AN EFFICIENT CROP AND WEED CLASSIFICATION USING ENSEMBLE MODIFIED CONVOLUTIONAL NEURAL NETWORK

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Abstract

Smart farming methodologies are highly necessitated for growing or supporting crop yield to uphold emergent worldwide population with minimal environmental effect. Crop health spatial survey key indicators as well as treatment, e.g., herbicides, pesticides, besides fertilizers, merely to pertinent areas are attained through precision agriculture methods. In a similar way pertaining to crop health besides yield, selective weed treatment is regarded as crucial phase. Weed detection with least damage to surrounding plants to neighboring plants in consistent as well as precise way pose another challenge. Quad Histogram with Modified Convolutional Neural Network (MCNN) is utilized previously for categorizing crop as well as weed. Here this research exploits quad tree decomposition for feature extraction in addition Modified Convolutional Neural Network (MCNN) for classification. Still, color features are exploited for weed categorization. Classification rate is enhanced through several texture features which are also necessitated. In addition, single classifier is also sufficient to yield improved outcomes, henceforth ensemble learning is desired for prediction performance upgrading. An Ensemble Modified Convolutional Neural Network (EMCNN) is a promising solution for categorizing crop as well as weed merely. Basically, the input images in this research are Near-Infrared (NIR) and red images. Normalized Difference Vegetation Index (NDVI) from NIR as well as red patch images extraction is accomplished through simple automated image processing techniques. Noise removal from images in a proficient way can be attained through dynamically weighted median filtering algorithm which is followed by color feature extraction via Quad Histogram. Texture features removal is performed through Improved Local Binary Pattern (ILBP) along with shape parameters computation such as contour and skeleton features for performance enhancement. Dynamic Non-linear Decreasing Strategy based Glowworm Swarm Optimization (DNDSGSO) algorithm is greatly utilized for optimal features selection. Ensemble Modified Convolutional Neural Network (EMCNN) plays its role for sample categorization into crop, weed and background. Improved performance is achieved with the help of suggested system in contradiction to prevailing research pertaining to precision, recall, f-measure and detection rate which is validated through experimentation outcomes.

Keywords: Normalized Difference Vegetation Index (NDVI), Improved Local Binary Pattern (ILBP), Crop and weed

1. INTRODUCTION

Agricultural advancement can be enhanced by two major issues namely productivity upsurge and promoting plantation systems. A weed corresponds to undesirable pests which subsists as well as reproduce in agricultural fields. Also, production is disturbed along with superiority due to the competition of crops for water, light, soil nutrients, and space and thereby inhibiting agricultural progress. Crop harvest might diminish from 95 to 10 percent because of these uncontrolled weeds [1-2]. Weed control strategies are thus crucial for sustaining crop productivity. Currently, numerous stratagems such as human laborers, mechanical cultivation, or applying herbicides [3-4] are exploited for weed removal. Herbicides application is regarded as one amid general technique which has better influence on both environment and human health. Sometimes tolerance may arise due to the similar sort of herbicides application frequently in a field for weed population removal which also increases various economic concerns. Traditionally, crops discrimination from weeds is performed using machine vision system for herbicides application effectually besides crop enhancement with diminished ecological degradation [5].

The amalgamation of statistical Grey-Level Co-Occurrence Matrix (GLCM), structural approach Fast Fourier Transform (FFT), and Scale-Invariant Feature Transform (SIFT) features is exploited for an oil palm plantation in a real-time weeds control system and thereby attained accuracy of 80% [6]. In [7] weed and corn seedling categroizaton is greatly achieved through GLCM and histogram statistics-based texture features in addition to SVM classifier. Weed finding is attained by assessment through Convolutional Neural Network (CNN) which is contrasted with Histogram of Oriented Gradients (HoG) [8]. Restricted leaf quantity is utilized for testing through this technique. An algorithm is established for image angular cross-sectional intensity computation categorizing images into broad and narrow class [9]. Nevertheless, precise categorization for more than one weed classes cannot be accomplished. Hence various techniques and investigation are also suggested but not achieved adequate outcomes.

Ensemble Modified Convolutional Neural Network (EMCNN) is involved for mitigating these issues for crop and weed categorization. The Preprocessed images are exploited for colour, texture and shape features extraction in this research. Feature selection is attained by Dynamic Non-linear Decreasing Strategy based Glowworm Swarm Optimization (DNDSGSO) algorithm for higher classification accuracy. Ensemble Modified Convolutional Neural Network (EMCNN) aids in image classification into crop, weed besides background on the selected aspects framework. EMCNN is opted as relatively faster can be attained than other algorithms while sustaining competitive performance.

The paper organization is specified here: Literature review is reported in section II. Explanation of Suggested procedure in given in section III. Experimental outcomes are charted in Section IV. Paper Conclusion is specified in Section V.

2. LITERATURE SURVEY

Various researches are being conducted for weed detection establishment through algorithm design for segmentation, feature extraction, representation and classification. The current techniques summary is presented in the ensuing section.

Prema and Murugan (2016) established a system for crop and weed discrimination through unique Angular Texture Pattern (ATP) extraction method exploiting curvelet transformation. Adaptive Median Filter (AMF) is also utilized for impulse noise filtering from the image. Green pixel extraction besides K-means clustering is performed for Plant image identification in addition to it Wrapping based Curvelet transform application is done to the plant image. Plant image angular texture pattern is obtained by Feature extraction. Particle Swarm Optimization (PSO) based Differential Evolution Feature Selection (DEFS) approach is involved here for optimal features selection. At that time, selected features learning is done besides passed through an RVM based classifier for weed detection. Weed recognition in the plant image is accomplished using Edge detection and contouring. Various levels of weed patchiness such as low, medium and high levels are recognized through Fuzzy rule-based methodology. The suggested approach accuracy is greater in contradiction to state-of art methodologies which is substantiated through experimentation outcomes [10].

Amruta and Aware (2016) suggested a system for crop and weed detection on the basis of texture and size features for yield verdict and weed management. Crop recognition is attained through five texture features such as inertia, energy, local homogeneity, entropy and contrast. Crop and weed identification is performed on the basis of morphological size based features. Outcomes are contrasted for making decision for crop and weed identification. Image segmentation utilizes image processing techniques for obtaining image cell. Cells spraying are regulated through decision making. Weed position location on real field is established for Cartesian robot manipulator through coordinate's computation to selectively spray herbicides [12].

Prema et al (2016) categorized weed through the combination of Curvelet Transform and Tamura Texture Feature (CTTTF) with Relevance Vector Machine (RVM) classification. A proficient curvelet make over besides patch level tamura texture feature extraction technique for weed sorting is suggested in this research. RVM is greatly exploited for crop and weeds sorting in addition to weed partitioning. Also, outcomes are contrasted with support vector machine and with random forest classifier technique to substantiate the performance of the proposed system pertaining to correctness, specificity and sensitivity [13].

