

ISSN:2731-538X | E-ISSN:2731-5398
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The maximum and minimum values for the last and first iterations can be represented as α and α in [6], The maximum iteration number is represented as T_{max}, and t represents the current number of iterations. The combination of the parameter $\alpha(T)$ is aimed at influencing the proposed algorithm's global exploration ability. High values of the parameter reinforce the cat's best global position and also tend to improve the solution.

$$] = [P_{lbest} - r,\ P_{lbest} + r]^{N} \quad (14)$$

max min

Local search method

A local search technique gives an outline for enhancing the solution quality in this sub section. The Tracing phase of the ICSO algorithm has been applied with the proposed technique. Guide the direction of research and provide optimal solutions are the main purposes of this process. The following points summarize the necessity of the local search method:

- Lead the way for the search direction and achieve the optimum solution in the search space.
- Deal with the local optimization issue by neighborhood information.

The current local best solution(P_{gbest}) is employed with this search procedure. Through (15), the neighborhood of the best solution can be determined.

$$[_{gb} \qquad neighbor\ P$$

The boundary of the neighborhood is denoted as "r",The current best solution is represented as P_{lb} alsosymbolized as $P_{gb}(0)$, and the populationis n.

$$P_{lb}(K) = min\{P^{1}_{lb}(K), ...P^{L}_{lb}(K), ... P^{N}_{lb}(K)\} \quad (15)$$

Here, the global best cat position in the Kth iteration is $P^{L}_{gb}(K)$, where $K = 1, 2, ..., X$ and $L = 1, 2,..., N$;

The number of iterations in the local search method can be denoted by X. It can visit N number of population in each iteration

Average-Inertia Weighted CSO

Limitations must be placed on the velocity equation to control the cat's speed for each aspect, examining whether the speed is within the highest range or not in the pure CSO. A parameter such as inertial weight is utilized for handling this issue for the adaptation. Now, the inertial weight value(w)might be selected randomly as well as the research outcomes designated to choose better w within the range$[0.4,\ 0.9]$, the velocity raises with time for every $w > 1$, influencing the cats to ultimately diverge away from the limit of the search space. For w<1, the speed reduces with time, finally reaching 0, and tends to converge. Therefore, the new equation for updating the best global position can be expressed as

$$V_{K,c} = WV_{k,c} + r_1 d_1 (P_{best} - P_{k,c}) \quad (16)$$

Here, the acceleration coefficient can be written as d_1,which is equivalent to 2.05 normally, consistently formed random value r_1 within the range of $[0,\ 1]$, and the ICSO is written as w.

The equation with a new method for position updating utilizes the considering two positions: The average current data in the initial method as well as the prior location in the succeeding method, thus the average current data and previous speed utilize the ICSO. Therefore, the new equation for the best global position is expressed as,

$$P = \frac{P_{i+1} + P_{i}}{} + \frac{V_{i+1} + V_{i}}{} \quad (17)$$

$i+1$ 2 2

The utilization of the ICSO in this task for attaining greater convergence with a few repetitions as well as enhancing its performance.

Algorithm 1: ICSO

1. Set the various parameters of the proposed algorithm such as amount of cats (n), SMP, SRD, neighborhood structure, β, α, $and\ A$ and arbitrarily placed n amount of cats in arbitrary space search.
2. Start with the position and velocity of every cat in the C-dimensional search space.
3. Calculate the fitness function and keep the best position of the cat in memory
4. While(i < maximum iteration)
5. According to the Flag value, arbitrarily distribute cats into tracing and seeking modes
6. If (Flag==1); Cat in seeking mode
7. For every cat, employ the seeking mode procedure
    a. Create j copies of all cats.
    b. Calculating the shift bit value for every cat by SRD.
    c. Add or subtract every cat to shift the value
    d. Calculate the fitness function for every new position of cats.
    e. Every time, select the average inertia weight (w) arbitrarily in the range of [0.4, 0.9] to control the cat's excessive roaming outside the search window
    f. Calculate new global best position updating through (16)
    g. Attain the current global best position through (17)
    h. Relate the fitness function value and retain the best position of the cat in memory
    i. End for
8. Else, the Cat in tracing mode
9. For every cat, employ the tracing mode process
    a. Update the velocity of all cat through (10).
    b. Update the position of all cat through (11).
    c. Calculate the fitness function for the newly generated position of the cat
    d. Relate the fitness function value and retain the best position of the cat in memory
    e. End for
10. Restore the cat's position and also find the best position for a cat
11. $IF\ (rand(0,\ 1) \leq Fit_i)$ then
12. Employ a Local Search Mechanism
    a. Get the current local best solution (P_{lbest}) through (14)
    b. Get the neighborhood of the best solution
    c. Attain current best local position through (15)
13. Restore the cat's position and the global best position.
14. End if
15. i = i + +
16. End while
17. Attain the final solution.

