Pest detection and identification using Optimised Neural Network Techniques

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Abstract: Plant pest detection and identification is a major challenge in the field of agriculture since detection and classification is much more difficult than common object detection because of the apparent differences between pest species. To fight the invasion by the pest, early diagnosis of pest is requiring to enhance the production crops and to reduce the economic loss. Different algorithms introduced to detect the different types of pests. Such techniques are not efficient for all the types of pests. To overcome the above said problems, this paper deals with pest detection and identification with Optimized Neural Networks.We can detect and identify the pests with Video or Image processing techniques to reduce the use of pesticides. Detection of pest includes video or Image collection then applying various pre-processing techniques to enhance the image, followed by feature extraction and classification to detect and identify the pest. However, each approach has its own limitations. This paper presents a Video and Image Processing approaches to detect and identify the pest with Optimized Neural Network.

Keywords: Crop management; pest detection; DA model

Abbreviation	Description
RDI	Relative Difference in Pixel Intensities
CSA	Channel-Spatial Attention
RPN	Region Proposal Network
FC	Fully Connected
PSSM	Position-Sensitive Score Map
ROI	Regions Of Interest
NSI	New Spectral Indices
M-SVM	Multi- Class Support Vector Machine
ANN	Artificial Neural Networks
GY	Grapevine Yellows
RPN	Region Proposal Networks
GT	Gabor Transform
GLCM	Gray Level Co-Occurrence Matrix
K-NN	K-Nearest Neighbours
RBF-SVM	Radial Basis Function Support Vector Machine
M5P	M5 Model Tree
mAP	Mean Average Precision
SVM	Support Vector Machine
NN	Neural Network
DA	Dragonfly Algorithm
CNN	Convolutional Neural Network
FPR	False Positive Rate
PSO	Particle Swarm Optimization Algorithm
FNR	False Negative Rate
FDR	False Discovery Rate

1. Introduction

Larger portion of population in India depends on agriculture. Considerable agricultural crop is lost every year, due to rapid invasion by pests. Research in agriculture is envisioned towards increase of production and food potentials at reduced spending in turn increase the profit. India is the bulkiest producer of pulses, rice, wheat, spices and spice products. India ranks 2nd position among the essential producers of fruits and vegetables [26]

[27] [28]. To reach this many countries looking for non-chemical control methods for pest's control or leaf infections. Different algorithms based on image processing have been developed. Maximum of the algorithms focused on small pest like whiteflies, thrips, aphids pest, some are limited to a greenhouse environment. The most common pests which occurrence on crops are Sesamiainferens (pink stem borer), Heliothisarmigera (Cotton bollworm), Achaea Janata (semi looper), Leptocorisa acuta (rice bug), whiteflies, thrips, aphids, army warm, pink boll worm, cotton leaf folder, flea etc.

Current advancement in deep learning algorithms (**Bulat and Tzimiropoulos, 2018; Zhou et al., 2018; Sermanet et al., 2013**) have led to significantly shown progress in detecting object, with the majority of research focuses on designing more difficult object detection systems for improved accuracy, such as Super-FAN (**Bulat and Tzimiropoulos, 2018**), Scale- Transferrable Object Detection (**Zhou et al., 2018**), unsupervised multi-stage feature learning (**Sermanet et al., 2013**) and other extended variants of these networks.

The optimization algorithms have undergone various enhancements and modifications to solve complex problems [34] [35] [36] [37]. control can be done by regular observation of the plant field by taking video or image and applying image or video processing techniques to detect the pest.

Numerous heuristic algorithms are reported in [35] [38] [39]. But dragonfly is one of the most recently developed heuristic optimization algorithms by **Mirjalili**[40], it has the ability to optimizing diverse real-world problems and it also offers the advantage of low cost, fast convergence. Inspired by the advantage of the DA this paper utilizes a new Dragonfly with New Levy Update (Modified-DA) algorithm.

2.Significance of The Study

Farmers are spending huge amount on disease management, often without adequate technical support, resulting in poor disease control, pollution, and harmful conditions [29] [30] [31]. By recognizing pest at early stage reduces the uses of pesticide and gives good crop yield [1]. Minimal use in pesticides is anticipated in pest control to cope with various problems affected by over-use of pesticides: very harmful to the crops, soil, air, water resources, humans and the animals [32] [20] [33]. If we can detect pest at early stage, we can spray organic pest control products which are environmentally friendly in its place of pesticides. Protection of crop gives food protection to almost half of the world population [2].