Bakhipour et al (2017) recommended weed segmentation process through texture features utilization from wavelet sub-images extraction. Investigation is done for wavelet texture features for their potential substantiating in weed recognition in a sugar beet crop. Wavelet texture features for every image sub-division in an artificial neural network is done through successive stages in a discrimination algorithm. Every multi-resolution image formed through single-level wavelet transform is obtained for Co-occurrence texture features. Neural network decision forms the basis for image segmentation for each sub-division labeling as weed or main crop. Algorithm optimization is done through weeds discrimination investigation from the main crop in two ways. 14 selections are done through 52 extracted texture features through Principal Component Analysis. Effective weed discrimination amid crops is achieved though substantial amount of occlusion besides leaves overlapping occurs [11] which is validated by experimental outcomes.

Fawakherji et al(2019) exploited deep learning approach for accomplishing an precise weed/crop sorting through two Convolutional Neural Networks (CNNs) sequence by means of robot. Initially pixelwise, plant-type agnostic, segmentation amid vegetation besides soil enabling for connected blobs set extraction demonstrating plant instances is accomplished through first network on the basis of encoder-decoder segmentation architecture. External, ready to use pixel-wise labeled data sets emerging from various contexts is greatly involved for network training. Every plant is categorized amid crop and weeds through second network. Improved classification outcomes are obtained on real world data and validated through quantitative experimental results for challenging images [14].

3. PROPOSED METHODOLOGY

Dynamic Non-linear Decreasing Strategy based Glowworm Swarm Optimization (DNDSGSO) algorithm with Ensemble Modified Convolutional Neural Network (EMCNN) is greatly exploited in this research for categorizing crop and weed in a precise approach. The Main modules involved in the system are dataset acquisition, pre-processing, feature extraction, feature selection in addition to EMCNN based classification. The suggested work flow diagram is revealed in figure 1.

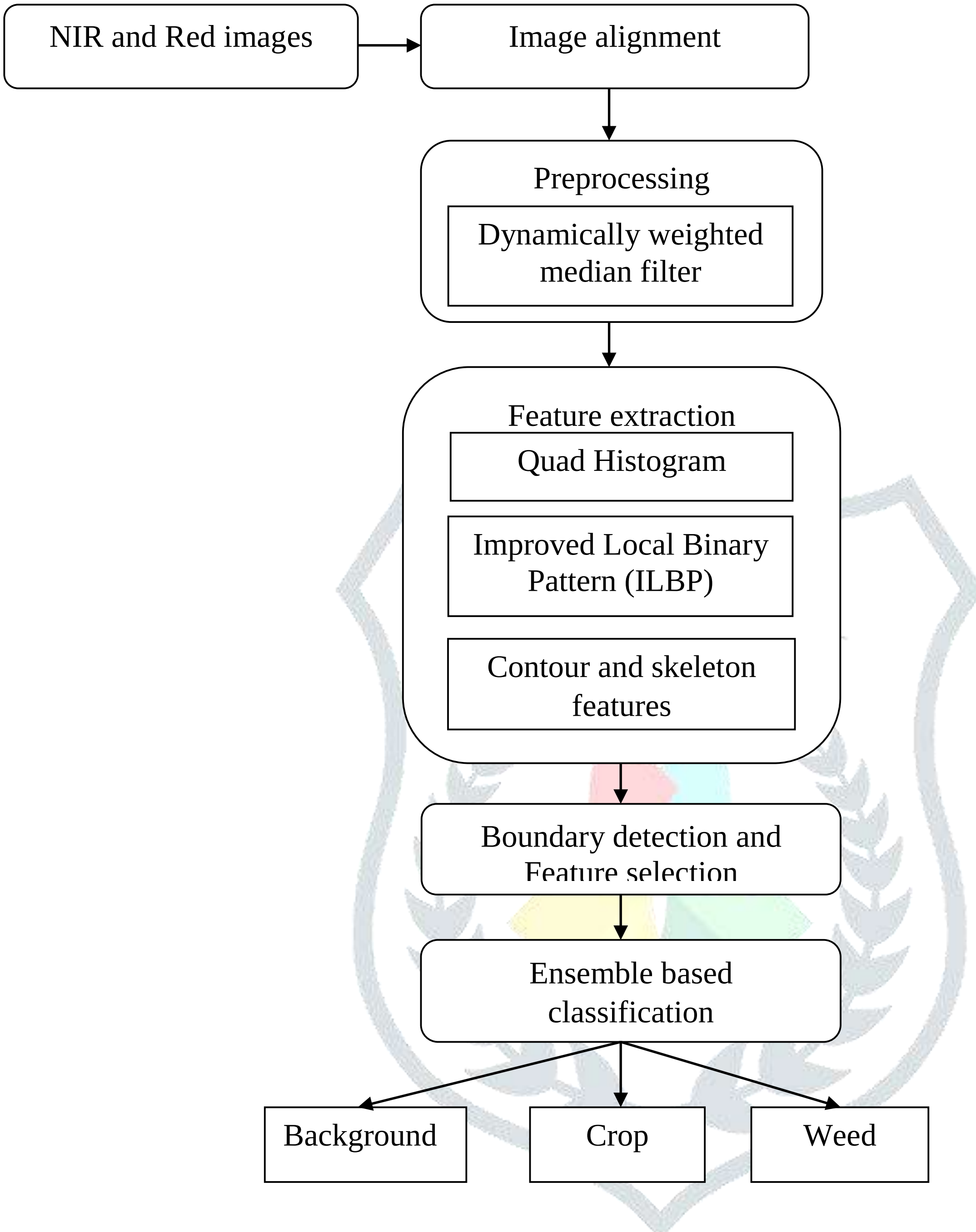

Figure 1: Flow diagram of the proposed research work

3.1 DATASET ACQUISITION

Sequoia multispectral sensor is utilized for image acquisition encompassing four narrow band global shutter imagers (1.2MP), besides one rolling shutter RGB camera (16MP).

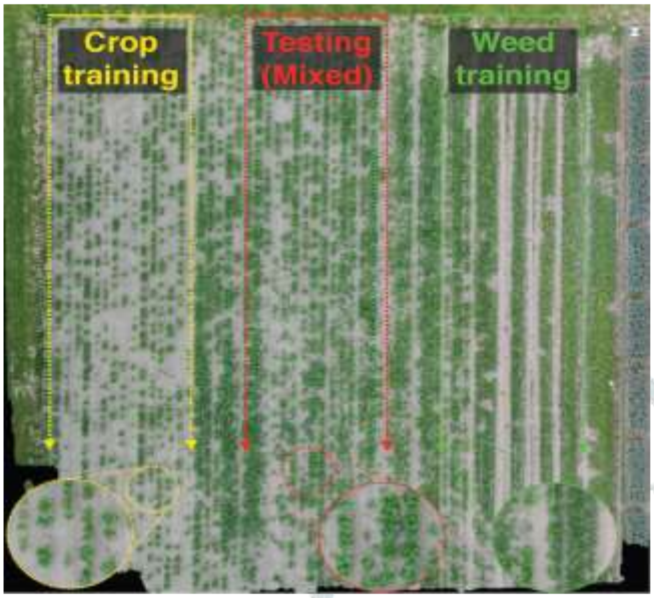

Figure 2: Aerial view of our controlled field with a varying herbicide level

Weed test field whose area is 40m×40m is utilized for this research. Various herbicide levels like max, mid, and min, corresponding to left (yellow), mid (red), and right (green) correspondingly are applied as exposed in figure 2. It is observed that crop-only, crop/weed, and weed-only are present from the left-to-right field patches. NDVI extraction is accomplished through simple automated image processing techniques from left and right patch images. Crop science specialists guidance is necessitated for manual crop weed images annotation. It also involves 60 mins/image typically for this process. Near-infrared (NIR, 790nm), Red channel (660nm), and NDVI imagery are mainly comprised in every training image/test image .