The innovation of the ICSO algorithm enhances the local and best global solutions through the local optimal values as well as the average value of the inertial weights. Therefore, categorizing the exact outcomes into crop, weed, and surrounding was attained by this algorithm.

3.5 Classification using EL-MCNN, WSVM, and ANFIS algorithm

Depending on the chosen attributes, EL with MCNN, WSVM, and ANFIS categorizes the input samples into crops, weeds, and the context in this research.

The MCNN is considered as an input for the chosen attributes. The CNN is designated as a powerful class of deep neural networks that contain many unknown layers that will execute convolution as well as sub sampling for extracting low to high-level features from the input data. Fundamentally, it comprises three layers: a convolutional layer, a sub sampling or pooling layer, and a fully connected layer. Admit input to the network is the selected feature. The network has an input layer that holds the features as input, an output layer from which the system takes the trained output, and hidden layers as intermediate layers. Thus, the feature weight values are optimized to obtain accurate outcomes by the proposed MCNN.

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Convolution layer

The size R∗C of an input image is integrated with size a∗a of a kernel (filter).In the input matrix, every block is independently integrated with the kernel and produces a pixel at the output. The obtained input results can be used to produce n output image features. In general, the kernel of the convolution matrix is called a filter while achieving the output image features and the input image are referred to the dimension i∗i of the feature maps.

The$C_j^{(l)}$ is referred to as the l-th convolution layer output, and comprises feature maps as evaluated below:

$$C_i^{(l)} = B_i^{(l)} + \sum_{j=1}^{a_i^{(l-1)}} K_{i,j}^{(l-1)} * C_j^{(l)} \qquad (18)$$

Here, the bias matrix is$B_i^{(l)}$, andtheconvolution filter $K_{i,j}^{(l-1)}$or kernel of size a∗a which connects the j-th feature map in layer (l − 1) in the i-th feature map in the identical layer. The output layer $C_i^{(l)}$comprises feature maps. The first convolutional layer$C_i^{(l-1)}$ is considered as the input space, i.e.,$C_i^{(0)} = X_i$.

The feature map is created by the kernel. The activation function is applied to the nonlinear transformation outputs after the convolution layer:

$$Y_i^{(l)} = Y(C_i^{(l)}) \qquad (19)$$

Here, the output of the activation function is$Y_i^{(l)}$, and the input $C_i^{(l)}$is received by it.

Sub sampling Layer

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Reducing the feature map's spatial dimension extracted through the preceding convolutional layer is considered to be the prime objective of this layer. A mask of size b∗b is chosen as well as the sub sampling operation among the feature map and mask will be implemented. The remainder of the sub sampling layer supports the previous layer to endure rig id transformations among input images. The optimal weights are updated depending on the average of the feature weights in this proposed work.

Weighted mean $w_H = \frac{N}{\sum_{i=1}^{N} wx_i}$ (20)

Here, the$number\ of\ features\ -\ N$, the weight value of the feature$-\ w$, and features- x_i.

Full Connection

The Soft max activation function is utilized by the output layer:

$$Y_i^{(l)} = f(z_i^{(l)}),\ \text{where}\ z_i^{(l)} = \sum_{i=1}^{m_i^{(l-1)}} w_H\, y_i^{(l-1)} \quad (21)$$

where w_H is the weighted Harmonicme an of the features. For each class representation, w_H can be adjusted by the last layer to passed through and the transfer function representing the nonlinearity is f. Categorization of the input images into three classes: background, crop, and weed.

The output probabilities by all the MCNNs are already averaged in generating a categorization for the provided input. The average output S_i for an output can be obtained by:

$$S_i = \frac{1}{n}\sum_{j=1}^{n} r_j(i) \quad (22)$$

The output i of network j is $r_j(i)$ for an assumed input pattern.