3.Review of Related Studies

Proposed a system called DeepPest for multiscale pest detection. Initially it builds a network by extracting information of the images for classifying pest categories. These images will combine pest contextual information from low to high convolutional layers for getting the best feature. Cascading CNN architecture for detecting small object and unbalanced data with multiple projection convolution blocks to detect in-field pest [3].

Developed a model for finding Apple's leaves disease using convolution neural network. This model also executed with the SVM, Decision Tree, Logistic Regression algorithms for the same data set. Achieved good results with respect to time and complexity in space for all algorithms [4].

Reviewed the deep learning algorithms for diagnosing the crop with image analysis. Described the current tools and deep learning methods used to identify and detect plant leaf disease and pest. Summarized and discussed the current challenges in leaf disease detection and future development avenues in plant phenotyping [5].

Reviewed the need for customizing the CNNs to regulate the process of feature extraction, to achieve good precision in the detection and classification processes. The quality of the input image, the number of objects per image, the hardware resources, and the large dataset required for training CNNs are factors. Considering deep learning, object detection proved to be more suitable for insects, while the image classification was more used to recognize plant, leaf and fruit diseases. Some discussed the techniques for overlapping pests. We did not identify the use of instance segmentation using deep learning. Therefore, we believe there are opportunities to combine image processing and CNN techniques for the treatment of connected or overlapping objects [6].

The crop pests and diseases can be monitored in real time-based framework by the occurrence of pests and diseases can be studies by analyzing climate changes. in advance. Detection and identification of the pest was done by applying the color histogram and contour detection technique by SVM [7].

The crop pests and diseases can be monitored and analyzed in real time with Internet of Things which uses the sensors and drones to collect the data. Drones and sensors are used to analyze large amounts of data are transmitted to the cloud data center for analyzing the degree of damage of pests and diseases based on spectrum analysis technology [8].

Detected six types of pest using Convolutional Neural Network. A fully connected layer is included with batch normalization, several dense and dropout which can help to utilize the model. By applying a sigmoid to this resultant convert the data to probabilities for each class [9].

Developed a model that was evaluated and compared with deep learning architectures such as AlexNet, ResNet, GoogLeNet and VGGNet for insect classification. Transfer learning approach was applied to retrain deep learning models and the insect classification tasks are evaluated in terms of accuracy and efficiency applied to fine-tune the pre-trained models. The translation techniques reflection, scaling and rotation are applied to prevent overfitting. The effectiveness of hyper parameters was analyzed in the proposed model to improve accuracy [10].

The proposed AlexNet and GoogleNet CNNs were trained the images of diseased and healthy soybean leaves for detecting the soybean leaf diseases. By using AlexNet and GoogleNet models achieved good learning rate by modifying the parameters the minibatch size, max epoch, and bias learning rate. Experimental results show that the proposed deep convolutional neural network model is well suited for soybean disease detection and classification [11].

Reviewed different papers and summarizes the different weed detection methods using imaging processing practices. The process comprises the image processing steps like pre-processing, segmentation, feature extraction and classification. The color indices and sorting techniques applied for separating plants from background, and achieved good. Weed finding is difficult since weed and crop have some common properties. Different features like morphological, spectral features, texture and spatial contexts, used as feature collection. The machine learning and deep learning algorithms used for the classification of weed. Deep learning algorithms show promising results, but big data set are needed for working out, which is cost effective for different applications. The new learning networks should consider semi-supervised learning, self-taught learning, generative adversarial systems. Concluded that the machine learning algorithms with the image processing algorithms is a skilled tool for weed and plant finding in the crop field [12].

Projected a method for detecting ten types of tea plant insect by combining CNNs and saliency methods. In image pre-processing stage created three dissimilar artificial images created for every saliency map to train the original data set on five convolutional neural networks and the created synthetic datasets by saliency methods [13].

Presented a review on plant disease recognition using Image Processing Techniques. The deep learning techniques have better classifiers trained using hand-crafted features. The importance of collecting big datasets with high variability, data rise, transfer learning and visualization of CNN activation maps in improving detection accuracy has been deliberated and reported the DenseNet201, ResNet-101 and Inceptionv3 CNN architectures are the most suitable models for normal computing environments while Shuffle Net and Squeeze Net are the best suited architectures for mobile and embedded applications [14].

Designed a novel module channel spatial attention attached into the convolutional neural network for feature extraction and enhancement. The features are input to the region proposal network for identifying the pest positions. For pest classification Position-sensitive score map and bounding box regression will replace fully connected layers. The PestNet works well on multi-class pest detection [15].

This approach applied on yellow rust, aphids, and powdery mildew. This method requires reduced redundancy information for extracting the most sensitive spectral vegetation indices for different invasions, need only fewer samples for training and calculating, and is flexible framework with modifiable characteristic spectral vegetation indices allows detection and identification of pests and diseases at the leaf and canopy level or larger scales [16].