3.2 PRE-PROCESSING

1) Image alignment:

Image correlation in addition to cropping is utilized for geometric transformation ∈SE3 assessment along with indices computation through image undistortion by performing simple image processing for NIR and Red images. There is only negligible processing time for these processes due to single transformation computation for cameras involved firmly with respect to each other. The similarity lack is another major concern for misalignment with other image channels e.g. Green and Red Edge. The matching difficulty is another concern deprived of depth assessment of every pixel precisely. Consequently, camera baseline is considered to be smaller than distance from ground as well as camera (~two orders of magnitude). Camera intrinsics has its significance on system besides radiometric and atmospheric corrections applications does not relate to the system.

2. **Dynamically weighted median filtering algorithm**

Dynamically Weighted Median Filter (DWMF) is greatly involved for preprocessing in this research. Value 0 weightage assigning is done to those locations in a W*W window that are identified as noisy pixels through this DWMF. 2D Gaussian surface is yet another aspect utilized for weightage window automatic selection. The peculiar property of Gaussian function is that its intensity rises as migrate towards center.

The DWMF inputs are Binary image I_b as well as noisy image I. Noise detection algorithm is utilized for obtaining Binary image I_b. Factors such as W*W patches, W_n and W_b are chosen across complete detected noisy pixels in mutually noisy image I in addition binary image I_b correspondingly. The Weightage window $W_{weights}$ of size W*W computation is done, however $W_{weights}$ location extraction is accomplished where W_b possess values of 1 (if complete entries of W_b are 1, $W_{weights}$ is substituted through W_b to elude exception). By this manner, 0 weightage is assigned for noisy pixel detection. Due to the gaps, allotted weights in $W_{weights}$ are shifted because of elements removal at noisy locations. For instance, if entire elements conforming to weightage of 4 are identified as noisy pixels, 4 weightage is detached from $W_{weights}$. Therefore, jump of 2 is perceived when migrating from weightage of 3 to 5 in $W_{weights}$. Weights reassigning is done for diminishing number of repetitions. Modified window is summed as well incrementing highest weights are done if the sum is even. The odd sum restriction is levied for evading two pixels averaged value which is ensued due to DWMF. After repeated window odd sum confirmation, final weightage window W_R creation is done for generating repetition array A_R. Noisy pixel substitution is done through A_R median value.

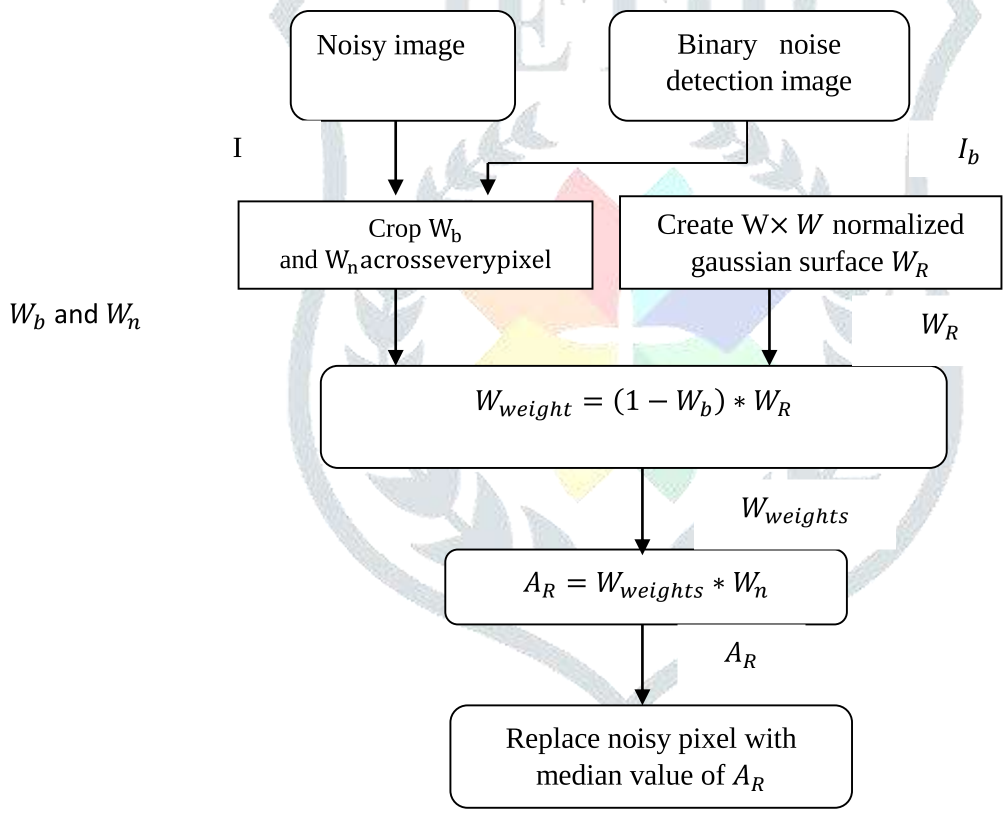

Figure 3: Flowchart of the proposed DWMF

3.3 FEATURE EXTRACTION

The Weed color, texture and shape features extraction is performed through effectual multi-resolution feature learning for weed separation enhancement.

- Enhanced Local Binary Pattern (ILBP)
- Computation of shape aspects such as contour and skeleton features were accomplished.

3.3.1 Color feature extraction by using Quad Histogram

Quad Histogram is greatly utilized for Color feature extraction in this research. Quad tree decomposition is deployed on the images in addition homogenous blocks with dissimilar size are quantified.

Histogram is regarded as pixel counting of different type as well rapid creation is done through single image pixel reading and histogram proper bin incrementing. On the basis of image block successive subdivision into quadrant which is contingent on block Quad tree decomposition complexity. There occurs sub image subdivision into four equal sized sub images till complete sub images are homogeneous block if sub image is not a homogeneous block which is presented in figure 4. A sub image is said to be a homogeneous block if block elements maximum value minus block elements minimum value is greater than its corresponding threshold. Three thresholds for red, green and blue blocks are exploited for RGB image of size M$\times N \times$ 3 in this method. Initially image in size of M$\times N$ is converted into $M' \times M'$square image. The M′ is a number greater than larger one amid M and N in addition in order of 2 besides multiple of n, where n×n notates smallest homogeneous block size .

