

# A multi-instance learning based approach for whitefly pest detection

Lal Chand, Amardeep Singh Dhiman, Sikander Singh

Department of Computer Science and Engineering, Punjabi University, Patiala, India

## Article Info

### Article history:

Received Aug 31, 2022

Revised Mar 9, 2023

Accepted Mar 12, 2023

### Keywords:

Classification accuracy

Multi instance learning

Precision agriculture

ResNet

Whitefly pest detection

## ABSTRACT

Agriculture constantly faces various challenges including attacks from new pests and insects. With large farm sizes and plummeting manpower in the agricultural sector, it becomes challenging to continuously monitor crops for pest infestation. In this research paper, a specific type of pest attack known as the white fly attack has been investigated which affects a variety of crops. This paper presents four different approaches for automated classification of whiteflies which are the Bayesian network, convolution neural network (CNN), ResNet and multi-instance learning-CNN. A comparative analysis with conventional machine learning and deep learning techniques has also been presented. The performance of the proposed technique has been evaluated in terms of the classification accuracy. The experimental results obtained show that the proposed technique attains a classification accuracy of 95.53%, 96.9%, 97.6%, and 98.13% for the four models respectively. A comparative analysis in terms of accuracy of classification, with existing techniques shows that the proposed technique outperforms baseline deep learning models identifying whitefly infestation.

*This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.*



## Corresponding Author:

Lal Chand

Department of Computer Science and Engineering, Punjabi University

Patiala, India

Email: lc.panwar5876@gmail.com

## 1. INTRODUCTION

The domain of agriculture has been witnessing major advancements and transformations in the recent times. The changes can be attributed to increasing farm sizes, crop concentration, and rapid technical advancements [1]. With growing population and increase in demands, better techniques of crop management and handling have become the need of hour [2]. With the advancements in the field of image processing, computer vision and machine learning, automated applications are being developed for agricultural applications [3]. One such critically important application of computer vision and machine learning is the automated detection of pests, which if not detected early may cause huge damage to crops [4]. Moreover, early detection is necessary as most of the pests have a very short reproduction cycle thereby multiplying rapidly [5], [6]. One such pest exhibiting a menacing effect on a variety of crops is the whitefly. The whitefly is also known as (*Bemisia tabaci*) is one of the most common types of pests which can spread plant-based diseases and can travel relatively large distances and can infest crops such as cotton, rice, cauliflower, pumpkin, cabbage, and soybean [7].

It spreads and multiplies very quickly necessitating swift action in the absence of which the crop decays very rapidly thereby resulting in huge losses. Indiscriminate use of pesticides not only adversely affects the crops and the yield, but is also hazardous for human consumption. Hence, mechanisms for detection of early infestations by white flies and nymphs are of critical importance [8]. Several computer vision and machine

learning based approaches have been developed to detect pests accurately at early stages, though generalized models have not been successful as different pests have different image features thereby needing separate data sets to train a machine learning algorithm to yield high accuracy of classification [9]. A typical plant leaf sample from the prepared dataset, infested by white flies is depicted in Figure 1.



Figure 1. A typical infestation of white flies

There are several challenges pertaining to the automated classification of pests using images captured by by drones or unmanned aerial vehicles (UAVS). Typically, such images are highly prone to noise and disturbance effects which can adversely affect the classification accuracy of the machine learning or deep learning algorithm [10], [11]. Aerial imaging through UAVs often suffer from degradations in the captured images due to insufficient pixels capyured for image recreating and/or blurring effects due to the motion of the caturing device [12]. The most coomonly used machine learning/deep learning model which is employed for crop-pest classification happens to be the convolutional neural nework and its variants [13]. Apart from the vanishing gradint and overfitting challenges, approaches such as featue fusion or feature pyramid networks (MFPN) tend to suffer from the problem of relatively lesser accuracy through a single forward pass through the convolutional neural network (CNN) architecture [14]. The feature fusion approaches using CNN may prove to be efficient provided a powerful graphics processing unit (GPU) but may be extremely computationally expensive employing region-based descriptor matching [15]. The other major challenge with automated pest detection happens to be the fact that small pests often remain undetected due to information loss during the network training stage [16]. Moreover, visual similarity leads to erroneous classification among various categories of pests [17]. Moreover, a similar pipeline of feature extractors, followed by high dimensional spatial representation and classification, such as CNN, region-based CNN (RCNN), and Yolo. have the limitation of not controlling the feature extraction stage but differing only in the baseline structure, loss function and training [18].

This paper investigates the commonly used techniques for pest detection and comes up with a multi-instance learning based approach for automated detection of whitefly pests. The rest of the paper is organized as: section 2 discusses the need for data pre-processing and feature extraction process. Section 3 discusses in detail the proposed method pertaining to the machine learning and deep learning classifiers designed. Section 4 presents and explains the experimental results in detail. Section 5 presents the concluding remarks and directions for future research.

## 2. DATA PRE-PROCESSING AND FEATURE EXTRACTION

In this work, whiteflies are to be detected which are extremely small in size and often bear resemblance in colour to the veins of the leaves of plants which they harbour. Noise effects may hinder the process of separate feature extraction in case of machine learning algorithms or one-shot learning in case of deep learning algorithms. Hence, image pre-processing and noise removal prior to the feature extraction stage play a crucial role.