Detected rice disease i.e. Leaf blast by artificially creating large training dataset from the existing dataset and performed random rotations, shifts, flips, crops, and sheers on image dataset with CNN. The input to the fully connected layer is weighted feature map will calculate the accuracy and loss. If there is a loss the weights of the internal nodes will be modified automatically to improve the result. [17].

Designed a DCNN network for blur boundaries and irregular shape object detection. Detected three categories of rice diseases and pests. Initially convert video into frames, sent these frames to the image detector which uses faster-RCNN as the framework and finally synthesized the frames into video. Images trained with machine learning classifier to detect blurry videos, and is classified [18].

4.Objectives of The Study

- To design and develop the Pest detection in the crop using video and image processing.
- To develop the Segmentation algorithm to detect object of interest.
- To design and develop the algorithm for the extraction of the texture, colour, edge, shape of Pest in the crop.
- Data obtained from extracted images is used for detecting the type of the pest.

5.Proposed Method

The study presented in this paper may overwhelms the drawback in the existing work. In existing systems detecting the pest using the image processing and extracting the features using different algorithms without any validation algorithms which will not help farmers to identify insect. Introduced the feature extraction of image captured by using the color histogram.

The automatic detection of different crop insect using deep learning methodology. The CNN architecture used for insect classification. Different insect images are collected from internet with insect present on leaves. In this work CNN was trained using RGB color model with 100 samples of each pest. The proposed architecture to steps shown in figure1.

A. Architecture Description

The projected Image and Video processing pest detection outline with five major phases, viz. Acquisition of Image or Video frames. Preprocessing for Image or video, Foreground and background estimation and object tracking for video. From the segmented image the features like shape, texture, colour, edge etc. are to be obtained. Classification of the object is done with these features with convolution neural networks.

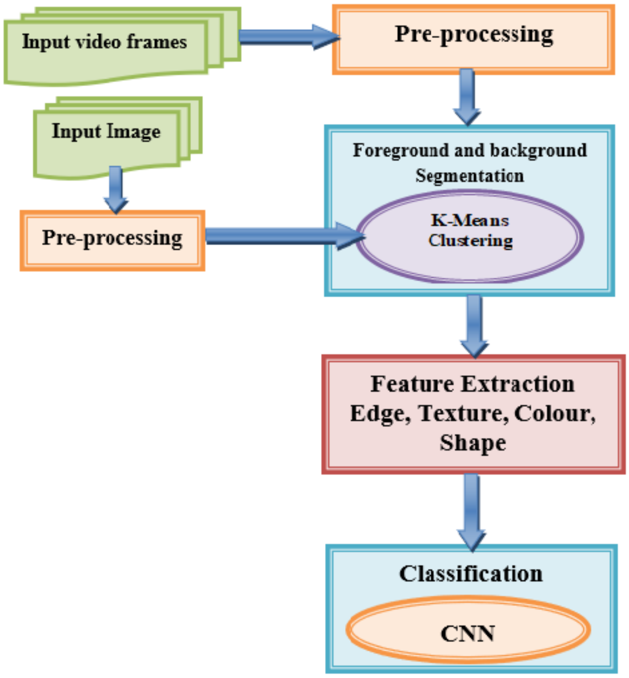

Fig.1.System Architecture

6.Pre-Processing and Segmentation

A. Pre-Processing

The pre-processing involves collecting images or video frames which involves the following.

The collected image has to be read by using the *read*() function. For video the given video has to be converted to frames using *VideoReader*() command, each frame then read by using *read*() function.

i=*VideoReader*() (1)

It is then resized to 512×512 by using the below function

I1=resize(i) (2)

Noise in the image or frame can be removed using median filter by using the below command

I2=*medfilt2*(I1).(3)

The Lab colour transform applied to the filtered output using

lab = *rgb2lab* (I2)(4)

For segmenting the image or image frame the K-means clustering is applied, which will help to identify the object by separating the foreground and the background.

B. Foreground/ Background Segmentation with K-means Clustering

Algorithm1: k-means clustering Algorithm

Segment the preprocessed image I into k clusters by using

I1 = imsegkmeans(I,k).(5)

Step 1: Choose the number of clusters from the pre-processed image or frame.

Step 2: Select centroids randomly from the clusters.

Step 3: To each cluster centroid assign the data points.

Step 4: The centroid is moved to the average of all the points assigned to it, recompute the centroids of newly formed clusters.

Step 5: Repeat steps 3 and 4 until no changes in cluster centres.