The output possibilities by all the MCNNs are increased with a weight α is predicted earlier for a given output pattern:

$$S_i = \sum_{j=1}^{n} \alpha_j r_j(i) \quad (23)$$

weighted mean is used to compute the weight α in this proposed work. The weight calculation is evaluated as,

$$\alpha_k = \frac{A_k}{\sum_{i=1}^{n} A_i} \quad (24)$$

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Accuracy A_k for the validation set of the k network, and i turns over the n. Inputs are categorized as background, crop, and weed by the average output of the MCNN network. The innovation of the EMCNN is utilized for categorizing the above layers with average best classifier values.

WSVM

This is a powerful machine learning method for information classification that attempts to determine a linear separating hyper plane with a maximum margin for data separation in a higher dimensional space. Conventional SVM algorithms have extended training times. The WSVM is presented in this work to solve this problem.

By separating different layers, WSVM achieves a level of separation close to the optimal level. Linear algebra and geometry can be utilized for information disintegrating which can be separated through nonlinear rules when WSVM indirectly embeds information by a high-dimensional feature space. Employing the hyper plane for the greatest possible portion of the training data separating on the same class, by increasing the distance of every class through the hyper plane [19]. In general, the WSVM splits as a higher-dimensional space by generating a hyper plane. The labeled displacement vector of each weed provides an image feature that can be applied as an input to the WSVM classifier, generating a training data model, which is then used for the dynamic classification of hidden attribute displacements. Testing is performed through the training data set model. It is a maximum-margin hyper plane classifier that reveals greater classification accuracy in training sets for more informative attributes.

Assigning all data with various weight depend on its relative importance in the class, thus it supports for the decision surface learning and it is considered to be the main idea for the WSVM. Assuming the weights, then the training data set is expressed below:

$$\{(x_i, y_i, W_i)\}_{i=1}^{l}, \quad x_i \in R^N, \quad y_i \in \{-1, 1\}, \quad W_i \in R \tag{25}$$

Here, the weight assigned is given by the scalar $0 \le W_i \le 1$ to data point x_i

The purpose of this method is to enlarge the separation margin and minimalize the errors of the classification to obtain good generalization ability when initializing the cost function construction. The C value is fixed as well and all training data points are treated equally through training, WSVM considers a penalty period to reduce the influence of less important data points. The constrained optimization problem is stated as follows,

$$Minimize\ \Phi(w) = \frac{1}{2} w^T w + C \sum_{i=1}^{l} W_i \xi_i \tag{26}$$

Subject to

$$y_i(\langle w, \phi(x_i)\rangle + b) \ge 1 - \xi_i, \quad i = 1, \dots l \tag{27}$$

$$\xi_i \ge 0 \quad i = 1, \dots l$$

In the above formulation, it assigns the weight W_i to the x_i data point. Therefore, the dual formulation turned out as,

$$W(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} \alpha_i \alpha_j z_i z_j K(x_i x_j) \tag{28}$$

subject to

A constant C is restricted through the upper limits of α_i in the SVM, although they are limited in dynamical boundaries considered as weight values CWi in the WSVM.

The classifier WSVM identifies that both the NIR and Red images have background, crop, or weed. With the proposed WSVM algorithm, the recognition accuracy will be improved.

ANFIS algorithm for classification

The ANFIS is a neuro-fuzzy system in which fusion is performed among the fuzzy inference system and the neural network. Fuzzy logic provides the fuzziness and system uncertainty being demonstrated where as neural networks offer adaptability sense. An initial fuzzy model integrates the input variables that are derived initially employing the rules removed in the system's input-output data through the utilization of a hybrid technique. Then, the neural network is used to refine the initial fuzzy model's rule to yield the ultimate system of the ANFIS model. For a given database it provides fast convergence, high accuracy, and adaptability.

ISSN:2731-538X | E-ISSN:2731-5398
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The ANFIS's internal structure is partitioned into the previous as well as the next part. These two halves are connected through the rules in the form of a network [20]. The fuzzy rules are identified for the particular input-output data set in the first stage, for refining these rules, the final stage is employed with the neural network. Two inputs x, y fixed by a typical Takagi-Sugeno's rule, and one output Z will be written as,

$$if\ x\ is\ A_1\ and\ y\ is\ B_1\ then\ f_1 = \alpha_1 x + \beta_1 y + r_1 \tag{29}$$

$$if\ x\ is\ A\ and\ y\ is\ B\ then\ f = \alpha x + \beta y + r \tag{30}$$

2 2 2 2 2 2

Here, the linear output parameters can be represented as α, β, and r. Fig.2 shows the resultant ANFIS structure. Containing five layers along with two node classes were characterized through the square and the circle. The fixed node is termed the circle node as it is unable to receive some parameters. The convergence rate is enhanced as they remain for higher image datasets with the support of the innovative ANFIS algorithm. Therefore, prediction outcomes in terms of weed, crop, and background for the specified classes are improved by this algorithm.