### 2.1. Image pre-processing

One of the most effective and commonly used techniques which acts as an effective denoising tool for images is the discrete wavelet transform (DWT) [19]. The wavelet transform can be thought of as a combination of high pass and low pass filtering techniques.

$$F(n) \xrightarrow{DWT} Z_{LPP}, Z_{HPP} \quad (1)$$

Here,

- $DWT$  represents the discrete wavelet transform operator.
- $Z_{LPF}$  are the low pass filtered co-efficient values.
- $Z_{HPF}$  are the high pass filtered co-efficient values [20].

Typically, the high pass co-efficient values contain the fluctuations and the low pass components contain the original information of the image [21]. The decomposition of the images using wavelet transform can be done as a decomposition tree in which each decomposition level would yield the approximate co-efficient values, the detailed co-efficient values, the horizontal co-efficient values and the vertical co-efficient values [22], [23]. Thus the image in the spatial domain would be converted to the wavelet domain co-efficients as [24].

$$F(x, y) \xrightarrow{DWT2} C_A, C_D, C_H, C_V \quad (2)$$

Here,

- $C_A$  represents the approximate co-efficient values.
- $C_D$  represents the detailed co-efficient values.
- $C_V$  represents the vertical co-efficient values.
- $C_H$  represents the horizontal co-efficient values.
- $DWT2$  represents the discrete wavelet transform on two-dimensional image data.

## 2.2. Feature extraction

Feature selection plays a critically important role prior to training an automated classifier [25]. The gray-level co-occurrence matrix (GLCM) based attributes or features which have been calculated to train the machine learning model in the proposed work are [26], [27].

- Mean or average:

$$Mean(\mu) = \frac{1}{N} \sum_i^N f_i X_i \quad (3)$$

- Standard deviation:

$$Standard\ Deviation(\sigma) = \sqrt{\frac{1}{N} \sum_i^N (X_i - \mu)^2} \quad (4)$$

- Variance:

$$var = \sigma^2 \quad (5)$$

- Skewness.

$$skewness = \frac{\sum_i^N (X_i - \mu)^3}{(N-1)\sigma^3} \quad (6)$$

- Kurtosis:

$$Kurtosis = E\left[\left(\frac{X-\mu}{\sigma}\right)^4\right] \quad (7)$$

- Energy:

$$Energy = \sum_{i,j}^N |p_{i,j}|^2 \quad (8)$$

- Contrast:

$$Contrast = \sqrt{\frac{1}{mn} \sum_{i,j}^{m,n} [X(i,j) - Mean(i,j)]^2} \quad (9)$$

- Entropy:

$$E = -P(I_{x,y}) \log_2 I_{x,y} \tag{10}$$

- Homogeneity:

$$H = \sum_{i,j}^{m,n} \frac{P_{i,j}}{1-|i-j|^2} \tag{11}$$

- Correlation:

$$Corr_{i,j} = \sum_{i,j}^{m,n} \frac{(i-\mu_x)(j-\mu_y)P_{j,x,y}}{\sigma_x\sigma_y} \tag{12}$$

- Inverse difference moment: it is defined as:

$$IDM = \sum_{i,j}^{m,n} \frac{1}{1+(i-j)^2} P_{i,j} \tag{13}$$

- The GLCM normalizing factor for the features of the image is calculated as [28].

$$N = \frac{X_{i,j}}{\sum_{i=0}^{m-1} \sum_{j=0}^{n-1} X_{i,j}} \tag{14}$$

Root mean square Value (rms): It is often computed as metric corresponding to squared averages or means. It is computed as (15).

$$rms = \sqrt{\frac{\sum_{i=1}^n X_i}{n}} \tag{15}$$

Here,

- $X_i$  denotes the instantaneous value associated with X.
- $I_{x,y}$  denotes the two dimensional image, a function of  $(x, y)$ .
- $m, n$  denotes pixel values along the x and y axes respectively.
- $mean$  denotes the average illuminance pertaining to the image under observation.
- $X$  denote samples belonging to the set.
- $f$  denotes values belonging to the the frequency function in the set.
- $N$  denotes the totallevels corresponding to the normalized GLCM matrix.
- $p_{i,j}$  denotes the normalized GLCM matrix
- $P_j$  denotes the conditional/joint probbability of events.
- $P$  denotes probability of a distinct event.

Based on the extracted features, different classification techniques can be employed [29]. Analyzing the latest benchmark techniques reveal that the most commonly used and effective techniques employ machine learning [30], [31]. Some of the most common machine learning techniques happen to be support vector machine (SVM), artificial neural networks (ANN), deep neural networks (DNNs), different variations of neural networks and deep learning, fuzzy logic, and adaptive neuro fuzzy inference systems [32], [33].

### 3. PROPOSED METHOD

The proposed approach investigates the effectiveness of both machine learning as well as deep learning-based approaches for automated detection of whitefly pests. The machine learning approach developed is the feature extraction followed by classification using the Bayesian network, while the deep learning approaches investigated in the paper are the CNN and ResNet. Further, in the proposed work, a multi-instance learning (MIL) based approach has been designed for classification of samples as infested or non-infested leaf. A comparative analysis has also been carried out among the feature extraction-machine learning and deep learning-based approaches in terms of classification accuracy.