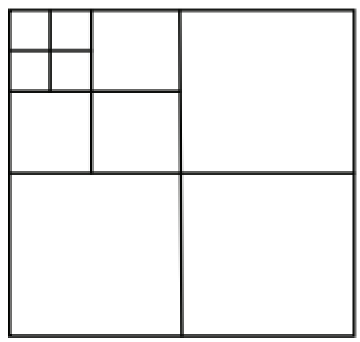

Figure 4: Quad tree subdivision

3.3.2 Improved Local Binary Pattern (ILBP)

Local Binary Pattern (LBP) algorithm is regarded as sort of local texture feature extraction technique. Binary coding is generated based on grey value dissimilarity amid centre pixel besides neighbourhood pixels in the sampling area in addition extensively utilized in image texture feature analysis. During conventional LBP operator encoding process, grey-scale variance amid central pixel besides neighbouring pixels in the local area reflection is done in the form of encoding. In the course of encoding, central pixel is zeroed as well as entire pixel spatial relationship ignoring is also accomplished. Central pixel in sampling areas enlargement is accomplished for solving conventional LBP operator issues amid sampling area and whole image which creates an improved LBP (ILBP) algorithm. Global besides local texture information might be regarded at the same time through grey value difference amid neighbouring pixels in diagonal position computation and central pixel grey value comparison is accomplished with all pixels. The computational complexity reduction is achieved through ILBP operator and thereby enhancing sparsity. ILBP operator encoding rules are definite as follows:

$$ILBP_{P,R}(C) = \sum_{i=1}^{\frac{P}{2}} S\left(f_i, f_{i+(\frac{p}{2})}\right).2^{i-1} + 2^{\left(\frac{P}{2}\right)+1} s(f_0 - f_a)\ (1)$$

Where,

P sampling points

R -Radius

f_i −Grey-scale value of 8 pixels

f_0 −centre pixel

$$f_a = \frac{1}{P}\sum_{i=1}^{P} f_i \quad (2)$$

$$S(a,b) = \begin{cases} 1, & a - b \geq 0 \\ 0, & a - b < 0 \end{cases} \quad (3)$$

On the basis of ILBP coding rules, various binary codes are generated through P samples. Only 32 coded values are produced for region of 8 sample points which is less than number of uniform modes in uniform LBP. Hence it is necessitated for any coding information rejection in ILBP coding. Normalization is accomplished for codes with more than 8 samples with interval based on the interval from 0 to 31 for ensuring the statistical code values acquired through ILBP operators with equal diverse sample points.

3.3.3 Shape feature extraction

For every image patch of NDVI image created in the aforementioned step, set of shape features computation such as contour and skeleton features are done.

3.4 DYNAMIC NON-LINEAR DECREASING STRATEGY BASED GLOWWORM SWARM OPTIMIZATION (DNDSGSO) BASED FEATURE SELECTION

Dynamic Non-linear Decreasing Strategy based Glowworm Swarm Optimization (DNDSGSO) is greatly utilized for extracted feature selection. Arbitrary deployment of glowworms swarm in GSO is performed in solution space. It consists of luminescence quantity called luciferin in GSO agents similar to glowworms. Their current locations fitness is encoded through glowworms which are assessed through objective function, into a luciferin value that they transmist to their neighbors [15-16].The neighbors are identified by glowworm as well movement computation is done through adaptive neighborhood exploitation which is bounded above through its sensor range. A probabilistic mechanism is utilized for selecting every glowworm and there occurs movement towards if that neighbor has a luciferin value higher than its own. The glowworms swarm are enabled for partitioning into disjoint subgroups that converge on manifold optima of a specified multimodal function [17] on the basis of local information and selective neighbor interactions.

The Process repetition takes place till termination condition is met through algorithm. The majority of individuals collect everywhere brighter glowworms now. It consist of six main phases in GSO: Glowworms' initialization, luciferin-update phase, neighborhood-select phase, moving probability-computer phase, movement phase, and decision radius update phase.

Glowworms' initialization: Glowworms are regarded as an image features in this phase,which are primarily spread arbitrarily in the established fitness function space. The same amount of Lucifer is encompassed in glowworms. In addition, current iteration is fixed to 1. Here classification accuracy is regarded as fitness value.

Luciferin-update phase:

On the basis of fitness value (accuracy) besides preceding luciferin value, luciferin updating is done and its rule specified through

$$l_i(t+1) = (1-\rho)l_i(t) + \gamma Fitness\ x_i(t+1)(4)$$

Where, $l_i(t)$ represents glowworm luciferin (feature) i at time t , ρ signifies luciferin decay constant (0< $\rho < 1$) , γ denotes luciferin enhancement constant, $x_i(t+1)\epsilon R^M$signifies glowworm (feature) location i at time in addition $Fitness x_i(t+1)$ characterizes fitness value at glowworm i's location at time $t+1$.

Neighborhood-Select Phase

Neighbors $N_i(t)$ of glowworm (feature) i at t time comprise of brighter ones which is given by

$$N_i(t) = \{j: \left|\left|d_{ij}(t) < r_d^i(t)\right|\right|;\ l_i(t) < l_j(t\ (5)$$

,$r_d^i(t)$ denotes variable local-decision domain, $d_{i,j}(t)$ signifies Euclidean distance amid features i in addition to j at time t.

Moving Probability-Computer Phase

A glowworm utilizes probability rule for moving towards other glowworms possessing higher luciferin level. The probability $p_{ij}(t)$ of glowworm (feature) i moving in the direction of its neighbor j can be quantified as trails:

$$p_{ij}(t) = \frac{l_j(t)-l_i(t)}{\sum_{k\in N_i(t)} l_k(t)-l_i(t)}(6)$$

Movement Phase

Presume glowworm (feature)i picks glowworm (feature)j ∈ $N_i(t)$ with $p_{ij}(t)$; the discrete-time model of glowworm (feature) i movement is specified by (4) as

$$x_i(t+1)\text{=}\ x_i(t) + s(t)\ (\frac{x_j(t)-x_i(t)}{||x_j(t)-x_i(t)||})(7)$$

Here, s reprsents step size and ||.|| denotes Euclidean norm operator

Decision Radius Update Phase

Glowworm (feature)i decision radius in every update is specified as trails:

$$r_d^j(t+1)\ \text{=min}\ \{r_s, \max\{0, r_d^j(t) + \beta(n_t - |N_i(t)|)\}\}(8)$$

Here, β represents constant, r_s denotes glowworm (feature) i sensory radius, and n_t signifies parameter for neighbor number control.