To get the accurate shape for the cluster frames the morphological operations such as closing and opening, and then subtracting the original frame to locate any changes that have been induced. For example, closing and subtraction operation together identify defects like cracks, tiny holes, and concavities.

$$I = A \bullet B - A \qquad (6)$$

Similarly, opening and subtraction operation together identify defects like locate spot noise, hairs, and prominences.

$$I = A - A \circ B \qquad (7)$$

The combinations of morphological operations, used above to identify a variety of size and shape defects.

After morphological operations the lab colour frame is binarized using an adaptive threshold Using Integral Image. The MATLAB command is,

bw2= imbinarize(I,'adaptive','ForegroundPolarity','dark');

imshow(bw2) (8)

This method uses a large-neighbourhood mean filter. The input image pixel value is larger than the mean filter, then the pixel value is set to white.

C. Feature Extraction

Texture Features: Energy, Entropy, Contrast, Homogeneity, local homogeneity,Correlation, Shade, Prominence,Coarseness.

stats = graycoprops(glcm,properties) (9)

Edge features calculated by canny edge detector. The calculation of the edge is by the gradient using the derivative of a Gaussian filter. Detection of strong and weak edges is done by calculating two thresholds. Need to include weak edges in the output if they are connected to strong edges. By using two thresholds, the Canny method is less likely than the other methods to be fooled by noise, and more likely to detect true weak edges. The canny edge detection is done for the gray scale imageusing the function

I = edge(I,'Canny') (10)

Shape features Sphericity, Irregularity, 3D surface, eccentricity, major axis length, minor axis length, area and perimeter calculated by the command

stats = regionprops (CC, properties) (11)

The colour features are extracted from Lab and HSV image frames. The standard deviation and mean of these channels are the statistical features. The mathematical formula for mean μ is shown mathematically μ=sum of entries/no. of entries (12)

The mathematical formula for standard deviation σ is expressed

$$\sigma = \sqrt{\frac{\sum (x-\mu)^2}{N}} \tag{13}$$

7.Weight Optimized Neural Network

It is a Deep Learning algorithm which can take in an input image, assign weights and biases to various objects in the image and be able to differentiate one from the other. The architecture of a Neural Network is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlaps to cover the entire visual area.This architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better.

The extracted edge, shape, texture and colour features are given as input to classification using weight optimized NN. The input to NN is the function of all extracted features $F(n) = \{f_{te} + f_{co} + f_{ed} + f_{sh}\}$. Where, n is the count of features.

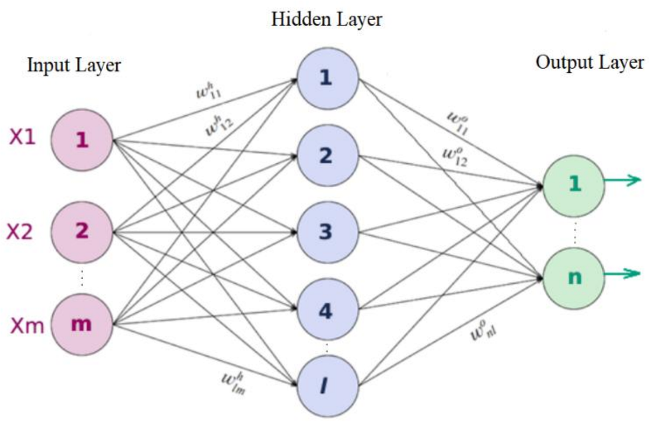

Fig. 2. Schematic representation of NN

The resultant from the hidden neurons is $e^{(H)}$, which is determined using Eq. (14).

$$e^{(H)} = A\left(W^{(H)}_{(Bh)} + \sum_{z=1}^{n_z} W^{(H)}_{(zh)} F(n) \right) \tag{14}$$

Here, A is the activation function. The notation $W^{(H)}_{(Bh)}$ is the bias weight of h^{th} hidden neuron and hidden neuron n_z is the count of input neurons. The bias weight of h^{th} hidden neuron from z^{th} input neuron is denoting as $W^{(H)}_{(zh)}$ .The output from NN is $\hat{G}_O$, which is determined using Eq. (15). Here, n_h indicatesthe number of hidden neurons. The bias weight of o^{th} neuron is $W^{(G)}_{(Bo)}$ and $W^{(G)}_{(ho)}$ is the weight to o^{th} neuron from h^{th} hidden neurons.

$$\hat{G}_{\hat{o}} = A\left(W^{(G)}_{(Bo)} + \sum_{h=1}^{n_h} W^{(G)}_{(ho)} e^{(H)} \right) \tag{15}$$