### 3.1. Machine learning and deep learning models for classification

While in machine learning, the features of the dataset are handpicked and computed prior to feeding them to a neural network, the deep learning algorithm is different in the sense that it doesn't require separate feature extraction followed by learning [34], [35]. The machine learning algorithm used in this paper is the deep Bayes Net which works on the principle of Bayes theorem of conditional probability [36]. The weights of the nnrtwork are updated such that the condition for maximization is satisfied of a new sample bearing a conditional probability defined as [37].

$$P\left(\frac{X}{X_i, k_1, k_2, M}\right) = \frac{P\left(\frac{X_i}{X, k_2, M}\right)P\left(\frac{X_i}{k_1, M}\right)}{P\left(\frac{X}{k_1, k_2, M}\right)} \quad (16)$$

Here,

- $P$  denotes the probability of occurrence of an event.
- $X_i$  denotes the vector corresponding to the bias and weight vaues of the network.
- $X$  denotes the training data set
- $M$  denotes the number of neurons and the hidden layers corresponding to the probabilistic network.
- $k_1$  and  $k_2$  denote the network regularization factor.

$\rho = \frac{k_1}{k_2}$  is termed as the network regularization factor corresponding to the cost function  $J$  for the network, whose primary goal is limiting the swing in the seight vector for the network [38]. The regularization based apprapph is more optimized in iterative training compared to forced truncation to achive faster convergence as forced truncation doesn't allow the weight vector to attain final convergence, as opposed to limiting weights to attain faster convergence as in case of regularization [39].

While the machine learning apprapph comprising of feature computation followed by classificaiton can be an effective technique, separate feature extraction may be extremely tedious for large datasets [40]. The CNN is a deep neural network computing low level features at the outer layers and higher-level features at the inner layers [41]. CNNs and its variants have been shown to be useful in automated detection of weeds, pests and diseases for precisison agriculture applications [42]. An alternative deep learning model (variant of the CNN) termed as the Residual Network (ResNet) has also been employed in the present research work. While the CNN has been employed in this paper for the classification problem, but unlike the typical convolutional networks, the ResNethas skip weight connections breaking the direct linkage among the layers [43]. This attributed results in the following advantages [44], [45]: i) Decreases chances of overfitting and ii) decreases the chances of fored truncation due to vanishing gradient ( $\frac{\partial e}{\partial w}$ ).

The structure of the ReNet employed in this research work comprises of 48 convolution layers and a Max-Pool layer. The rectified linear (ReLU) activation function is used for the designed network along with a stride of 2. Skip connections among the cascaded convolution layers have been employed to avoid overfitting and vanishing gradient issues, as discussed above [46]. The ResNet designed has input filter size of  $243 \times 243 \times 3$  corresponding to the  $(R, G, B)$  channels of the input. Pooling of  $2 \times 2$  has been employed along with the feature layer of Fc1000 corresponding to 1,000 feature values.

### 3.2. The multi-instance-learning (MIL) approach

For a bipolar nature of samples, belonging to one of the two categories—infested or non-infested, the data can be represented as (17).

$$S_i = X_{i=1}^n, y_i \quad (17)$$

Here,

$y_i$  is the target vector for binary classification.

Thus:

$$y_i \in \{0, 1\} \quad (18)$$

The MIL approach considers a bipolar belongingness of data sample to positive (1), or negative (0) cases of a condition. Moreover, the instance of one of more instances in the bag of classes makes the bag positive. Typically, the class of the weakly labelled bags are not clearly known and hence it is assumed that the class inherits the class from the bag which it belongs to. The multi-instance learning (MIL) algorithm can be used for convolutional neural networks for instance level or bag level training. Multiple instance training ensures a more bolstered weight update rule for each of the labelled classes. The MIL can thus be categorized as [47]:

- Instance-level: In this approach, bag level estimates are made from instance level estimates.
- Embedding Level: In this approach, a learning approach based on low level embedding is performed which further trains a bag-level classifier based on the embedding samples in the bag.

The feature extraction phase from shallow and deeper level of the CNN can be followed by pooling and an embedding space, following which the category or class is predicted based on the pooled data embedding. The lower dimensional embedding retains the speed of computation of the system. The essence of the MIL-CNN is to overcome the limitation of narrow CNNs to extract information or critical features from larger datasets [48]. Mathematically, if  $F$  is the feature extractor, then  $F$  operates on the data instances  $I$  to render a low dimensional embedding space. The pooling function  $P$  is typically unaffected by permuted pairs and can be used in three different forms: i) Element wise max  $P_{max}$ , ii) Element wise mean  $P_{mean}$ , and iii) log sum exponential pooling function  $P_{LSE}$ .

The feature extractor operating on the instances generates the feature embedding vector given by:

$$F\{I\} \xrightarrow{\text{embedding}} E_I \tag{19}$$

the pooling over the embedding vector renders the pooled instances given by (20).

$$P_E = P\{E_I\} \tag{20}$$

In this work, the CNN is used as the feature extractor tool. Similarly, the ResNet could have also been used as the feature extractor function  $F$ . However, to overcome the vanishing gradient problem and the chances of overfitting, the ResNet was employed in the first place, hence an empirical MIL-Bag comprising of CNN extracted features has been used for embedding. The updating of the weights are thus not directly based on the consecutive cascading of the convolution and pooling layers but are based on the embedding space of the multi-instance bag. The embedded bag is generated and the classifier (CNN) is used to predict the label of the bag of instances as:

$$Y_{CNN}^F = w_i P_E + b_i \tag{21}$$

here,

- $w_i$  is the weight vector
- $b_i$  is the bias of the network
- $P_E$  is the vector rendered by pooling over embedding.