Dynamic Non-linear Decreasing Strategy based Glowworm Swarm Optimization (DNDSGSO) algorithm

Dynamic non-linear decreasing strategy is greatly involved for enhancing GSO algorithm convergence speed and its robustness. GSO algorithm performance besides efficacy is chiefly determined through Step-size s which is fixed and regarded as complex optimization problem for determining algorithm performance. Variable step-size search stratagem is utilized in this research. Convergence ability is enhanced since algorithm possesses greater exploration ability in the prophase besides better development capability in the late stage. To reduce parameter value s linearly pertaining to changes in number of iterations given by

$$s(t)=(s_0 - s_{min})(\frac{t}{T_{max}})^2 + (s_{min} - s_0)(\frac{2t}{T_{max}})+s_0 \quad (9)$$

Where, s_0 and s_{min} represents initial value in addition termination value of step-size s respectively. T signifies number of iterations t.

Now substitute equation (9) in equation (7)

$$x_i(t+1)= x_i(t) + (\ (s_0 - s_{min})(\frac{t}{T_{max}})^2 + (s_{min} - s_0)(\frac{2t}{T_{max}})+s_0)\ (\frac{x_j(t)-x_i(t)}{||x_j(t)-x_i(t)||}) \quad (10)$$

Furthermore, every glowworm i picks glowworm (feature)j ∈ $N_i(t)$ with $p_{ij}(t)$ besides feature j weight value, in future glowworm t movement (feature) i is given below,

$$x_i(t+1)= x_i(t) + s(t)w_j\ (\frac{x_j(t)-x_i(t)}{||x_j(t)-x_i(t)||}) \quad (11)$$

Here, s denotes step size,w_j signifies neighboring feature weight value and||.|| is Euclidean norm operator. The equations are updated as follows

$$x_i(t+1)= x_i(t) + (\ (s_0 - s_{min})(\frac{t}{T_{max}})^2 + (s_{min} - s_0)(\frac{2t}{T_{max}})+s_0)\ * w_j *\ (\frac{x_j(t)-x_i(t)}{||x_j(t)-x_i(t)||}) \quad (12)$$

Algorithm 1: Dynamic Non-linear Decreasing Strategy based Glowworm Swarm Optimization (DNDSGSO) algorithm

1. Fixed number of dimensions = m
2. Initialize the number of features
3. Set generation G = 1
4. Let s be the step size
5. Glowworms (features) are randomly uniformity distributed in search space
6. While (G < max generation) do
7. for each glowworm (feature) i do
8. Luciferin update according to (equation 4)
9. Confirm set of neighbors rendering to (5)
10. Compute probability of movement according to (6)
11. Glowworm i moves toward j conferring to Equation (12);
12. Calculate next position x(t+1) besides next decision radius $r_d(t+1)$ of each glowworm.
13. Update neighborhood range according to Equation (5)
14. Update position
15. Return selected features
16. End for
17. End while

3.5 ENSEMBLE MODIFIED CONVOLUTIONAL NEURAL NETWORK (EMCNN)

Modified Convolutional Neural Network (MCNN) is one in which selected features are given as an input besides regarded as most potent deep networks encompassing multiple hidden layers accomplishing convolution in addition sub sampling for extracting low to high levels of input data features. Mostly, there are three layers in a network: convolution layers, subsampling or pooling layers, and full connection layers.

The features are given as input, output layer from where the system acquires trained output besides intermediate layers known as hidden layers which is revealed in figure 5. The proposed Modified Convolutional Neural Network (MCNN), optimization of features weight values for attaining precise outcomes.

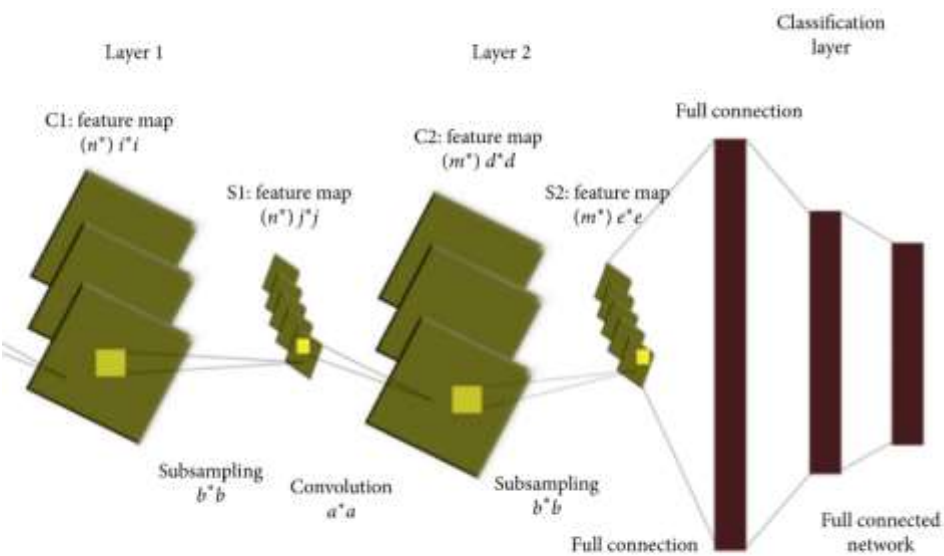

Figure 5 : Convolutional Neural Network

Convolution layer

The convolution is performed for an input image of size R∗C with a kernel (filter) of size a∗a. An output pixel is obtained through independent convolution of every input matrix block with kernel. In a similar way, output image features are produced through convolution of the input image in addition to kernel. Primarily convolution matrix kernel is termed as filter although output image features attained through convolution of kernel besides input images are termed as feature maps of size i∗i.

CNN encompasses multiple convolutional layers, inputs in addition to outputs of next convolutional layers are the feature vector. It also comprises group of n filters in each convolution layer. These filter convolution is attained with input besides created feature maps (n∗) depth is equivalent to number of filters. Every filter map is deliberated as explicit feature at a definite input image locality.

The l-th convolution layer output, signified as $C_j^{(l)}$, encompassing feature maps which is estimated by

$$C_i^{(l)} = B_i^{(l)} + \sum_{j=1}^{a_i^{(l-1)}} K_{i,j}^{(l-1)} * C_j^{(l)} \quad (13)$$

Where, $B_i^{(l)}$ represents bias matrix , $K_{i,j}^{(l-1)}$ signifies convolution filter or kernel of size a∗a relating j-th feature map in layer $(l-1)$ with the i-th feature map in the alike layer. The output $C_i^{(l)}$ layer comprises of feature maps. In (14), first convolutional layer$C_i^{(l-1)}$ is input space, that is, $C_i^{(0)} = X_i$.

Feature map s generated through kernel. Nonlinear transformation of convolutional layer ouputis obtained by activation function application after convolution layer,

$$Y_i^{(l)} = Y(C_i^{(l)}) \quad (14)$$

Where, $Y_i^{(l)}$ signifies activation function output in addition to $C_i^{(l)}$is the input that it receives.

