ISSN 2347 - 3983
Volume 8. No. 7, July 2020
International Journal of Emerging Trends in Engineering Research
Available Online at http://www.warse.org/IJETER/static/pdf/file/ijeter161872020.pdf
https://doi.org/10.30534/ijeter/2020/161872020

Meta-Heuristic based Trained Deep Convolutional Neural Network for Crop/Weed Classification

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ABSTRACT

Computer vision and camera sensors are hopeful technologies for capturing information and processing to facilitate autonomous cultivation with machine learning. Nowadays, field robots are widely utilized, which autonomously navigates in fields tasks for advanced developments. However, manual activities are also required for certain needs, for instance, controlling weed in organic carrot farming is carried out manually and it is essential to evade considerable crop yield loss. This paper makes an attempt to introduce a new automatic crop/weed classification under three major phases: (i) Pre-processing (ii) Feature Extraction and (iii) Classification. Initially, the images are converted to greyscale images under pre-processing stage. Further, from the pre-processed image, the features like "Grey Level Co-occurrence Matrix (GLCM) and Grey Level Runlength Matrix (GLRM) based texture features" are extracted. Finally, the classification is done by the hybrid classifiers, where both the Deep Convolutional Neural Network (DCNN) and Neural Network (NN) is incorporated. Finally, both the classified outputs are ORed to get the final classification output. Moreover, in order to enhance the performance of proposed work, it is planned to tune the hidden neurons of NN optimally via a new improved Moth Search Algorithm (MSA) and is named as Moth Search with new Step Length evaluation (MS-SL). Finally, the performance of proposed work is evaluated over other state-of-the-art models with respect to certain performance measures.

Key words: Crop classification; GLCM; GLRM; DCNN; Moth Search Algorithm

Nomenclature

Abbreviation	Description
GLCM	Grey Level Co-occurrence matrix
GLRM	Grey Level Runlength Matrix
DCNN	Deep Convolutional Neural Network
MSA	Moth Search Algorithm
MS-SL	Moth Search with new Step Length evaluation
WSNs	Wireless Sensor Networks
FAO	Food and Agriculture Organization
UN	United Nations
LSTM	Long Short-Term Memory
Conv1D	one-dimensional convolutional
SCDCA	Spherical Contact Distribution Classification Algorithm
LCDCA	Linear Contact Distribution Classification Algorithm
CV	Coefficient of Variation
SAR	Synthetic Aperture Radar
NN	Neural Network
HoG	Histogram of Oriented Gradients
GLN	Grey Level Non Uniformity
RLN	Run Length Non Uniformity
LGRE	Low Grey level Run Emphasis
HGRE	High Grey Level Run Emphasis
LBP	Local Binary Patterns
MCC	Maximum Correlation Coefficient
SVM	Support Vector Machine
RF	Random Forest
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
FPR	False Positive Rate
FNR	False Negative Rate
FDR	False Discovery Rate
NPV	Net Present Value

1.INTRODUCTION

Crop field monitor technology is considered as a tactical tool that obtains information for maintaining the crops by adopting advanced agriculture technologies [1] [2] [3]. There exist varied practices for monitoring the crop, among them WSNs are identified as a better one for collecting and processing data in the agricultural area with reduced energy consumption and minimal cost. WSNs provide an improved temporal and spatial resolution for monitoring the crops [4] [5] [6] via sensor nodes that are positioned across the field. These nodes are linked in a wireless manner and they transmit information by means of multi-hop communication. In the agricultural field, thousands of crops were grown-up, which are classified together or more specifically grouped into diverse classes depending on unique purpose, seasonal, agronomic classification types and so on [7] [8] [9]. The intention of the crop classifications is to gain knowledge regarding the agricultural crops more accurately and deeply to evaluate their features so that the finest crop management practices could be exploited to acquire the highest yield and production [10] [11] [12].

In a geographical study, the farming area of plants and crops [13] [14], their development, their yield, and distribution are examined in terms of time and space. Therefore, there raised a requirement to categorize the crops for an efficient geographical study. Globally, the most important classifications of crops [15] [16] [17] are portrayed by the FAO of UN. Therefore, more awareness is needed regarding the classification of crops and plants for better knowledge of their distribution across the globe and in India [18] [19] [20]. Accordingly, depending on climate, the crops can be classified into temperate (crops that grow up well in chill atmosphere. e.g. Potato, Oats, Wheat, Gram, etc) as well as tropical (crops grow up well in hot and warm climate. e.g. Jowar, sugarcane, rice, etc).

Generally, the researchers exploited the visual data for monitoring and classifying the crops [21] [22]. However, a major problem in exploiting the visual imagery is the existence of shadows and clouds, which results in severely deformed or missing values. At the local range, it is feasible to obtain cloud-free images during the critical phase of vegetation cycle, but this is not the condition for huge areas [23] [24].

The major contribution of this paper is depicted below.

1. The presented framework establishes a novel automatic crop/weed classification model using three major phases: (i) Pre-processing (ii) Feature Extraction and (iii) Classification.
2. At first, the images are transformed to greyscale images during pre-processing stage. Subsequently, from the pre-processed image, the features like GLCM and GLRM based texture features are extracted.
3. At last, the classification is carried out by the hybrid classifiers, where both the DCNN and NN are incorporated.
4. Furthermore, to improve the adopted performance, the hidden neurons of NN are tuned optimally using MS-SL model.
5. At last, the performance of the adopted scheme is evaluated over other traditional schemes and the outcomes are attained.

The arrangement of the paper is given as: Section II analyzes the review. Section III portrays the proposed crop classification model: pre-processing, feature extraction and classification and section IV portrays the proposed classification process: hybridized NN plus CNN. Further, section V illustrates the optimal tuning of hidden neurons: introduction to MS-SL algorithm. Section VI portrays the results and the paper is concluded by section VII.

2.LITERATURE REVIEW

2.1Related works

In 2019, Zhong *et al.* [1] have carried out a research using two kinds of deep learning approaches, initial one was dependent on LSTM, and the second one was dependent on Conv1D layers. The experimentation was conducted at California that included varied farming systems subjugated by monetary crops. Finally, the experimental outcomes have pointed out the effectiveness of the Conv1D model with noteworthy developments over earlier schemes.