4 EXPERIMENTAL RESULTS

The sets of data are taken from the link.https://github.com/inkyusa/weedNet/tree/master/data/Sequoia. This work utilizes MATLAB to assess existing CNN, EMCNN and proposed EL-MCNN, WSVM, and, ANFIS classification performance. The performance of the proposed EL-MCNN, WSVM, as well as ANFIS are compared with the existing EMCNN and CNN classification for weed detection by precision, recall, f-measure, and specificity. Table 1 shows the number of images in each crop, weed, and crop-weed class for training, and testing datasets.

Table 1:Datasets for training and testing images

NIR+Red+NDVI	Crop	Weed	Crop-weed	Num.multispec
Training	132	243	-	375
Testing	-	-	90	90
Altitude	2	2	2	-

Plant a 40m x 40m test field of sugar beets with different levels of herbicides utilized to collect ground-truth mechanism automatically. The demonstration of the system has 243, 132, and 90 multispectral imageriesfor the classes: weeds, crops, and crop-weed mixtures. Every single training/test includes (NIR, 790 nm), Red (660 nm), and NDVI images.

Performance evaluation

The execution of the suggested EMCNN when related to the provided MCNN-based classification by recall, precision, and f-measure.

Precision

The proportion of properly predicted definite instances to the total predicted definite instances can be defined as precision. Through equation (31), the precision can be computed.

$$Precision = \frac{TP}{TP+FP} \quad (31)$$

Recall

A *recall* is the proportion of correctly predicted positive observations in the weed prediction that are regained successfully.

$$Recall = \frac{TP}{TP+FN} \quad (32)$$

F1 score

A measure of the harmonic mean of precision and recall can be defined as the F1 score. It has been utilizedfor statistical measures to evaluate the classifier's performance. Hence, it takes into account both FP and FN results. Equation (33) can be used for computing the F1 score.

$$F - measure = 2 \frac{Precision*Recall}{Precision+Recall} \quad (33)$$

Graph Results

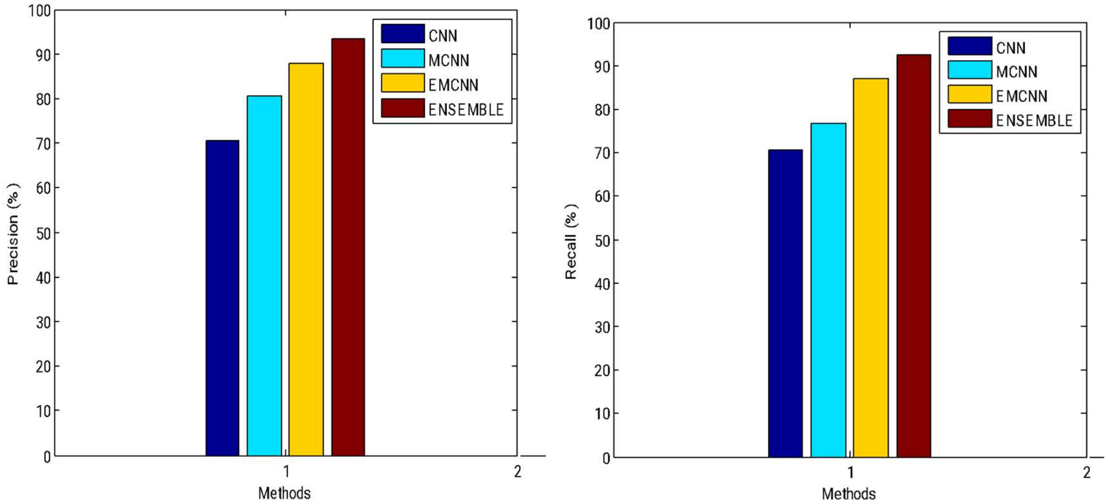

Fig 2 (a) Precision **Fig 2 (b) Recall**

Fig2Comparison of the recall and precision performance

From Fig 2, the recall and precision performance of the existing CNN, MCNN, EMCNN, and proposed EL-classification are compared. In the x-axis existing method is taken and precision and recall metrics are taken as the y-axis. The experimental results show that the existing CNN MCNN, EMCNN-based classification provide slower precision and recall values whereas the proposed ensemble-based MCNN, WSVM, and ANFIS classification provides higher precision and recall values. The proposed system provides more accurate results since the ICSO algorithm selects optimal features through the best fitness values and ensemble-based MCNN, WSVM & ANFIS are used to classify more accurate weed, crop, and background from the given dataset.