Generally sigmoid, tanh, besides rectified linear units (ReLUs) are the various activation functions utilized here. ReLUs signified as $Y_i^{(l)} = \max(0, Y_i^{(l)})$ are exploited in deep learning models due to benefit of diminished interaction and nonlinear effects. ReLU transforms output to 0 if it takes a negative input, while it yields the same input value if it is positive. Fastest training is one of the prominent advantages of this activation function in contrast to other functions since error derivative tends to be very trivial in saturating region and hence vanishing of weights update takes place which is termed as vanishing gradient problem.

Sub sampling Layer

This layer mainly concentrates for diminishing spatially the features map dimensionality taken out from the earlier convolution layer for which mask of size b∗b is chosen. Subsequently, sub sampling operation amid mask as well as feature maps is achieved. A sub sampling layer supports convolution layer for rotation and translation tolerance amid input images. The optimal weights updating is done on the basis of mean of features weight in this research.

Weighted mean $w_H = \frac{N}{\sum_{i=1}^{N} w x_i}$ (15)

Where,

N − Number of features

w- Feature Weight value

x_i- Features

Full Connection

Softmax activation function is greatly exploited in the output layer.

$$Y_i^{(l)} = f(z_i^{(l)}), \text{ where } z_i^{(l)} = \sum_{i=1}^{m_i^{(l-1)}} w_H y_i^{(l-1)} \quad (16)$$

where $w_H$represents features weighted Harmonic mean which might be tuned through wide-ranging fully connected layer for each class representation and f denotes transfer function representing nonlinearity. Input image Categorization such as background, crop and weed is also attained. Finally, fully connected layer connection is attained through a classifier as well as output layer for acomplishing classification selection task.

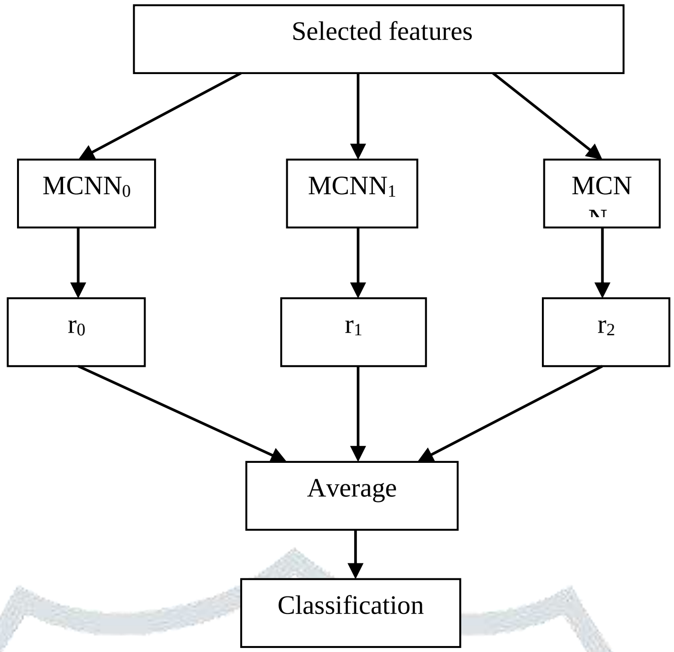

Figure 6:Ensemble Modified Convolutional Neural Networks

The averaging of output probabilities from all MCNN is performed for specified input, before acquiring categorization. Average output S_i for output i, is specified through:

For a specified input, averaging of output probabilities from entire MCNN is accomplished

$$S_i = \frac{1}{n}\sum_{j=1}^{n} r_j(i) \tag{17}$$

Where $r_j(i)$ signifies network j output i for a specified input pattern.

Every network is provided with varying weight in this methodology. Higher classification accuracy is attained for larger weight during results merging in the validation set. Assumed some input pattern, output probabilities from entire MCNNs are multiplied through weight α before the prediction:

$$S_i = \sum_{j=1}^{n} \alpha_j r_j(i) \tag{18}$$

Weighted mean computation is accomplished for weight α estimation. Weight estimation computation is as trails

$$\alpha_k = \frac{A_k}{\sum_{i=1}^{n} A_i} \tag{19}$$

Where, A_k denotes accuracy in the validation set for the network k, i runs over the n. On the basis of MCNN network average output, categorization of background, weed and crop is accomplished.

EXPERIEMNTAL RESULTS

During this study, the classification performance of Ensemble Modified Convolutional Neural Network (EMCNN) has evaluated under the MATLAB environment. Besides the obtained results have compared with the classification in accordance with current Modified Convolutional Neural Network

(MCNN) for weed detection process, in which the performance parameters, such as Recall, Precision And F-Measure. In Table 1, the image datasets for training and testing have been enlisted.

Table I: Image datasets for training and testing

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

For acquiring the automated ground-truth, a 40m×40m test sugarbeet field that has been applied with different levels of herbicide. Table 1 demonstrates the annotation of the system with 132, 243, and 90 multispectral images of crops, weeds, and crop-weed mixtures. There are near-infrared (NIR, 790nm), Red channel (660nm), and NDVI imagery have included in each training image/testing image.

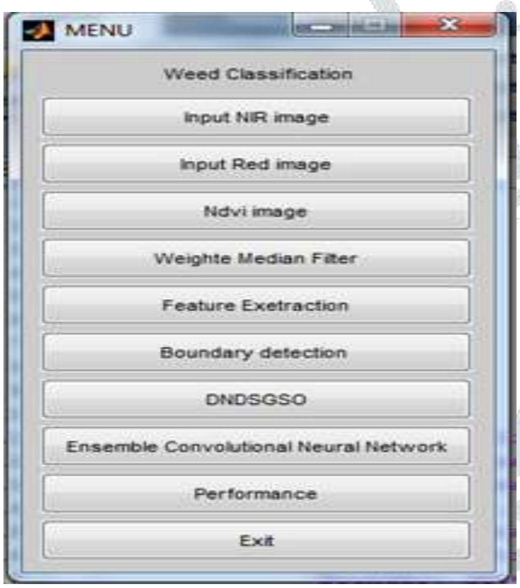

Figure 7 : Main menu

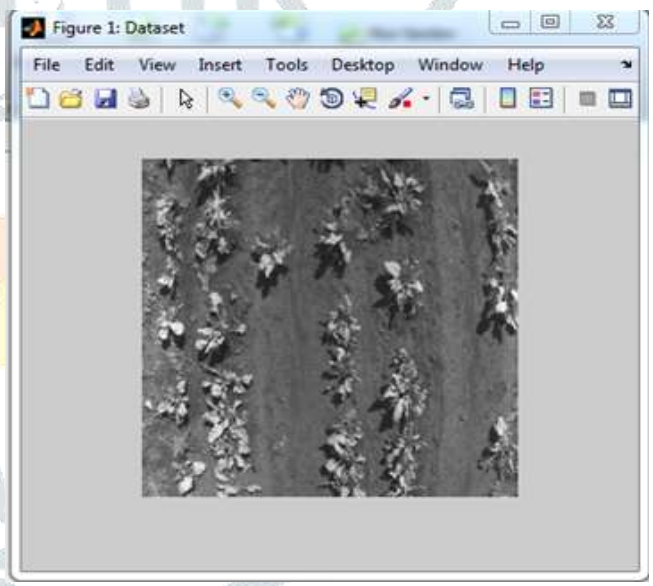

Figure 8: Input NIR image

The main menu has depicted in Figure 7, beside Figure 8 and Figure 9 NIR image, and Red channel image have considered being the input. The Normalized Difference Vegetation Index (NDVI) image have extracted from the associated NIR and Red images, which has represented in Figure 10.