In 2019, Kavitha *et al.* [2] have developed an “unsupervised” approach known as SCDCA, which have considered the 1st order information, globular distributions, and arithmetical morphology. In addition, SCDCA was evaluated over LCDCA. Finally, the quantitative analysis has confirmed the effectiveness of the SCDCA algorithm, whose complexity was much minimal over LCDCA scheme.

In 2018, Tracy and Paul [3] have demonstrated the CV for classifying the croplands by means of SAR data. Here, if the pixels with CV values goes beyond a specified threshold, then they were categorized as crops, and if it was lower than the threshold, then they were categorized as non-crops. In addition, the presented approach has exploited the L-band SAR data for classifying the eleven areas in the US with varied crops. Finally, the investigational results have demonstrated the efficiency of the CV model in monitoring the crops at a wide range.

In 2018, Hariharan *et al.* [4] have suggested an RF oriented feature selection model, which was designed particularly for physical scattering system with PolSAR classification. Here the presented approach had detected the features, which varied considerably with crop phenology. In addition, the correlated features were eliminated and experimental outcomes have shown the superiority of the presented approach in terms of accuracy.

In 2017, Kussul *et al.* [5] have adopted a multilevel DL framework, which targeted the crop type and land cover classification from satellite images. Accordingly, NN was exploited for segmenting the images and it further restores the missing data that occurred owing to shadows and clouds. Moreover, the adopted scheme had provided a better classification of the summer crops like soybeans and maize and it had yielded a better accuracy overall major crops.

In 2017, Damian [6] has established a novel multitemporal data-oriented classification scheme, which included the information regarding the phenological variations on crops. Furthermore, it recognizes the sequence patterns of varied crops and it also contained accurate data regarding the phenology of the plant. Experimentations have illustrated that the introduced scheme have accurately classified the crops such as potatoes, sugar beets, canola, and maize.

In 2019, Farooq *et al.* [7] have introduced patch-oriented classification scheme for determining the spectral similarity among crops and weeds. In addition, HoG and CNN techniques were compared and evaluated. Also, various bands were provided at varied spatial resolutions by the huge count of sensors. Further, the introduced technique was determined to be exploited for efficient and accurate weed classifications.

In 2018, Bosilj *et al.* [8] have designed a novel scheme that focused on pixel-oriented schemes for classifying the crops vs. weeds, particularly for multifaceted cases. Here, the advantages of multi-scale and morphology-oriented descriptors were examined and evaluated over the conventional descriptors like HoG and LBP. Furthermore, the robustness of the implemented approach in providing higher resolution was proved from the simulation outcomes.

2.2Review

Table 1 shows the reviews on crop classification models. At first, CNN model was introduced in [1], which represents the time series and it also offers better accuracy. However, it has to be extended using human knowledge for better classification. SCDCA approach was exploited in [2] that solve the complex issues and it also provides low execution time, but it requires consideration on the structuring elements. In addition, CV classification was deployed in [3] that offer higher accuracy and it also reduces the errors. Anyhow, have to focus more on the climatic impacts on CV values. Likewise, RF scheme was exploited in [4], which offers accurate and effective outcomes and it is more reliable. However, it has to focus on domain knowledge. Also, CNN algorithm was employed in [5], which offers effective computation and it offers improved accuracy; however, it has to focus on the smoothening process. PSP scheme was implemented in [6], which was sensitive and it also offers an optimal feature extraction, but it has to concern more on redundancy of data. CNN algorithm was exploited in [7] that provide more effective classification and optimal patch size, anyhow, accuracy decreases with decrease in resolution. At last, LBP was suggested in [8] that offers better classification rates and it provides improved precision. However, it has to focus more on precision agriculture.

Table 1: Features and challenges of crop classification models using various techniques

Author [citation]	Adopted methodology	Features	Challenges
Zhong *et al.* [1]	CNN model	❖ Represents the time series. ❖ Better accuracy.	❖ Have to be extended using human knowledge for better classification.
Kavitha *et al.* [2]	SCDCA approach	❖ Solves the complexity issues. ❖ Low execution time.	❖ Requires consideration on the structuring elements.
Tracy and Paul [3]	CV classification	❖ Higher accuracy. ❖ Reduces the errors.	❖ Have to focus more on the climatic impacts on CV values.
Hariharan *et al.* [4]	RF scheme	❖ Accurate and effective outcomes. ❖ More reliable.	❖ Have to focus on domain knowledge.
Kussul *et al.* [5]	CNN approach	❖ Effective computation ❖ Improved accuracy	❖ Have to focus on the smoothening process.
Damian *et al.* [6]	PSP scheme	❖ Sensitive approach ❖ Optimal feature extraction	❖ Needs consideration on the redundancy of data
Farooq *et al.* [7]	CNN algorithm	❖ More effective classification. ❖ Optimal patch size.	❖ Accuracy decreases with a decrease in resolution
Bosilj *et al.* [8]	LBP	❖ Better classification rates. ❖ Improved precision.	❖ Have to focus more on precision agriculture

3.PROPOSED CROP CLASSIFICATION MODEL: PRE-PROCESSING, FEATURE EXTRACTION, AND CLASSIFICATION

3.1Implemented Architecture

The adopted crop classification model is revealed in figure 1. In this work, a novel crop classification model is implemented, which consists of three major phases: (i) Pre-processing (ii) Feature Extraction and (iii) Classification. Initially, the given input crop image, Im is converted to greyscale images during pre-processing stage. From the pre-processed crop image Im_p , the features namely, GLCM and GLRM based texture features are extracted during the feature extraction process. Finally, the classification process is done using hybrid classifiers, where both the DCNN and NN are incorporated. In addition, for enhancing the performance of proposed work, the hidden neurons of NN are optimally tuned using the MS-SL approach, such that the accuracy of classification should be maximal. Further, the efficiency of the proposed crop classification is proved by means of experimentations.