The error (E^*)between the actual and the predicted outcomes is evaluated using Eq. (16). Here, n_o indicates output neuron count.

$$E^* = \underset{\{W^{(H)}_{(Bi)}, W^{(H)}_{(zh)}, W^{(G)}_{(Bo)}, W^{(G)}_{(iho)}\}}{\arg\min} \sum_{=1}^{n_o} \left| G_o - \hat{G}_o \right| \tag{16}$$

Where, G_o and $\hat{G}_o$ refers the actual and predicted output respectively.

a. Objective Function and Solution Encoding

The weight of NN $(W(n))$ plays a crucial role in enhancing the detection accuracy. In NN instead of levenberg based weight update, the modified DA algorithm is deployed.

To enhance the classification accuracy (Acc) of NN, which is mathematically expressed in Eq. (17).

$$ob = \max(Acc) \tag{17}$$

b. Modified DA Algorithm

The standard DA [19] is based on the static and dynamic swarming behaviour of dragonflies. They have the potential of acquiring the global solutions, without getting trapped into the local minima. But, here the convergence of the standard DA is lower [21][21]. In literature, the significance and usage of adaptive meta-heuristic operators have been reported [20]. Thus, certain modifications need to be introduced in order to enhance the algorithm, thereby proposing a new modified DA algorithm and the mathematical modelling of the algorithm is as follows:

Separation (S_g)**:** It is mechanism of avoiding the static collision of the search agents from its neighbours. The mathematical formula for S_g is evaluated using Eq. (18). The position of the present search agent is denoted as X and X_g is the position of its neighbour. In addition, the count of g^{th} neighbours are symbolized as N .

$$S_g = \sum_{g=1}^{N} X - X_g \tag{18}$$

Alignment (A_g) **:**It is mechanism of matching the velocity (V) of the current search agent with its neighbours.The mathematical for alignment is expressed in Eq. (19).

$$A_g = \frac{\sum_{g=1}^{N} V_g}{N} \tag{19}$$

Cohesion (C) **:**It is the potential of the search agent to move towards the centre of the mass of the neighbours. The mathematical formula for cohesion is expressed in Eq. (20).

$$C_g = \frac{\sum_{g=1}^{N} X_g}{N} - X \tag{20}$$

The attraction of the search agent towards the food source (F) is determined using Eq. (21). Here, X^+ is the position of the food source.

$$F_g = X^+ - X \tag{21}$$

Moreover, the distraction of the search agent away from enemy (E) is expressed in Eq. (22). The position of the enemy is X^- .

$$E_g = X^- + X \tag{22}$$

The position of the current search gent is updated with the aid of the step vector ΔX and the position vector X . The direction of the search agent movement is determined with the step vector ΔX , which is expressed mathematically in Eq. (23).

$$\Delta X_{t+1} = \bar{s}.S_g + \bar{a}.A_g + \bar{c}.C_g + \bar{f}.F_g + \bar{e}.E_g + \bar{w}.\Delta X_t \tag{23}$$

Here,

$\bar{s}$ → separation weight,

$\bar{a}$ → alignment weight,

$\bar{c}$ → cohesion weight,

$\bar{f}$ → food factor,

$\bar{e}$ → enemy factor

$\bar{w}$ → inertia weight and

t → current iteration

The position vector X is determined using Eq. (24)

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{24}$$

During the absence of the neighbours, the dragonflies tend to have a random walk (Le´vy flight $(levy)$). This random walk enhances the randomness, exploration and stochastic behaviour of the dragonflies. The new update solution of Le´vy flight $(levy)$ is expressed in Eq. (25), in which

$$X_{t+1} = X_t + \alpha_t \times levy(dia) \times X_t + (1-\alpha_t) G(\mu,\sigma) \tag{25}$$

Here, α_t is expressed mathematically in Eq. (26).

$$\alpha_t = \frac{t}{Max_t} = \frac{\text{Current iteration}}{\text{Maximum iteration}} \tag{26}$$

$G(\mu,\sigma)$ → Gaussian random number $\begin{pmatrix} \mu = 0 \\ \sigma = 1 \end{pmatrix}$

The mathematical formula for $levy(dia)$ is expressed in Eq. (27).

$$levy(dia) = 0.01 \times \frac{ra_1 \times \psi}{[ra_2]^{1/\beta}} \tag{27}$$

The dimension of position vector is symbolized as dia and random numbers in the range [0, 1] are denoted as ra_1 as well as ra_2, and β a constant. The pseudo-code of the modified DA model is shown in Algorithm 2.