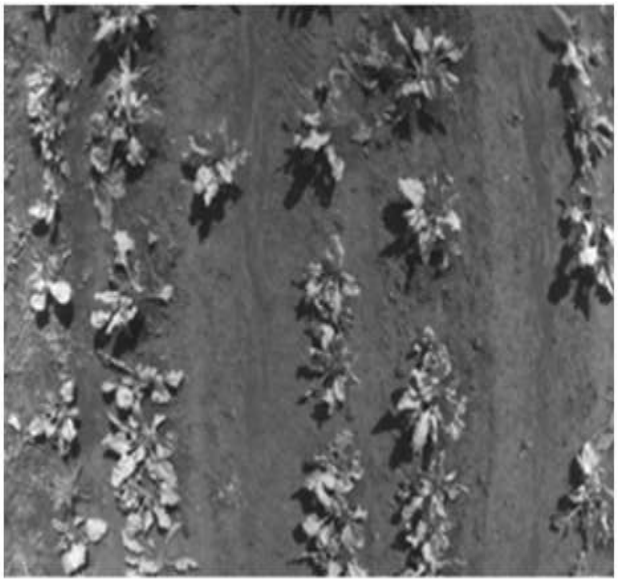

Figure 9: Red image

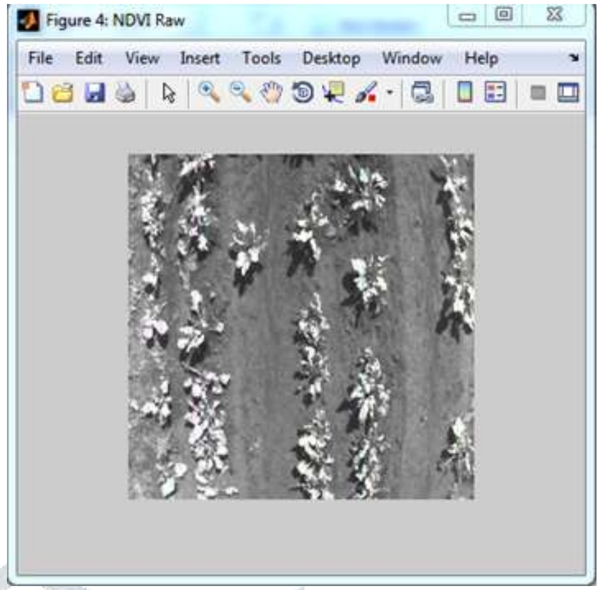

Figure 10: NDVI image

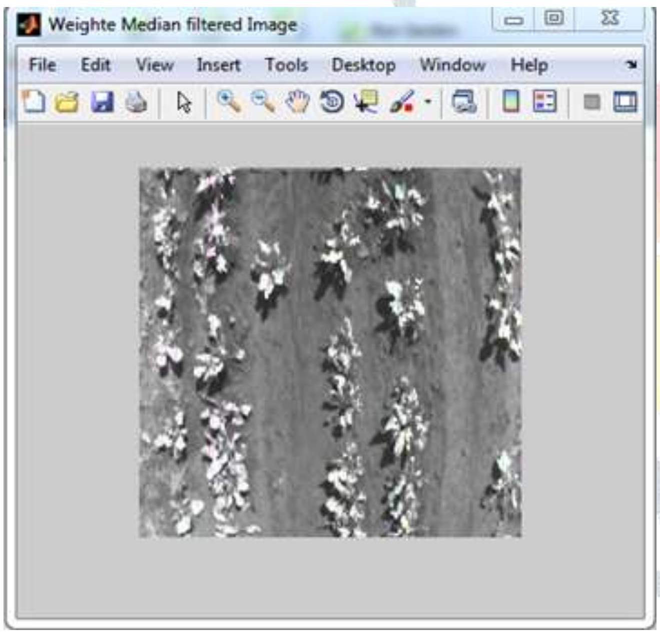

Figure 11 : Weighted median filtering image

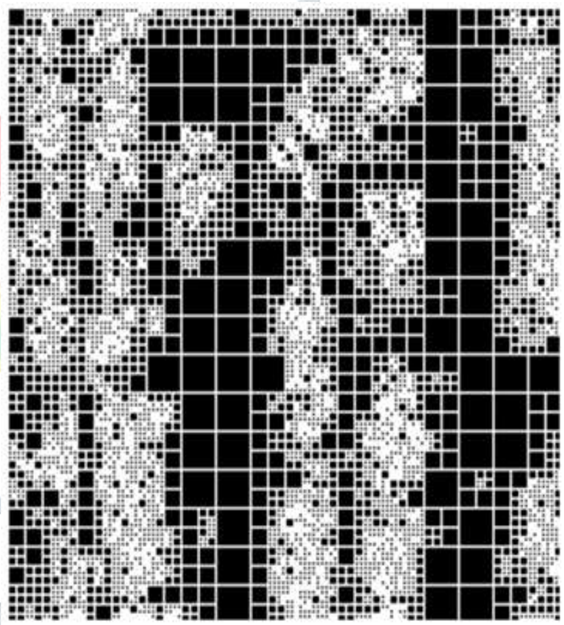

Figure 12: Quad Histogram

Dynamically Weighted Median Filter (DWMF) has involved in preprocessing during the proposed study, as depicted by Figure 11. Application of the quad tree decomposition has initiated over the image and homogenous blocks that accompanies the specification of various sizes. Figure 12 demonstrates Quad decomposition.