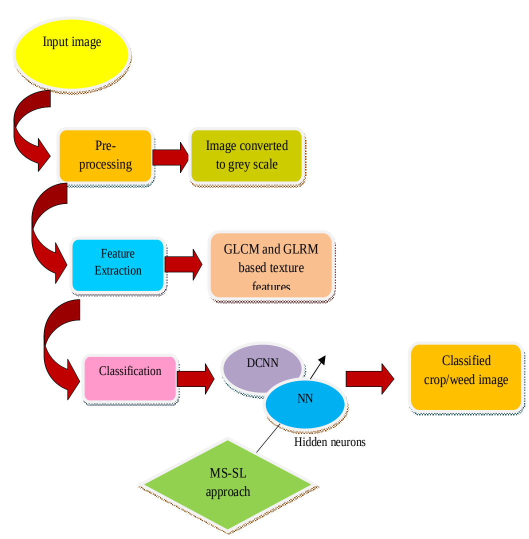

Figure 1: Overall design of the proposed scheme

3.2 Feature Extraction

The pre-processed image Im_p is subjected to feature extraction, where the features like GLCM and GLRM are extracted. The portrayal of the GLCM [26] and GLRM [27] features are portrayed below.

GLCM features:

1. **Energy** is specified by $E=\sum_{\tilde{i}}\sum_{j} g_{a\tilde{i}j}^{2}$, here $g_{a\tilde{i}j}$ is the $(\tilde{i},j)^{th}$ entry in GLCM
2. **Entropy** is denoted by $Ent=-\sum_{\tilde{i}}\sum_{j} g_{a\tilde{i}j}\log_2 g_{a\tilde{i}j}$
3. **Contrast** is indicated by $Con=\sum_{\tilde{i}}\sum_{j}(\tilde{i}-j)^2 g_{a\tilde{i}j}$
4. **Variance** is denoted by $V=\sum_{\tilde{i}}\sum_{j}(\tilde{i}-\mu)^2 g_{a\tilde{i}j}$, where μ specifies the mean of $g_{a\tilde{i}j}$
5. **Homogeneity** is symbolized by $H=\sum_{\tilde{i}}\sum_{j}\frac{1}{1+(\tilde{i}-j)^2} g_{a\tilde{i}j}$
6. **Correlation** is specified by $C=\frac{\sum_{\tilde{i}}\sum_{j}(\tilde{i}j)g_{a\tilde{i}j}-\mu_x\mu_y}{\sigma_x\sigma_y}$, where σ_x,σ_y, μ_x,μ_y are the std deviations and mean of g_{a_x}, g_{a_y}
7. **Sum Average** is specified by $SA=\sum_{\tilde{i}=2}^{2N_g}\tilde{i}\, g_{a_{x+y}}(\tilde{i})$, where N_g indicates the varied gray levels in image.
8. **Sum Entropy** is symbolized by $SE=\sum_{\tilde{i}=2}^{2N_g} g_{a_{x+y}}(\tilde{i})\log\{g_{a_{x+y}}(\tilde{i})\}$
9. **Sum Variance** is denoted by $SV=\sum_{\tilde{i}=2}^{2N_g}(\tilde{i}-SA)^2 g_{a_{x+y}}(\tilde{i})$
10. **Difference Variance** is indicated by DV=variance of $g_{a_{x-y}}$
11. **Difference Entropy** is specified by $DE=\sum_{i=0}^{N_{g-1}} g_{a_{x-y}}(\tilde{i})\log\{g_{a_{x-y}}(\tilde{i})\}$
12. **MCC** (2nd higher Eigen value of Q)$^{0.5}$ is indicated by $MCC=\sum_{k}\frac{g_a(\tilde{i},k)g_a(j,k)}{g_{a_x}(\tilde{i})g_{a_y}(k)}$
13. **Information Measures of Correlation 1** is indicated by $IMC1=\frac{HXY-HXY1}{\max\{HX,HY\}}$
14. **Information Measures of Correlation 2** is specified by $IMC2=\sqrt{(1-\exp[-2.0[HXY2-HXY]])}$, where
$HXY=-\sum_{\tilde{i}}\sum_{j} g_{a\tilde{i}j}\log_2 g_{a\tilde{i}j}$
$HXY1=-\sum_{\tilde{i}}\sum_{j} g_{a\tilde{i}j}\log_2\{g_{a_x}(\tilde{i})g_{a_y}(j)\}$
$HXY2=-\sum_{\tilde{i}}\sum_{j} g_{a_x}(\tilde{i})g_{a_y}(j)\log_2\{g_{a_x}(\tilde{i})g_{a_y}(j)\}$

GLRM features:

1. **Small Run Emphasis** is given by $SRE=\frac{1}{n}\sum_{\tilde{i},j}\frac{p(\tilde{i},j)}{j^2}$, in which p denotes probability of $(\tilde{i},j)$ in diverse distances.
2. **Long Run Emphasis** is given by $LRE=\frac{1}{n}\sum_{\tilde{i},j} j^2 p(\tilde{i},j)$.
3. GLN is given by $\frac{1}{n}\sum_{\tilde{i}}\left(\sum_{j} p(\tilde{i},j)^2\right)$.
4. RLN is given by $\frac{1}{n}\sum_{\tilde{i}}\left(\sum_{\tilde{i}} p(\tilde{i},j)^2\right)$.
5. **Run percentage** is given by $RP=\sum_{\tilde{i},j}\frac{n}{p(\tilde{i},j)j}$
6. LGRE is given by $\frac{1}{n}\sum_{\tilde{i},j}\frac{p(\tilde{i},j)}{\tilde{i}^2}$.
7. HGRE is given by $\frac{1}{n}\sum_{\tilde{i},j}\tilde{i}^2 p(\tilde{i},j)$.

The features attained by means of GLRM and GLCM is denoted by G and D respectively that are combined and represented as $I_f=D+G$.

4.PROPOSED CLASSIFICATION PROCESS: HYBRIDIZED NN PLUS CNN CLASSIFIER

In the proposed work, a hybrid classification process is used for crop/weed classification. As mentioned above, DCNN and NN models are used. The proposed hybrid classification process is as follows: The image is given as the input to DCNN model, from which the classified output is attained. Similarly, the extracted features are given as the input to NN and attain respective classified output. Finally, both the classified outputs are ORed to get the final classification output. Further, to improve the classification output, the hidden neurons of NN will be optimally tuned by an improved algorithm, which is explained in the further section. The diagrammatic illustration of proposed classification is given in figure 2.