The overlapping probabilities for a typical log-likelihood distribution are depicted in Figure 2.

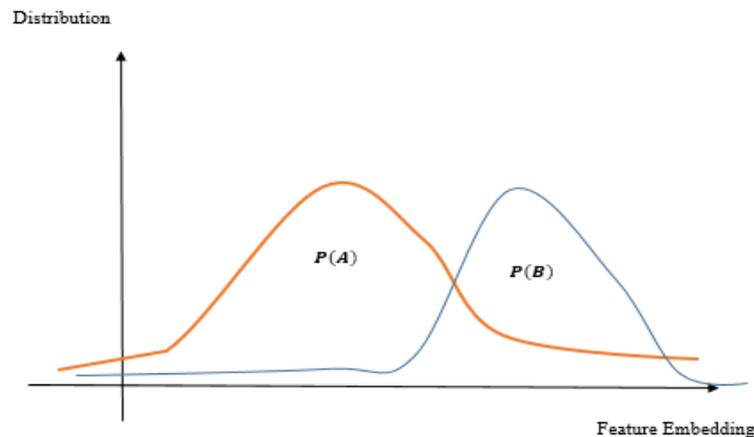


Figure 2. The log-likelihood function used for MIL CNN architecture

Typically, such a CNN-feature extractor exhibits a classification probability function resembling a Bernoulli function given by:

$$f_{Bernoulli} = pn + (1 - p)(1 - n) \tag{22}$$

Here,

- $f_{Bernoulli}$  represents the probability distribution.
- $p$  represents probability.
- $n$  represents the total possible outcomes.

The cost function is chosen as the log-likelihood function given by [49]:

$$f_c = -\log_e\{y_{CNN}^F | y = 0\} - \log_e\{1 - y_{CNN}^F | y = 1\} \quad (23)$$

The significance of the log-likelihood function lies in the fact that the area under the curve of the probability distribution for either of the classes has to maximize over infinity being asymptotic to the x-axis (values of features) to render a clear output. This may serve as the steepest conjugate gradient for fuzzy classification problems [50]. Thus the MIL-CNN can prove to be effective in case of overlapping or fuzzy boundaries among the data features extracted by the conventional CNN [51]. Finally, the performance metrics computed are [52], [53].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (24)$$

$$Sensitivity \text{ or } Recall = \frac{TP}{TP+FN} \quad (25)$$

$$Specificity = \frac{TN}{TN+FP} \quad (26)$$

#### 4. RESULTS AND DISCUSSION

The fundamental step towards classification of images lies in the data acquisition, processing and feature extraction. An experimental setup for the same has been explained in brevity in this section. A dataset of 12,000 images have been prepared for cotton crops from the Malwa region of Mansa, Bathinda, Abohar and Fazilka, Punjab India. Images have been labelled by the authors to create an exhaustive dataset comprising of images of two categories, which are: i) Whitefly infested and ii) Whitefly non-infested.

The data is split in the ratio of 75:25 for training and testing. Figure 3 depicts the cases of both infestation and non-infestation of leaves in the cotton plants. Figure 3(a) depicts a non-infested case while Figure 3(b) depicts an infested case.

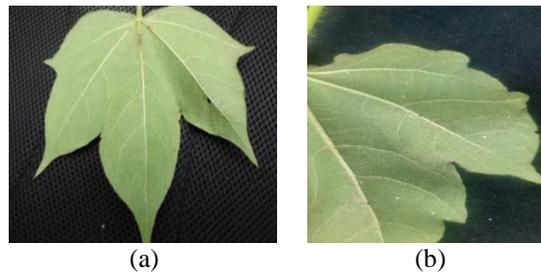


Figure 3. Sample of leaves used in the dataset (a) non-infested and (b) infested

It should be noted here that some leaves may have a few sporadic appearances of whiteflies which should not be considered as infestation. The labelling of the data as infested has been done if the number of flies is more than 5 or 6 per leaf although a clear boundary for demarcation has not been chosen based on the count, primarily because the UAV captured images would have extremely miniaturized images of the flies which may not be distinguishable for actual counting. A comparative Analysis of the results attained using the different approaches is summarized in Table 1.

Table 1. Summary of results

Approach	Accuracy	Sensitivity	Specificity
BayesNet	95.53	94.8	96.26
CNN	96.9	97.0	96.8
ResNet	97.6	97.46	97.73
MIL-CNN	98.13	98.06	98.2

To evaluate the performance of the proposed approach in comparison with the benchmark contemporary techniques, a comparison in terms of the classification accuracy has been made with two categories of models which happen to be feature extraction followed by classification using an ML model and also with state-of-the-art deep learning techniques. Gondal and Khan [55] presented the image restoration, contrast enhancement and feature extraction followed by SVM based classification, for automated identification of Whitefly pests. Legaspi *et al.* [54] and Li *et al.* [56] employ the different versions of the YOLO-CNN deep learning model for detection of whiteflies. Parab *et al.* [57] proposed the use of RCNN and YOLO v.4 models for automated whitefly detection. A comparative analysis with the existing techniques clearly shows that the proposed MIL-CNN approach outperforms existing baseline approaches. A comparative analysis with existing work in the domain has been tabulated in Table 2. It can be seen that the proposed MIL based approach outperforms existing techniques in terms of classification accuracy.