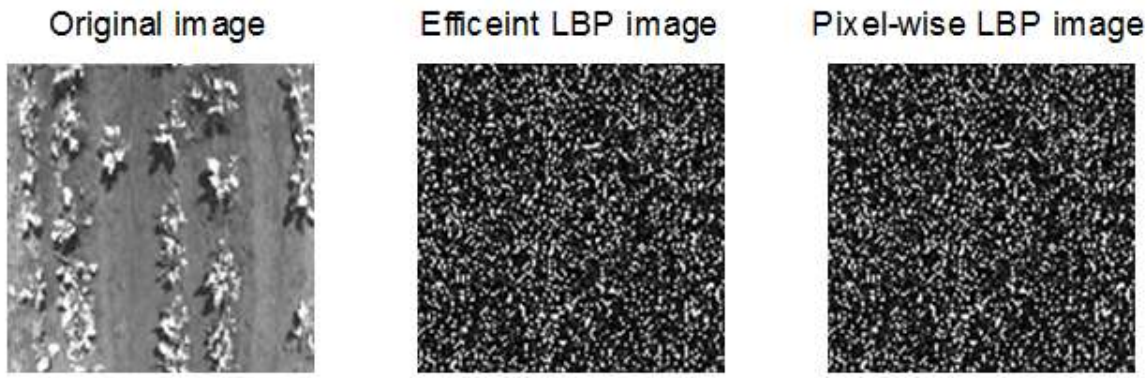

Figure 13: ILBP

Figure 13 illustrates the extraction of local texture feature, which has accomplished through the Improved Local Binary Pattern (ILBP) algorithm.

Clear edge within vegetation and other factors (such as, shadows, soil, and gravel) have derived using an auto-threshold boundary detection technique, which has depicted in Figure 14. During the segmentation process, the EMCNN has exploited, which has illustrated in Figure 5.

4.1 Performance evaluation

By considering the performance factors, such as precision, recall, f-measure and detection rate, proposed EMCNN and existing MCNN have compared to evaluate their efficiency.

Precision

It defines the proportion of appropriately predicted positive observations among the overall positive observations predicted. It can be formulated as follows,

$$Precision = \frac{TP}{TP + FP} \quad (20)$$

Recall

It refers to the ratio of actual true instances which have retrieved successfully.

$$Recall = \frac{TP}{TP+FN} \quad (21)$$

F1 score

The weighted average of precision and recall has defined as F1 score, which has regarded as a statistical measure in the evaluation of the classifier performance. Hence, both false positive as well as false negative will be considered by this score. The following equation expresses the estimation of F1 score.

$$F - measure = 2\frac{Precision * Recall}{Precision + Recall} \quad (22)$$

Moreover, there are two possibilities while taking decision about the detected result, (i.e. appropriate (true) or inappropriate (false)). Hence, the possibilities have categorized as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), in terms of decision.

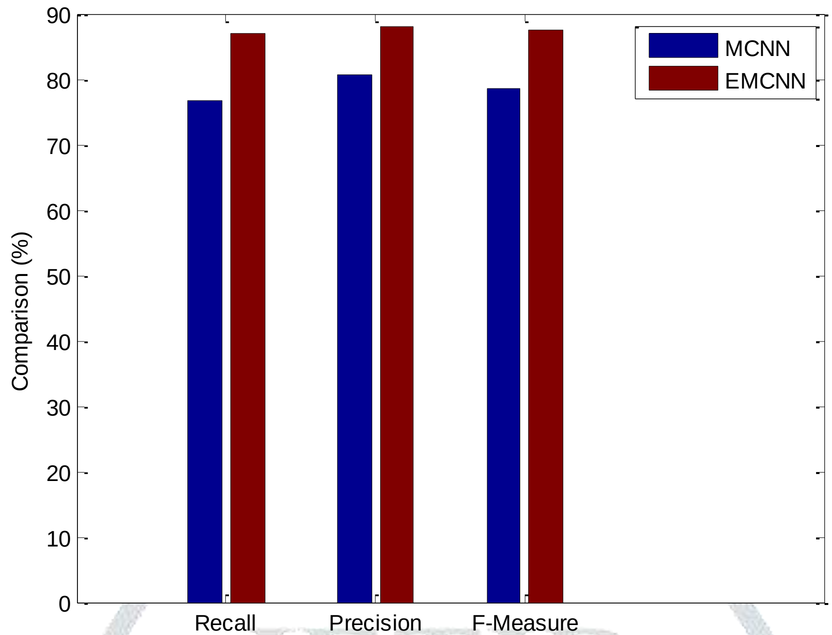

Figure 16: Performance comparison of existing system

Figure 16 compares the values of Recall, precision and F-measure obtained by proposed EMCNN and the existing MCNN approach. Post-completion of feature extraction the selection of optimal features has carried out through the algorithm, namely Dynamic Non-linear Decreasing Strategy based Glowworm Swarm Optimization (DNDSGSO) during the proposed study, which considerably enhances the rate of true positive. The empirical findings proves the efficiency of proposed EMCNN to obtain 87.98%, 88% and 87.49% of values in terms of recall, precision, and f-measure, respectively, which is superior to the existing approach, as the MCNN-based classification has the ability to obtain 77% of recall, 80.5% of precision and 79.5% f-measure.

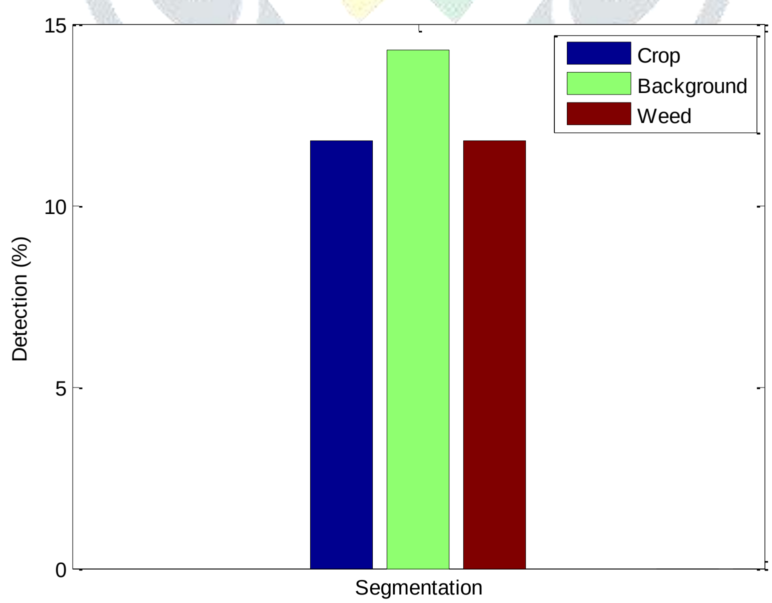

Figure 17: Performance comparison of proposed system

In Figure 17, the graph represents the comparison of proposed EMCNN and current EMCNN based classification, where the proposed method procures the optimum detection rate.

5. CONCLUSION

An Ensemble Modified Convolutional Neural Network (EMCNN) is greatly utilized in this research for categorizing crop as well as weed merely. Noise removal from images in a proficient way can be attained through dynamically weighted median filtering algorithm which is followed by color feature extraction via Quad Histogram. Dynamic Non-linear Decreasing Strategy based Glowworm Swarm Optimization (DNDSGSO) algorithm is greatly utilized for optimal features selection. Ensemble Modified Convolutional Neural Network (EMCNN) plays its role for sample categorization into crop, weed and background. Improved performance is achieved with the help of suggested system in contradiction to prevailing research pertaining to precision, recall, f-measure and detection rate which is validated through experimentation outcomes.

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