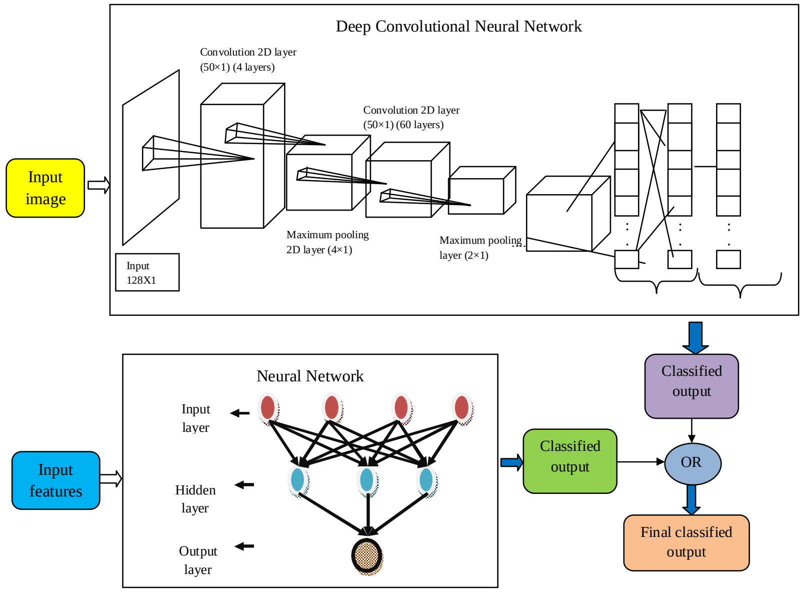

Figure 2: Diagrammatic illustration of proposed classification

4.1Deep Convolutional Neural Networks

In fact, DCNNs [30] are CNNs that contains several layers and it imitates the hierarchical principle. Following numerous convolutional layers, deep CNNs usually includes one or more wholly-connected layers, i.e., layers with denser weight matrix W. Apart from the input, spatial location is both relatively inappropriate and partially lost and hence the local receptive regions of CNNs cannot be used. CNN [34] was one of the deep learning algorithms that were usually used to analyze visual images. CNN architecture was similar to multilayer perceptions (MLP) which had several layers such as input, multiple hidden layers, and output to process data in the form of dimensions, in the process of deep learning the data will be used as training and testing.The deep CNN's output is provided for evaluation, which is based on the purpose of the net. To carry out classification, the outputs can be used as inputs to a SVM or RF or, The SVM classification model is generated from the training process with the training data. The main concept of SVM [35] is using hyper-planes for defining decision boundaries that separate between data points of different classes. Optimal hyper-plane is the hyper-plane with the maximum if the classifier needs input quantity, which behaves like probabilities, the output phase can be a soft max function as given in Eq. (1), in which 1 denotes a column vector of ones.

$$u = \sigma(x) = \frac{\exp(x)}{1^T \exp(x)} \tag{1}$$

In practical, the entire quantities are made positive by exponential, and normalization guarantees that the entries of u adds up to 1. In general, the "softmax function" could be observed as a multidimensional generalization of sigmoid function exploited in logistic regression (LR) [29]. This function is so-called "softmax" as one of the x_i entries, for e.g. x_{i0}, is higher over the others, then $1^T \exp(x) \approx \exp\left(x_{i_0}\right)$ and hence Eq. (2) is formulated. The above function efficiently performs as an indicator among the highest entry in y. Thus Eq. (3) is formed.

$$u_{i_0} \approx 1 \quad \text{and} \quad u_i \approx 0 \quad \text{for} \quad i \neq i_0 \tag{2}$$

$$\lim_{\alpha \to \infty} x^T \sigma(\alpha x) = \max(x) \tag{3}$$

In short, DCNN carries out the below formulations mentioned in Eq. (4)-Eq. (7), in which the output activation function f_x might be softmax, identity, or other function.

$$z^{(0)} = z \tag{4}$$

$$z^{(q)} = \pi\left(f\left(W^{(q)} \tilde{z}^{(q-1)}\right)\right) \quad for \;\; q = 1, \ldots, Q_c \tag{5}$$

$$z^{(q)} = f\left(W^{(q)} \tilde{z}^{(q-1)}\right) \quad for \;\; q = Q_c + 1, \ldots, Q \tag{6}$$

$$x = f_x\left(z^{(Q)}\right) \tag{7}$$

The matrix $W^{(q)}$ includes $F^{(q)}$ rows and $F^{(q-1)}+1$ columns with $F^{(0)}=F$ and $F^{(q)}$ for $q>0$, which is equivalent to the output count in q^{th} layer. The initial Q_c layers are convolution and the remaining ones are wholly-connected.

4.2 Neural Network

NN [31] considers the features as input as given by Eq. (11), where nu indicates the total count of features.

$$F_D=\{F_{D1},F_{D2},.......F_{Dnu}\} \tag{11}$$

Since the NN includes input, output, and hidden layer, it is required to find out the hidden layer output. The output of hidden layer $e^{(H)}$ is portrayed as per Eq. (12), nf signifies the activation function, $\hat{i}$ and j and $\hat{o}$ indicates the hidden, input and output neurons, $W^{(H)}_{(B\hat{i})}$ denotes bias weight to $\hat{i}^{th}$ hidden neuron, $n_{\hat{i}}$ specifies count of input neurons, $W^{(H)}_{(j\hat{i})}$ denotes the weight from j^{th} input neuron to $\hat{i}^{th}$ hidden neuron, and F_D refers to the input features. Moreover, the general network output $\hat{G}_o$ is determined from the output layer, which is shown in Eq. (13), n_h specifies the hidden neuron count, $W^{(G)}_{(B\hat{o})}$ denotes bias weight to output of $\hat{o}^{th}$ neuron, and $W^{(G)}_{(\hat{i}\hat{o})}$ indicates weight from $\hat{i}^{th}$ hidden neuron to output of $\hat{o}^{th}$ neuron. Also, the error among the predicted and actual values is computed as per Eq. (14) that should be reduced. In Eq. (14), n_G indicates the number of output neurons, $G_{\hat{o}}$ denotes the actual output and $\hat{G}_{\hat{o}}$ denotes the predicted output. The model of NN is given by Figure. 4.