Algorithm 2: Pseudo code of Modified DA model	
Step 1:	Initialize ΔX_t and X_t $(t = 1,2,\ldots,j)$
Step 2:	In case of the non- satisfying the termination criterion
Step 3:	Evaluate the fitness of search agents
Step 4:	Update $\bar{s}$, $\bar{a}$, $\bar{c}$, $\bar{e}$. and $\bar{f}$
Step 5:	Compute S , A , C , .F and E using Eq. (18-22)
Step 6:	Update the radius of the neighbor
Step 7:	If neighbor>1
	Update the velocity of the search agent using Eq. (23)
	Update the position of the search agent using Eq. (24)
	Else

	Update the velocity of the search agent using Eq. (25)
Step 8:	Verify the novel positions, depending on the variable boundaries
Step 9:	End

Step 1: Initialize step vector ΔX_t and position vector X_t.

Step 2: If the termination criterion is not satisfied, then calculate the fitness of search agents.

Step 4: The separation weight $\bar{s}$, alignment weight $\bar{a}$, cohesion weight $\bar{c}$, enemy factor $\bar{e}$, and food factor $\bar{f}$ is updated.

Step 5: Evaluate separation S , alignment A , cohesion C, food W and enemy E using Eq. (18-22).

Step 6: The radius of the neighbour is updated and if the neighbour greater than one. Then the velocity of the search agent is updated using Eq. (23).

Step 9: The position of the search agent is updated by utilizing Eq. (24).

Step 10: The velocity of the search agent is updated by employing Eq. (25).

Step 11: The novel positions, depending on the variable boundaries, is verified.

8.Results and Discussion

A. Simulation procedure

The proposed pest detection approach with optimized NN was implemented in MATLAB and the acquired resultants were noted accordingly. The video frames are manually collected from the internet, which includes the video of pests like the grasshopper, leafhopper, Spodopetera frugiperda, and stem borer. Subsequently, the analysis was also done for the image dataset which includes images of pests like Tetranychusurticae, Romalea guttata, Cicadellidae, Ostrinia nubilalis, Diabroticaundecimpunctata, Leptinotarsa decemlineata, Anasa tristis, Tenthredoscrophulariae, Spodoptera frugiperda, Armadillidium vulgare, Phyllocnistiscitrella, dermaptera, respectively. The sample frames, output from gray images, Segmented image and Edge features extracted are shown in Fig. 4. The evaluation of the presented model (optimized NN+ Modified DA) is accomplished by comparing it over the extant classifiers like SVM [23], KNN [24], CNN [25], and NN [26] in terms of both positive and negative performance. The accuracy, sensitivity, specificity, and precision come under the positive measures, while FPR, FNR and FDR are the negative measures.

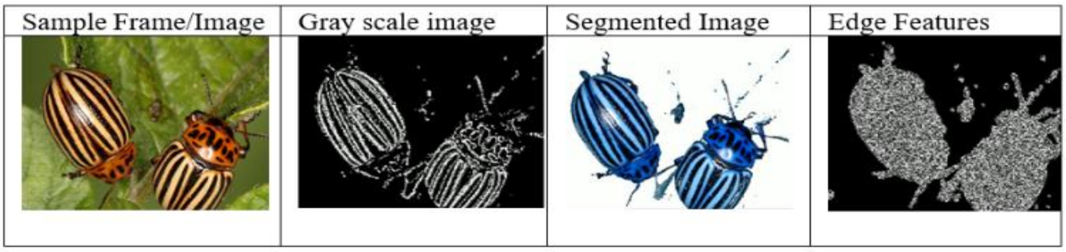

Fig.4. Image results of proposed work

B. Performance Evaluation with respective Positive Measures

The presented work as well as existing classifiers, is trained with all the extracted features (DI-LBP based texture, shape, edge and color features). The evaluation is done by varying the training percentage (TP). The resultant acquired is shown graphically in Fig. 5. The accuracy of the presented work at TP=75 in Fig. 5(a) is 95%, which is 13.3%, 3.2%, 2.2%, and1.9% better than SVM, KNN, CNN, and NN, respectively. The sensitivity of the presented work at TP=75 in Fig. 5(b) is 94.9%, which is 8.9%, 2.3%, 1.6% and 1.3% better than SVM, KNN, CNN, and NN, respectively.The specificity of the presented work in Fig. 5(c) is 94.7%, while the specificity of SVM, KNN, CNN and NN are 70, 89, 91 and 92, respectively at TP=75. Thus, from the evaluation, it's clear that the presented work has the highest specificity while compared to the others. The precision of the presented work is higher than the extant one as per Fig. 5(d). Thus, from the evaluation, it is clear that the presented work has the highest positive measures than the conventional ones.