Table 2. Comparison with benchmark techniques

S.No.	Author	Classification accuracy
1.	Legaspi <i>et al.</i> [54]	83.07% (YOLO-CNN)
2.	Gondal and Khan [55]	97% (GLCM Feature extraction and SVM classifier)
3.	Li <i>et al.</i> [56]	87% (YOLOv4 CNN)
4.	Parab <i>et al.</i> [57]	97.16% (Faster RCNN: Double Shot) 96.10% (Yolov4: Single Shot)
5.	Proposed Work	98.13% (MIL-CNN)

## 5. CONCLUSION

This paper employs different training models v.i.z. the Deep Bayes Net, the CNN, the ResNet and the MIL-CNN automated classification of whitefly infestation in crops. To investigate the choice and performance of the most optimized machine model for the purpose, both feature extraction followed by classification using the Bayesian network as well as deep learning models have been used to identify whitefly infestation. While the machine learning model has the advantages of handpicked feature extraction and control over feature optimization, the complexity corresponding to feature selection and feature combination can be reduced substantially using the deep learning models. Classification accuracies of 95.53%, 96.9%, 97.6%, and 98.13% have been achieved for the Bayesian network, CNN, ResNet and MIL-CNN approaches respectively. Thus the MIL-CNN based approach outperforms the remaining models in terms of classification accuracy. A comparison with baseline contemporary approaches exhibits the fact that the proposed MIL-CNN model achieves higher accuracy of classification for whitefly infestation compared to the baseline techniques. While high classification accuracy is promising, labelling of the data set particularly for large image sets can be both time consuming and prone to errors. Thus future enhancements can be thought of employing self-supervised learning (SSL) models. Transfer learning can also be employed for identifying whitefly infestation as the approach has the advantage of using a pre-trained model for classification for a different category of data. This would completely bypass the necessity for cumbersome data collection, processing and labelling of multiple images pertaining to precision agriculture applications.

## ACKNOWLEDGEMENTS

The authors acknowledge the valuable suggestion, critical comments and suggestions of the members of the department of computer science and Engineering, Punjabi University, Patiala, India which have immensely helped in shaping the paper.

## REFERENCES

- [1] N. Khan, R. L. Ray, G. R. Sargani, M. Ihtisham, M. Khayyam, and S. Ismail, "Current progress and future prospects of agriculture technology: Gateway to sustainable agriculture," *Sustainability (Switzerland)*, vol. 13, no. 9, p. 4883, Apr. 2021, doi: 10.3390/su13094883.
- [2] J. Treboux and D. Genoud, "Improved machine learning methodology for high precision agriculture," in *2018 Global Internet of Things Summit, GIoTS 2018*, Jun. 2018, pp. 1–6, doi: 10.1109/GIoTS.2018.8534558.
- [3] D. Brunelli, A. Albanese, D. d'Acunto, and M. Nardello, "Energy neutral machine learning based IoT Device for pest detection in precision agriculture," *IEEE Internet of Things Magazine*, vol. 2, no. 4, pp. 10–13, Dec. 2020, doi: 10.1109/iotm.0001.1900037.
- [4] S. M. Pedersen and K. M. Lind, *Precision Agriculture – From Mapping to Site-Specific Application*. Springer Nature, 2017, doi: 10.1007/978-3-319-68715-5\_1.
- [5] J. F. Tsubira *et al.*, "Improving In-field cassava whitefly pest surveillance with machine learning," in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2020, vol. 2020-June, pp. 303–309, doi: 10.1109/CVPRW50498.2020.00042.