$$e^{(H)}=nf\left(W^{(H)}_{(B\hat{i})}+\sum_{j=1}^{n_{\hat{i}}}W^{(H)}_{(j\hat{i})}F_D\right) \tag{12}$$

$$\hat{G}_{\hat{o}}=nf\left(W^{(G)}_{(B\hat{o})}+\sum_{\hat{i}=1}^{n_h}W^{(G)}_{(\hat{i}\hat{o})}e^{(H)}\right) \tag{13}$$

$$E^{*}=\underset{\left\{W^{(H)}_{(B\hat{i})},W^{(H)}_{(j\hat{i})},W^{(G)}_{(B\hat{o})},W^{(G)}_{(\hat{i}\hat{o})}\right\}}{\arg\min}\sum_{\hat{o}=1}^{n_G}\left|G_{\hat{o}}-\hat{G}_{\hat{o}}\right| \tag{14}$$

Finally, the classified output results whether the image is crop or weed in a precise manner.

5.OPTIMAL TUNING OF HIDDEN NEURONS: INTRODUCTION TO MS-SL ALGORITHM

5.1 *Solution Encoding and Objective Function*

In the presented work, for an improved crop/weed classification model, it is planned to train the NN model using the new MS-SL algorithm by selecting the optimal hidden neurons $(\hat{i})$ of NN (training). The solution encoding for the proposed crop/weed classification is shown in Figure. 3, in which NH represents the count of hidden neurons in NN. Here, the objective function of the presented work aims to raise the accuracy of classification as shown by Eq. (15), where Acc denotes the accuracy.

$$Objective\ \ function=Max(Acc) \tag{15}$$

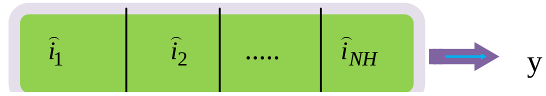

Figure 3: Solution encoding

5.2 Moth Search Algorithm

MSA [25] approach was introduced by Wang, which includes a higher capability of tackling the issues in global optimization. Moths have the tendency to fly near the light sources and this phenomenon is termed as photo taxis. As this behavior is still unidentified, there were several theories to describe this incident. One among the theory is that celestial is exploited in “transverse orientation” when flying. Usually, the moth flies without taking turns for remaining at a permanent angle to the celestial light (e.g. moon).One more feature is said to be the Levy flights, which is regarded as a chief flight pattern in a normal environment. Levy flights and photo taxis from moths are exploited for designing the two major processes in MS approach: exploitation and exploration.

The moths with reduced distance form the best one will flutter in the region of the optimal moth in the type of Levy flights. Levy flights portray a set of random walks, where the step length r are given by Eq. (16), in which d and v are attained from a normal distribution and α indicates the index [28]. This behavior is portrayed by Eq. (17), in which y_i^{t+1} denotes the updated position and y_i^t indicates the moth i ’s original position in present generation t , correspondingly [25].

$$r=\frac{d}{|v|^{1/\alpha-1}} \tag{16}$$

$$y_i^{t+1}=y_i^t+\beta L(r) \tag{17}$$

$L(r)$ points out the step obtained from Levy distribution and β indicate the scaling factor, which is formulated depending on the optimization issue. Here, in the presented work, β is specified as in Eq. (18), [25], which $R_{\max}$ indicates the highest walk step and its value is determined based on the specified issue.

$$\beta=R_{\max}/t^2 \tag{18}$$

$L(r)$ specified in Eq. (9) can be represented as mentioned in Eq. (19), in which r is higher than zero and Γ denotes the gamma function [25].

$$L(r)=\frac{(\alpha-1)\Gamma(\alpha-1)\sin\left(\frac{\pi(\alpha-1)}{2}\right)}{\pi r^{\alpha}} \tag{19}$$

Moths, which are at a higher distance from light source fly in the direction of the light source in line, which is portrayed as per Eq. (20), in which the best moth in a generation t is indicated by y_{best}^{t} and η and Φ are scaling factors and acceleration, correspondingly [25].

$$y_i^{t+1}=\eta\times\left(y_i^t+\Phi\times\left(y_{best}^t-y_i^t\right)\right) \tag{20}$$

Moreover, the moth could fly towards the last position, which is away from the optimal moth in the population. Thus, the final position of moth can be given as in Eq. (21) [25]. The pseudo code of the conventional MSA model is specified by algorithm 1.

$$y_i^{t+1}=\eta\times\left(y_i^t+\frac{1}{\Phi}\times\left(y_{best}^t-y_i^t\right)\right) \tag{21}$$

Algorithm 1: Conventional MSA model [25]			
Initialize $t=1$, $R_{\max}$, β, Φ, $Max\ gen$ and assign population Po of NP moths in a random manner			
Fitness evaluation			
While $t < Max\ gen$ do			
	Sort as per the fitness of moths		
	for $i=1$ to $NP/2$ do		
		Produce y_i^{t+1} by carrying out levy flights as given in Eq. (19)	
	end for i		
	for $i=NP/2+1$ to NP do		
		if $rand > 0.5$ then	
			Produce y_i^{t+1} by Eq. (20)
		else	
			Produce y_i^{t+1} by Eq. (21)
		end if	
	end for i		
	Compute the populations based on new updated positions		
	$t=t+1$		
end while			
Attain the optimal solution			
End			

5.3Proposed Algorithm

The conventional MSA tends to be a better approach for resolving the global optimization issues; however, certain inadequacies were noticed during the exploration of subpopulation 2. Thus to overcome this issue, an improvement is done in the existing MSA model, by which the inadequacies can be overwhelmed. The procedure of the adopted scheme is as follows: In the conventional MSA scheme, the step length is determined as per Eq. (16), where the parameters d and v were chosen in a random manner. As per the proposed model, the parameters d and v in Eq. (16) are chosen based on the best positions, i.e. d denotes best position 1 and v indicates best position 2. More clearly, the position of the 1st best fitness is said to be best position 1 and accordingly, the position of the 2nd best fitness is said to be best position 2. As the modification is done based on the step length, the presented model is termed as MS-SL model. Algorithm 2 depicts pseudo-code of the proposed MS-SL algorithm and the flowchart representation is given by Figure. 4.