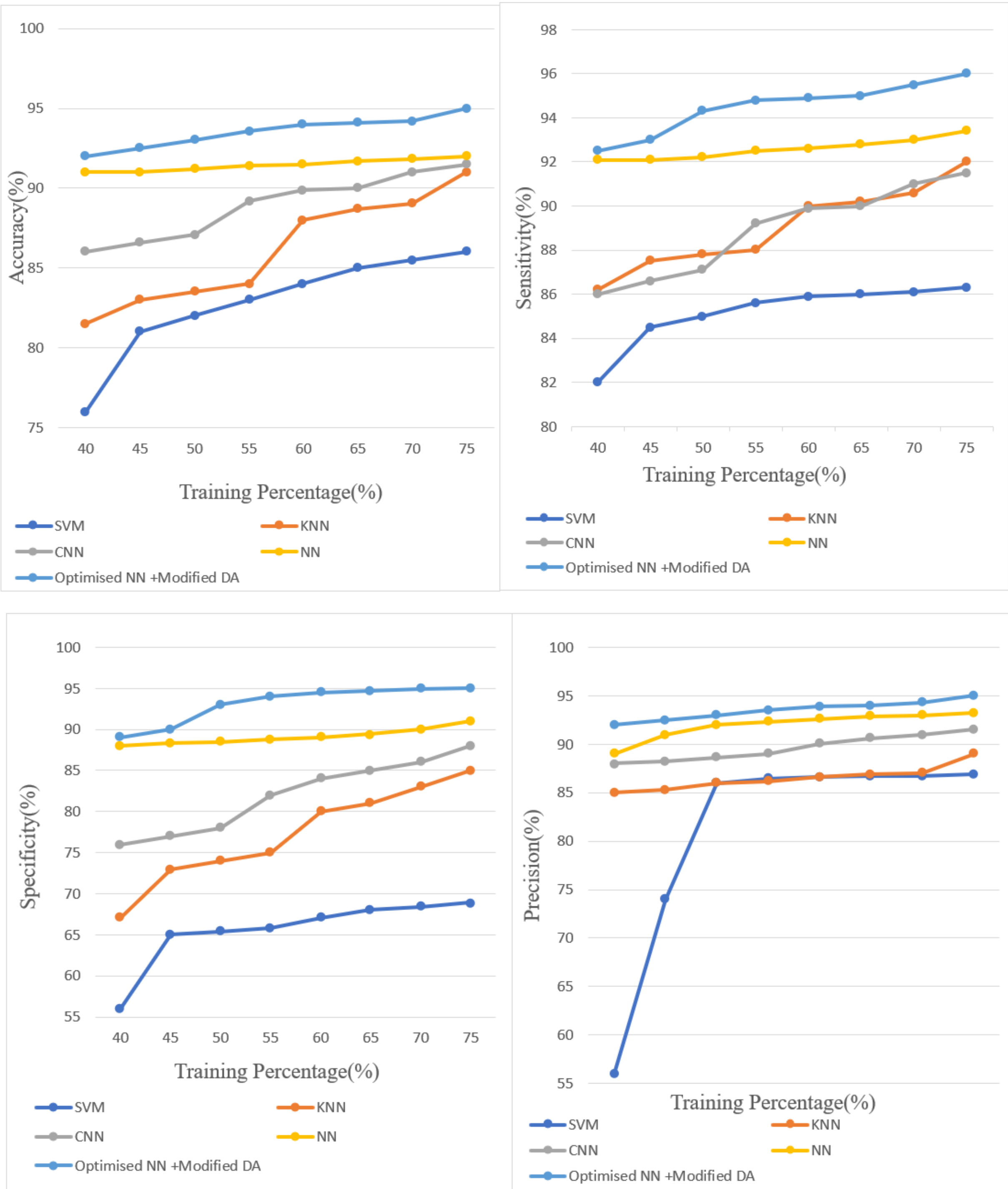

Fig. 5.Performance of Presented work over Existing with respect to (a) Accuracy, (b)Sensitivity, (c) Specificity

and (d) Precision.

C. Performance Evaluation with respect to Negative Measures

The resultant of the presented work, as well as the traditional works in case of negative performance, is exhibited in Fig. 6. This evaluation is undergone by varying the training percentage. In Fig. 6(a), FNR of the presented work at TP=75 is 1.73, while FNR of SVM, KNN, CNN and NN are 8.5, 4.2, 2.6 and 2.2, respectively, Thus, the presented work is said to have the lowest FNR. Further, the FPR of the presented work at TP =75 is 96%, 83%, 75% and 71% better than the conventional models like SVM, KNN, CNN and NN, respectively. Thus, from the evaluation, it is obvious that the presented work has the lowest negative measures.