- [6] R. M. Saleem, R. Kazmi, I. S. Bajwa, A. Ashraf, S. Ramzan, and W. Anwar, "IOT-based cotton whitefly prediction using deep learning," *Scientific Programming*, vol. 2021, pp. 1–17, Jul. 2021, doi: 10.1155/2021/8824601.
- [7] I. Sani, S. I. Ismail, S. Abdullah, J. Jalinas, S. Jamian, and N. Saad, "A review of the biology and control of whitefly, *bemisia tabaci* (Hemiptera: Aleyrodidae), with special reference to biological control using entomopathogenic fungi," *Insects*, vol. 11, no. 9, pp. 1–18, Sep. 2020, doi: 10.3390/insects11090619.
- [8] T. Moranduzzo and F. Melgani, "A SIFT-SVM method for detecting cars in UAV images," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, Jul. 2012, pp. 6868–6871, doi: 10.1109/IGARSS.2012.6352585.
- [9] A. Sriwastwa, S. Prakash, Mrinalini, S. Swarit, K. Kumari, and S. S. Sahu, "Detection of pests using color based image segmentation," in *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*, Apr. 2018, pp. 1393–1396, doi: 10.1109/ICICCT.2018.8473166.
- [10] K. S. @ Sankaran and N. V. Nagappan, "Noise free image restoration using hybrid filter with adaptive genetic algorithm," *Computers & Electrical Engineering*, vol. 54, pp. 382–392, Aug. 2016, doi: 10.1016/j.compeleceng.2015.12.011.
- [11] A. Khmag, S. A. R. Al Haddad, R. A. Ramlee, N. Kamarudin, and F. L. Malallah, "Natural image noise removal using nonlocal means and hidden Markov models in transform domain," *Visual Computer*, vol. 34, no. 12, pp. 1661–1675, 2018, doi: 10.1007/s00371-017-1439-9.
- [12] P. Radoglou-Grammatikis, P. Sarigiannidis, T. Lagkas, and I. Moscholios, "A compilation of UAV applications for precision agriculture," *Computer Networks*, vol. 172, p. 107148, May 2020, doi: 10.1016/j.comnet.2020.107148.
- [13] M. Turkoglu, B. Yanikoğlu, and D. Hanbay, "PlantDiseaseNet: convolutional neural network ensemble for plant disease and pest detection," *Signal, Image and Video Processing*, vol. 16, no. 2, pp. 301–309, 2022, doi: 10.1007/s11760-021-01909-2.
- [14] S. Dong *et al.*, "Automatic crop pest detection oriented multiscale feature fusion approach," *Insects*, vol. 13, no. 6, 2022, doi: 10.3390/insects13060554.
- [15] L. Jiao, C. Xie, P. Chen, J. Du, R. Li, and J. Zhang, "Adaptive feature fusion pyramid network for multi-classes agricultural pest detection," *Computers and Electronics in Agriculture*, vol. 195, p. 106827, Apr. 2022, doi: 10.1016/j.compag.2022.106827.
- [16] P. Parameswari, N. Rajathi, and K. J. Harshanaa, "LoRa based framework to detect whitefly infestation in coconut trees," in *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation, ICAECA 2021*, Oct. 2021, pp. 1–5, doi: 10.1109/ICAECA52838.2021.9675775.
- [17] D. C. Amarathunga, J. Grundy, H. Parry, and A. Dorin, "Methods of insect image capture and classification: A Systematic literature review," *Smart Agricultural Technology*, vol. 1, p. 100023, Dec. 2021, doi: 10.1016/j.atech.2021.100023.
- [18] D. Sheema, K. Ramesh, P. N. Renjith, and A. Lakshna, "Comparative Study of major algorithms for pest detection in maize crop," *2021 International Conference on Intelligent Technologies, CONIT 2021*, 2021, doi: 10.1109/CONIT51480.2021.9498280.
- [19] V. A. Pimpalkhute, R. Page, A. Kothari, K. M. Bhurchandi, and V. M. Kamble, "Digital image noise estimation using DWT coefficients," *IEEE Transactions on Image Processing*, vol. 30, pp. 1962–1972, 2021, doi: 10.1109/TIP.2021.3049961.
- [20] D. A. Zebari, H. Haron, S. R. M. Zeebaree, and D. Q. Zeebaree, "Enhance the mammogram images for both segmentation and feature extraction using wavelet transform," in *2019 International Conference on Advanced Science and Engineering, ICOASE 2019*, Apr. 2019, pp. 100–105, doi: 10.1109/ICOASE.2019.8723779.