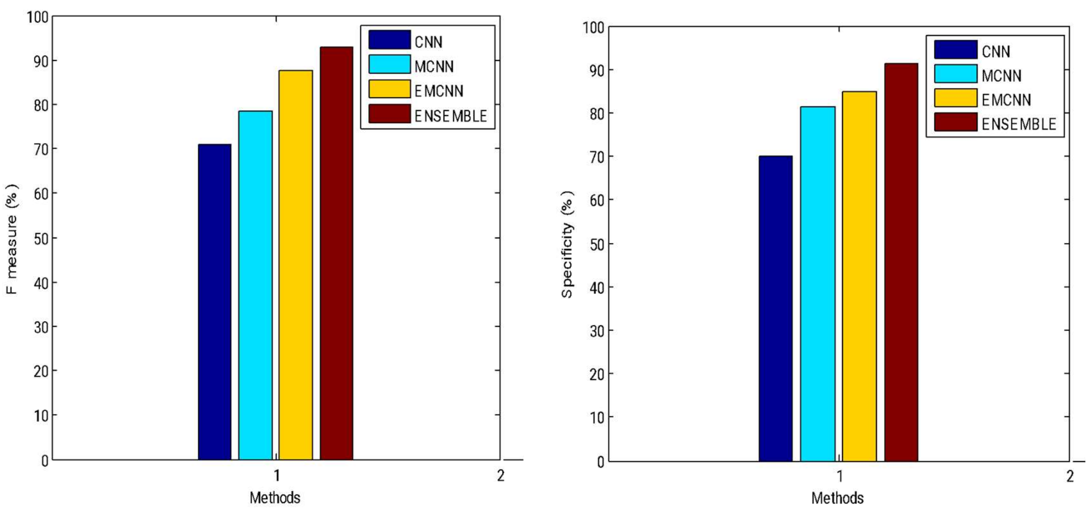

Fig 3 (a) F-measure **Fig 3 (b) Specificity**

Fig3 comparison of the f-measure and specificity performance

Fig 3 shows the F-measure and specificity performance for the existing CNN, MCNN, EMCNN, and proposed EL-MCNN, WSVM, and ANFIS classification algorithms. The results obtained through the graph conclude the suggested EL-MCNN, WSVM, and ANFIS classification approach achieves higher f-measure and specificity whereas the existing CNN, MCNN, and EMCNN approach provides lower f-measure and specificity. Compared with the existing system the proposed EL-MCNN, WSVM, and ANFIS classification algorithms achieve better performance. The ICSO computes best fitness values using local and global optimal features which are used to

ISSN:2731-538X | E-ISSN:2731-5398
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increase the classification accuracy results.

Table 2 Comparison Table for performance metrics

Metrics/ Methods	CNN	MCNN	EMCNN	Ensemble algorithm
Precision (%)	70.52	80.63	88	93.47
Recall (%)	70.75	76.62	86.99	92.45
F-measure (%)	71	78.57	87.49	92.96
Specificity (%)	70	81.34	85.02	91.47

5 CONCLUSION

The proposed system designed an EL-MCNN, WSVM, and ANFIS for accurate crop and weed classification. To remove the noises from images, a dynamically weighted median filtering algorithm is utilized. Then, image sharpening is done by using a piecewise regression model which is used for enhancing its quality. The execution of the feature selection by the quad histogram and GLCM is more effective. Also, the EOH and shape features are removed in the given images. The optimal features are selected through the ICSO algorithm via local search and inertia weight optimization. Finally, according to the selected features the EL-MCNN WSVM, and ANFIS classify the samples into crop, weed, and background. Research outcomes indicate that the proposed system improved performance than the existing works by the metrics. In future work, it will be related to the identification of different weed species. Moreover, it will work with the other image processing methods and hybrid optimized deep learning models including the boundary detection and its combination with the current findings.

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