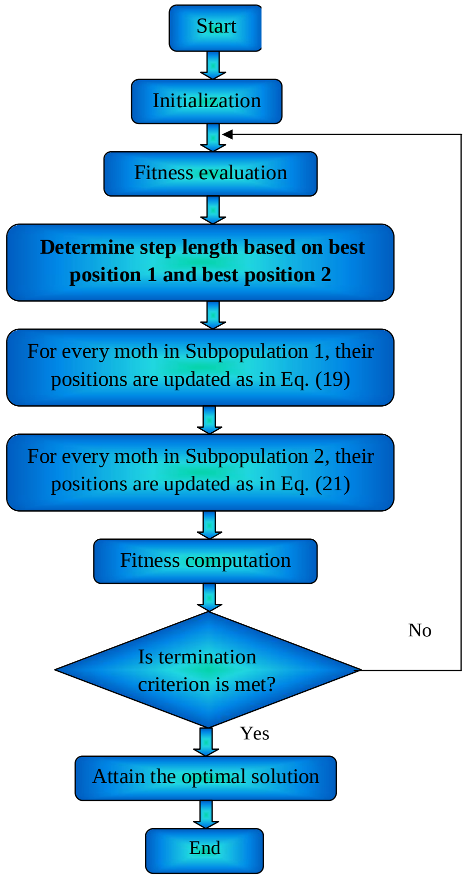

Figure 4: Flowchart of the proposed MS-SL model

Algorithm 2: Proposed MS-SL model			
Initialize $t=1$, $R_{\max}$, β, Φ, $Max\ gen$ and assign population Po of NP moths in a random manner			
Fitness evaluation			
While $t < Max\ gen$ do			
	Sort as per the fitness of moths		
	for $i=1$ to $NP/2$ do		
		Produce y_i^{t+1} by carrying out levy flights as given in Eq. (19)	
		Determine step length based on best position 1 and best position 2	
	end for i		
	for $i=NP/2+1$ to NP do		
		if $rand > 0.5$ then	
			Produce y_i^{t+1} by Eq. (20)
		else	
			Produce y_i^{t+1} by Eq. (21)
		end if	

	end for i
	Compute the populations based on new updated positions
	$t = t + 1$
end while	
Attain the optimal solution	
End	

6.RESULTS AND DISCUSSION

6.1Simulation procedure

The adopted crop/weed classification was executed in MATLAB and the corresponding outcomes were attained. The dataset was taken from "https://github.com/cwfid/dataset)". Here, the performance of the presented technique was compared over the other conventional schemes like NN [31], DCNN [30], PSO [32], GA [33] and MSA [25] in terms of "accuracy, sensitivity, specificity, precision, FPR, FNR and FDR" by varying the learning percentages from 20, 40, 60 and 80. Further, statistical analysis was also held to validate the performance of the presented work.

6.2Performance Analysis

The performance analysis of the adopted MS-SL for crop/weed classification is given in Figure.5 for varied learning percentages. From the analysis, better performance is attained by the presented approach for all the measures. Accordingly, higher values are attained for the positive measures and lower values are attained for the negative measures. More specifically, from Figure 5(a), the adopted MS-SL model in terms of accuracy is high at 80th learning percentage, which is 56.52%, 10.87% and 10.87% superior to DCNN, GA and MSA algorithms. On considering sensitivity, from Figure 5(b), the proposed method is 9.09%, 96.67% and 96.67% superior to DCNN, GA and MSA algorithms at 30th learning percentage. From figure 5(c), the specificity of the implemented MS-SL model at 50th learning percentage is 50%, 3% and 2% superior to DCNN, GA and MSA algorithms. Moreover, from Figure 5(d), the precision of the suggested model is high at 70th learning percentage is 85%, 82%, 85%, 87%, and 90% better than NN, DCNN, PSO, GA and MSA algorithms. The FDR that is attained from Figure 5(h) is 85%, 82%, 80%, and 83% better than NN, DCNN, GA and MSA algorithms at 70th learning percentage. Thus the effectiveness of the proposed algorithm has been proved over other models.