- [21] L. Zhao, Y. Liu, and L. Wang, "Image compression and reconstruction of transmission line monitoring images using compressed sensing," in *2017 8th International Conference on Mechanical and Aerospace Engineering (ICMAE)*, Jul. 2017, pp. 371–375, doi: 10.1109/ICMAE.2017.8038674.
- [22] A. A. Abdulrahman, M. Rasheed, and S. Shihab, "The analytic of image processing smoothing spaces using wavelet," *Journal of Physics: Conference Series*, vol. 1879, no. 2, 2021, doi: 10.1088/1742-6596/1879/2/022118.
- [23] M. Hemalatha, S. Varadarajan, and Y. M. M. Babu, "Comparison of DWT, DWT-SWT, and DT-CWT for low resolution satellite images enhancement," in *2017 International Conference on Algorithms, Methodology, Models and Applications in Emerging Technologies, ICAMMAET 2017*, Feb. 2017, vol. 2017-Janua, pp. 1–5, doi: 10.1109/ICAMMAET.2017.8186662.
- [24] M. M. I. Ch, M. M. Riaz, N. Iltaf, A. Ghafoor, and S. S. Ali, "A multifocus image fusion using highlevel DWT components and guided filter," *Multimedia Tools and Applications*, vol. 79, no. 19–20, pp. 12817–12828, May 2020, doi: 10.1007/s11042-020-08661-8.
- [25] F. C. Huang, S. Y. Huang, J. W. Ker, and Y. C. Chen, "High-performance SIFT hardware accelerator for real-time image feature extraction," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 22, no. 3, pp. 340–351, Mar. 2012, doi: 10.1109/TCSVT.2011.2162760.
- [26] W. K. Wong, Z. Lai, J. Wen, X. Fang, and Y. Lu, "Low-rank embedding for robust image feature extraction," *IEEE Transactions on Image Processing*, vol. 26, no. 6, pp. 2905–2917, Jun. 2017, doi: 10.1109/TIP.2017.2691543.
- [27] W. Xie, L. Jiao, and J. Zhao, "PolSAR image classification via D-KSVD and NSCT-domain features extraction," *IEEE Geoscience and Remote Sensing Letters*, vol. 13, no. 2, pp. 227–231, Feb. 2016, doi: 10.1109/LGRS.2015.2506718.
- [28] X. Wang, X. Bai, W. Liu, and L. J. Latecki, "Feature context for image classification and object detection," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun. 2011, pp. 961–968, doi: 10.1109/CVPR.2011.5995696.
- [29] T. Sutojo, D. R. I. M. Setiadi, P. S. Tirajani, C. A. Sari, and E. H. Rachmawanto, "CBIR for classification of cow types using GLCM and color features extraction," in *Proceedings - 2017 2nd International Conferences on Information Technology, Information Systems and Electrical Engineering, ICITISEE 2017*, Nov. 2018, vol. 2018-Janua, pp. 182–187, doi: 10.1109/ICITISEE.2017.8285491.
- [30] B. S. Ghyar and G. K. Birajdar, "Computer vision based approach to detect rice leaf diseases using texture and color descriptors," in *Proceedings of the International Conference on Inventive Computing and Informatics, ICICI 2017*, Nov. 2018, pp. 1074–1078, doi: 10.1109/ICICI.2017.8365305.
- [31] Anjna, M. Sood, and P. K. Singh, "Hybrid system for detection and classification of plant disease using qualitative texture features analysis," *Procedia Computer Science*, vol. 167, pp. 1056–1065, 2020, doi: 10.1016/j.procs.2020.03.404.
- [32] K. Dimillier and S. Zarrouk, "ICSPI: Intelligent classification system of pest insects based on image processing and neural arbitration," *Applied Engineering in Agriculture*, vol. 33, no. 4, pp. 453–460, 2017, doi: 10.13031/aea.12161.
- [33] L. Deng, Y. Wang, Z. Han, and R. Yu, "Research on insect pest image detection and recognition based on bio-inspired methods," *Biosystems Engineering*, vol. 169, pp. 139–148, May 2018, doi: 10.1016/j.biosystemseng.2018.02.008.
- [34] N. Nandhini and R. Bhavani, "Feature extraction for diseased leaf image classification using machine learning," in *2020 International Conference on Computer Communication and Informatics, ICCCI 2020*, Jan. 2020, pp. 1–4, doi: 10.1109/ICCCI48352.2020.9104203.