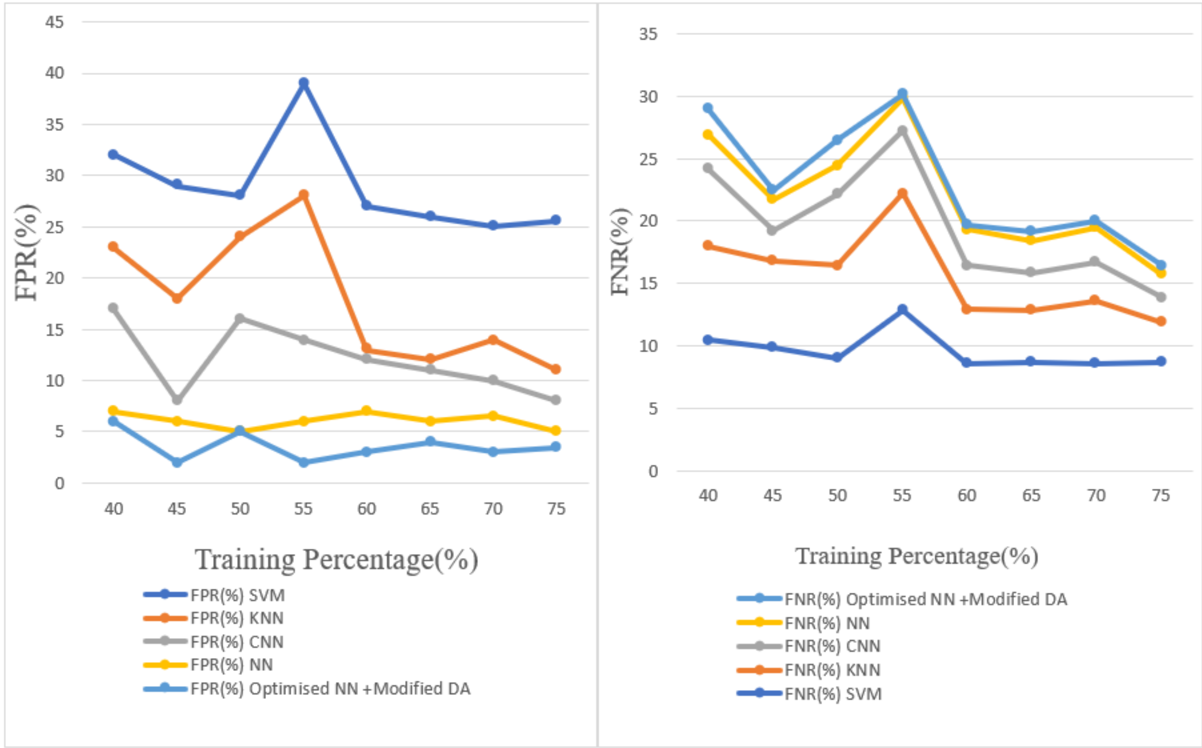

Fig. 6. Performance of the Presented work over Existing Models with respect to FNR and FPR.

D. Computational Time

This section discusses the computational time of the proposed Modified DA over the conventional models. On observing Table I, it can be noticed that the optimized NN+ Modified DA model is 48%, 95.8%, 92.8%, and 61% higher than existing models like NN, CNN, KNN, and SVM, respectively. Thus, the performance of the Modified DA model is proved efficiently.

TABLE I. Computational Time

S.No	Methods	Time (sec)
1.	NN	4.80
2.	CNN	60.20
3.	KNN	35.41
4.	SVM	6.61
5.	Optimized NN+ Modified DA	2.70

9.Conclusion

This paper has proposed a video processing-based pest detection framework by following six major phases, viz. (a) Video Frame Acquisition, (b)Pre-processing, (c) Object Tracking, (d) Foreground and Background Segmentation (e) Feature Extraction and (f) Classification. Initially, the moving frames of videos were pre-processed, and the movement of the object were tracked with the aid of the foreground and background segmentation approach via K-Means clustering. Then, from the segmented image frames, the features like edge, texture, colour and shape were classified with a weight-optimized NN. As a novelty, the training of NN was carried out using a new optimization algorithm termed as Modified DA, which is the extended version of standard DA. The performance of the proposed model was analysed over other conventional models with respect to certain performance measures. The accuracy of the presented work at TP=75 in is 95, which is 13.2%, 3.1%, 2.3% and 1.9% better than SVM, KNN, CNN, and NN, respectively. From the analysis, it is proved that the proposed model was more effective in detecting the pest accurately.

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