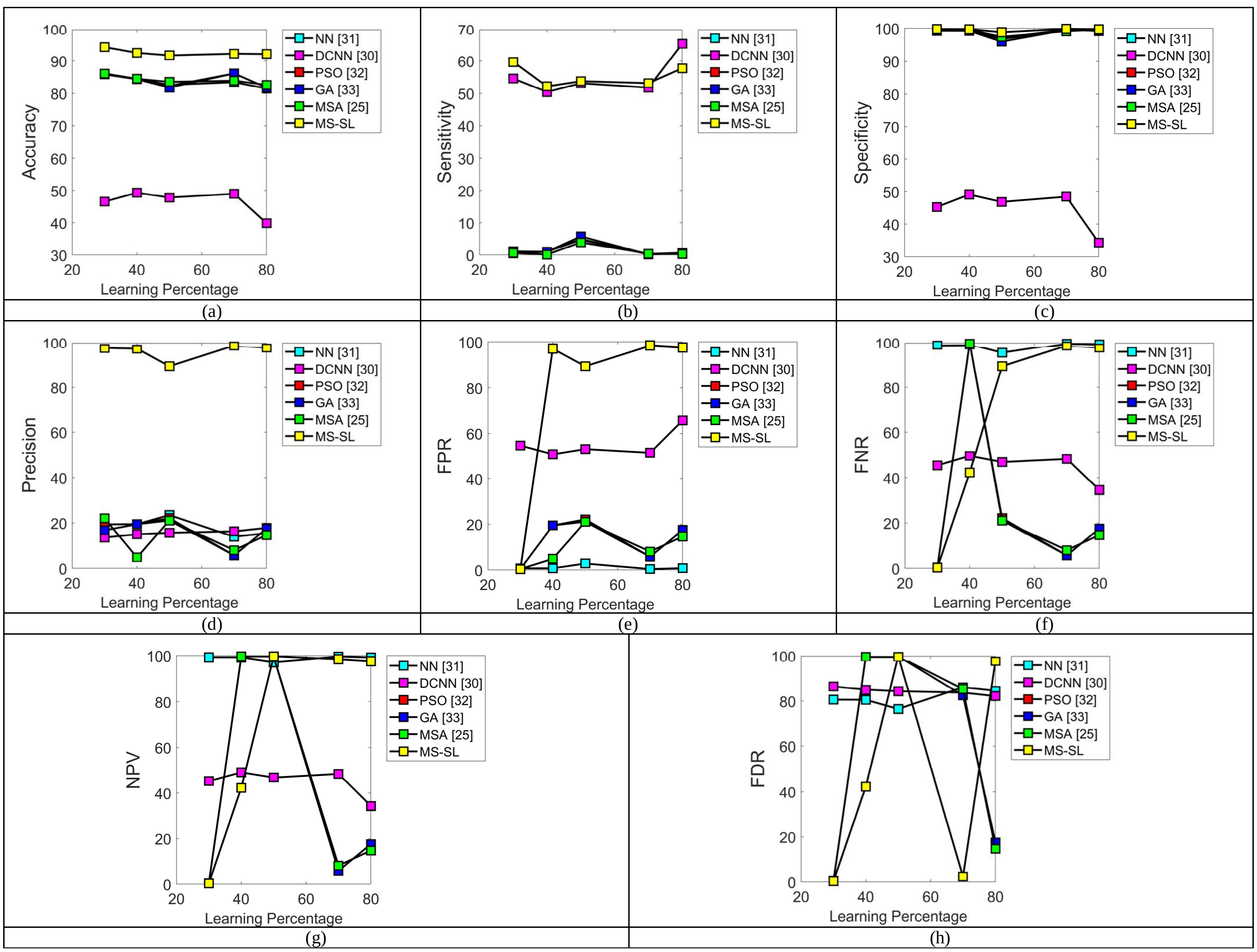

Figure 5: Performance analysis of adopted and existing schemes with respect to (a) accuracy (b) sensitivity (c) specificity (d) precision (e) FPR (f) FNR (g) NPV (h) FDR

6.3Impact of Threshold

Figure 6 shows the impact of threshold for the adopted MS-SL approach for effective crop/weed classification. On observing the attained outcomes, improved performance is achieved by the offered approach over the other compared schemes. Accordingly, from Figure 6(a), the presented MS-SL scheme with regards to accuracy at a threshold of 0.4 is 3.29%, 1.38% and 0.32% superior to the values of threshold at 0.1, 0.2 and 0.3 at 30^{th} learning percentage. In addition, the suggested MS-SL technique in terms of sensitivity at a threshold of 0.1 is 5.88%, 10.29% and 11.76% superior to the values of threshold at 0.2, 0.3 and 0.4 at 30^{th} learning percentage. Similarly, the specificity of MS-SL scheme at 80^{th} learning percentage for a threshold of 0.4 is 5%, 1%, and 1% better than the values of threshold at 0.1, 0.2 and 0.3. Further, the NPV of the implemented MS-SL technique at a threshold of 0.1 is 5.88%, 10.29% and 11.76% superior to the values of threshold at 0.2, 0.3 and 0.4 at 30^{th} learning percentage. Thus the effectiveness of the proposed MS-SL algorithm for better crop/weed classification has been proved by the attained results.