- [35] S. Loussaief and A. Abdelkrim, "Machine learning framework for image classification," *2016 7th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications, SETIT 2016*, pp. 58–61, 2017, doi: 10.1109/SETIT.2016.7939841.
- [36] L. Mei, S. Wang, and J. Liu, "A pests image classification method based on improved Wolf Pack algorithm to optimize bayesian network structure learning," *Communications in Computer and Information Science*, vol. 951, pp. 70–81, 2018, doi: 10.1007/978-981-13-2826-8\_7.
- [37] I. Khan *et al.*, "Design of neural network with levenberg-marquardt and bayesian regularization backpropagation for solving pantograph delay differential equations," *IEEE Access*, vol. 8, pp. 137918–137933, 2020, doi: 10.1109/ACCESS.2020.3011820.
- [38] H. Zhang *et al.*, "High-precision indoor visible light positioning using deep neural network based on the Bayesian Regularization with sparse training point," *IEEE Photonics Journal*, vol. 11, no. 3, pp. 1–10, Jun. 2019, doi: 10.1109/JPHOT.2019.2912156.
- [39] F. Ong, P. Milanfar, and P. Getreuer, "Local kernels that approximate bayesian regularization and proximal operators," *IEEE Transactions on Image Processing*, vol. 28, no. 6, pp. 3007–3019, Jun. 2019, doi: 10.1109/TIP.2019.2893071.
- [40] S. A. Burhan, D. S. Minhas, D. A. Tariq, and M. N. Hassan, "Comparative study of deep learning algorithms for disease and pest detection in rice crops," *Proceedings of the 12th International Conference on Electronics, Computers and Artificial Intelligence, ECAI 2020*, 2020, doi: 10.1109/ECAI50035.2020.9223239.
- [41] N. T. Nam and P. D. Hung, "Pest detection on traps using deep convolutional neural networks," *ACM International Conference Proceeding Series*, pp. 33–38, 2018, doi: 10.1145/3232651.3232661.
- [42] D. R. Anamisa, M. Yusuf, W. Agustiono, and M. Syarif, "Technologies, methods, and approaches on detection system of plant pests and diseases," *International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, pp. 163–170, 2019, doi: 10.23919/EECSI48112.2019.8976962.
- [43] A. S. B. Reddy and D. S. Juliet, "Transfer learning with RESNET-50 for malaria cell-image classification," *Proceedings of the 2019 IEEE International Conference on Communication and Signal Processing, ICCSP 2019*, pp. 945–949, 2019, doi: 10.1109/ICCSP.2019.8697909.
- [44] Q. Xu, M. Zhang, Z. Gu, and G. Pan, "Overfitting remedy by sparsifying regularization on fully-connected layers of CNNs," *Neurocomputing*, vol. 328, pp. 69–74, 2019, doi: 10.1016/j.neucom.2018.03.080.
- [45] P. Thanapol, K. Lavangnananda, P. Bouvry, F. Pinel, and F. Leprevost, "Reducing overfitting and improving generalization in training convolutional neural network (CNN) under Limited Sample Sizes in Image Recognition," *InCIT 2020 - 5th International Conference on Information Technology*, pp. 300–305, 2020, doi: 10.1109/InCIT50588.2020.9310787.
- [46] Y. Jiang, Y. Li, and H. Zhang, "Hyperspectral image classification based on 3-D separable resnet and transfer learning," *IEEE Geoscience and Remote Sensing Letters*, vol. 16, no. 12, pp. 1949–1953, Dec. 2019, doi: 10.1109/LGRS.2019.2913011.
- [47] F. Martínez-Plumed, R. B. C. Prudêncio, A. Martínez-Usó, and J. Hernández-Orallo, "Item response theory in AI: Analysing machine learning classifiers at the instance level," *Artificial Intelligence*, vol. 271, pp. 18–42, Jun. 2019, doi: 10.1016/j.artint.2018.09.004.
- [48] W. Huang, L. Zhang, W. Gao, F. Min, and J. He, "Shallow Convolutional neural networks for human activity recognition using wearable sensors," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, 2021, doi: 10.1109/TIM.2021.3091990.
- [49] Y. Chen, Y. Ping, Z. Zhang, B. Wang, and S. He, "Privacy-preserving image multi-classification deep learning model in robot system of industrial IoT," *Neural Computing and Applications*, vol. 33, no. 10, pp. 4677–4694, May 2021, doi: 10.1007/s00521-020-05426-0.
- [50] A. S. Ahmed, H. M. Khudhur, and M. S. Najmuldeen, "A new parameter in three-term conjugate gradient algorithms for unconstrained optimization," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 23, no. 1, p. 338, Jul. 2021, doi: 10.11591/ijeecs.v23.i1.pp338-344.
- [51] M. N. Mohammed Ali, R. I. Sabri, and F. A. Sadiq, "A new properties of fuzzy b-metric spaces," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 26, no. 1, p. 221, Apr. 2022, doi: 10.11591/ijeecs.v26.i1.pp221-228.
- [52] N. W. S. Wardhani, M. Y. Rochayani, A. Iriany, A. D. Sulistyono, and P. Lestantyo, "Cross-validation metrics for evaluating classification performance on imbalanced data," in *2019 International Conference on Computer, Control, Informatics and its Applications: Emerging Trends in Big Data and Artificial Intelligence, IC3INA 2019*, Oct. 2019, pp. 14–18, doi: 10.1109/IC3INA48034.2019.8949568.
- [53] J. C. F. Caballero, F. J. Martinez, C. Hervas, and P. A. Gutierrez, "Sensitivity versus accuracy in multiclass problems using memetic pareto evolutionary neural networks," *IEEE Transactions on Neural Networks*, vol. 21, no. 5, pp. 750–770, May 2010, doi: 10.1109/TNN.2010.2041468.
- [54] K. R. B. Legaspi, N. W. S. Sison, and J. F. Villaverde, "Detection and classification of whiteflies and fruit flies using YOLO," in *2021 13th International Conference on Computer and Automation Engineering, ICCAE 2021*, Mar. 2021, pp. 1–4, doi: 10.1109/ICCAE51876.2021.9426129.
- [55] M. D. Gondal and Y. N. Khan, "Early pest detection from crop using image processing and computational intelligence," *International Journal of Scientific Research in Engineering and Management*, vol. 06, no. 06, Jun. 2022, doi: 10.55041/ijrem14606.
- [56] W. Li, D. Wang, M. Li, Y. Gao, J. Wu, and X. Yang, "Field detection of tiny pests from sticky trap images using deep learning in agricultural greenhouse," *Computers and Electronics in Agriculture*, vol. 183, p. 106048, Apr. 2021, doi: 10.1016/j.compag.2021.106048.
- [57] C. U. Parab *et al.*, "Comparison of single-shot and two-shot deep neural network models for whitefly detection in IoT Web application," *AgriEngineering*, vol. 4, no. 2, pp. 507–522, Jun. 2022, doi: 10.3390/agriengineering4020034.

**BIOGRAPHIES OF AUTHORS**

**Lal Chand**    is currently working as an Assistant Professor in the Department of Computer Science and Engineering at Punjabi University, Patiala. He has experience of more than 14 years in academia and research. His areas of interest are machine learning, computer vision and computer networks. Presently he is working in the domain of applications of machine learning in agriculture. He can be contacted at email: lc.panwar5876@gmail.com.



**Amardeep Singh Dhimanis**    a Professor in the Department of Computer Science and Engineering at Punjabi University, Patiala. In his teaching experience of more than 20 years, he has guided 40 research scholars at Master's level and Twelve research scholars at Doctorate level. He has to his credit more than 40 research papers published in reputed international and national journals, besides two books on Bioinformatics Computing and Soft Computing. He has successfully handled a number of the State funded projects. He can be contacted at email: amardeep\_dhiman@yahoo.com.



**Sikander Singh**    is currently working as an Assistant Professor in Department of Computer Science and Engineering, Punjabi University, Patiala. His areas of interest include computer vision, pattern recognition, deep learning and data science. He has several research articles to his name published in leading national and international journals. He can be contacted at email: sikander@pbi.ac.in.