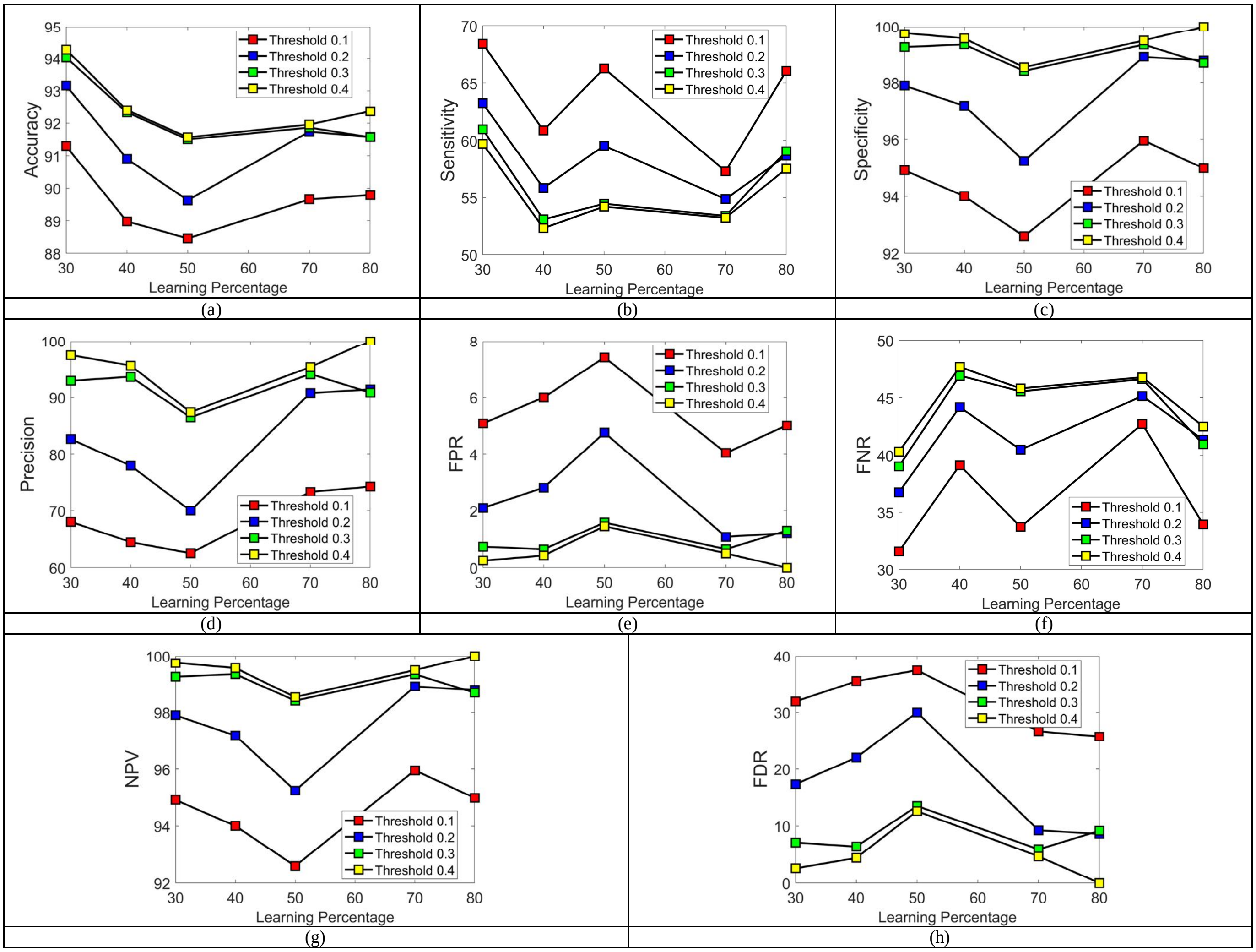

Figure 6: Impact of threshold: Adopted and existing schemes with respect to (a) accuracy (b) sensitivity (c) specificity (d) precision (e) FPR (f) FNR (g) NPV (h) FDR

6.4 Statistical Analysis

The statistical analysis of the presented MS-SL scheme for effective crop/weed classification is demonstrated in this section. As met heuristic algorithms are stochastic in nature, the results are simulated for five times and the outcomes are taken. From the outcomes, the presented scheme has attained better performance when evaluated over the other existing schemes for all the measures. More specifically, from Table II, the best performance of adopted MS-SL model in terms for accuracy at 80^{th} learning percentage is 11.19%, 11.19% and 10.72% superior to PSO, GA and MSA algorithms. Also, the median of the presented model is 11.2%, 11.2% and 10.73% superior to PSO, GA and MSA algorithms. In addition, on considering sensitivity, the adopted model for mean performance is 98.92%, 98.92% and 99.09% enhanced than PSO, GA and MSA scheme. Also, the presented scheme in terms of median performance is 98.87%, 98.87%, and 99.09% better than PSO, GA and MSA algorithms. When computing the specificity, the adopted model in terms of best performance is 1.12%, 1.12%, and 0.7% better than PSO, GA and MSA algorithms. Also, the median of presented scheme is 1.13%, 1.13% and 0.7% superior to PSO, GA and MSA algorithms. Moreover, the precision of presented model in terms of worst performance is 90%, 90%, and 90% better than PSO, GA and MSA algorithms. Hence, it can be concluded that the adopted scheme is efficient over the other traditional schemes.

Table 2: Statistical analysis: proposed and conventional models in terms of performance measures

Accuracy				
Methods	**PSO [32]**	**GA [33]**	**MSA [25]**	**MS-SL**
Best	0.82742	0.8274	0.83094	0.92005
Worst	0.83094	0.83094	0.83094	0.92012
Mean	0.82829	0.82829	0.83094	0.9201
Median	0.8274	0.8274	0.83094	0.92012
STD	0.001767	0.001767	0	3.49E-05
Sensitivity				
Methods	**PSO [32]**	**GA [33]**	**MSA [25]**	**MS-SL**
Best	0.004714	0.004714	0.004714	0.51803
Worst	0.005856	0.005856	0.004714	0.51825
Mean	0.005571	0.005571	0.004714	0.51819
Median	0.005856	0.005856	0.004714	0.51825
STD	0.000571	0.000571	0	0.000107
Specificity				
Methods	**PSO [32]**	**GA [33]**	**MSA [25]**	**MS-SL**
Best	0.98714	0.98714	0.99158	0.99822
Worst	0.99158	0.99158	0.99158	0.99826
Mean	0.98825	0.98825	0.99158	0.99825
Median	0.98714	0.98714	0.99158	0.99826
STD	0.002222	0.002222	0	2.08E-05
Precision				
Methods	**PSO [32]**	**GA [33]**	**MSA [25]**	**MS-SL**
Best	0.081349	0.081349	0.098214	0.98259
Worst	0.098214	0.098214	0.098214	0.983
Mean	0.085565	0.085565	0.098214	0.9829
Median	0.081349	0.081349	0.098214	0.983
STD	0.008433	0.008433	0	0.000203
FPR				
Methods	**PSO [32]**	**GA [33]**	**MSA [25]**	**MS-SL**
Best	0.008415	0.008415	0.008415	0.001743
Worst	0.012859	0.012859	0.008415	0.001784
Mean	0.011748	0.011748	0.008415	0.001753
Median	0.012859	0.012859	0.008415	0.001743
STD	0.002222	0.002222	0	2.08E-05

7.CONCLUSION

The presented framework establishes a novel automatic crop/weed classification model using three major phases: (i) Pre-processing (ii) Feature Extraction and (iii) Classification. At first, the images are transformed to greyscale images during pre-processing stage. Subsequently, from the pre-processed image, the features like GLCM and GLRM based texture features are extracted. At last, the classification is carried out by the hybrid classifiers, where both the DCNN and NN are incorporated. Furthermore, to improve the adopted performance, the hidden neurons of NN are tuned optimally using MS-SL model. At last, the performance of the adopted scheme is evaluated over other traditional schemes and the outcomes are attained. From the analysis, the adopted MS-SL model for accuracy was high at 80^{th} learning percentage, which is 56.52%, 10.87% and 10.87% superior to DCNN, GA and MSA algorithms. On considering sensitivity, the proposed method was 9.09%, 96.67% and 96.67% superior to DCNN, GA and MSA algorithms at 30^{th} learning percentage. Thus, the betterment of the presented scheme is proved.

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