International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

A Machine Learning Based Approach for Identifying Crop Pests for Precision Agriculture Applications

Rajat Rathod[1] Prof. Ankita Chouhan[2]

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 a multiple instance learning based deep learning approach based on Convolutional Neural Networks for the detection of whitefly pests. A comparative analysis with conventional machine learning and deep learning techniques has also been presented. The performance of the proposed system has been evaluated in terms of the classification accuracy. The experimental results obtained show that the proposed technique attains a classification accuracy of 98.5% and outperforms both separate feature trained machine learning models and well as baseline deep learning models in terms of classification accuracy.

Keywords: Precision Agriculture, Whitefly Pest Detection, Feature Extraction, Machine Learning, Deep Learning, Multi Instance Learning (MIL), Classification Accuracy.

I. 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. With growing population and increase in demands, better techniques of crop management and handling have become the need of hour. With the advancements in the field of image processing, computer visions and machine learning, automated applications are being developed for agricultural applications [1]. The use of technology in the domain of agriculture is often termed as precision agriculture [2]. One of the major challenges which agriculturists face is the attack of pests on the crops which can severely damage the crops and subsequent yield. Different crops are subjected to infestations by variety of pests. Due to the rapid multiplication of pests, it becomes necessary to devise mechanisms for quick and accurate detection. Manual detection is often a tedious and time consuming job, which becomes even more difficult if the farm size is large. Thus, accurate automated systems are necessary for pest infestation detection. Use of high end drone technology combined with image recognition methods based on machine learning, automated detection of pest attacks has gained prominence.

Precision agriculture entails an approach for farming management based precise observation and measurement methods of variety of crops depending on their variability. One of the major catalysts for precision agriculture is use of unmanned aerial vehicles (UAVs) for capturing data and sending it for observation and analysis [3]. The UAVs are generally less expensive and equipped with image capturing technologies. Vegetative images capturing methods are supported by these machines that can facilitate the detection and classification of a large variety of pests.

Figure 1. A typical infestation of white flies

The use of artificial intelligence (AI) and machine learning (ML) based techniques can aid in the process of pest detection and control. The use of automated tools greatly facilitates the process of technology driven agricultural systems optimizing the use of resources and increasing productivity [4]. Precision agriculture has thus emerged as a promising and much sought after technique for automated and quick detection of pests in agricultural farms. The development of such automated integrated pest management (IPM) techniques allow higher productivity, lesser use of pesticides and insecticides and reduced losses. The whitefly also know as (Bemisia tabaci) is one of the most common types of pests which spread plant based diseases and can travel relatively large distances and can infest crops such as cotton, rice, cauliflower, pumpkin, cabbage, soybean etc [5]. A plant infested by white flies is depicted in figure 1 [6].

The detection of white flies is particularly challenging due to the extremely small size of the white flies which often resemble spots on the leaves. The whitefly undergoes four major stages prior to development into an adult fly. The stages are depicted in figure 2 [7]. The most effective way to tackle the white fly attack is to detect in in the nymph stage. Adult flies multiply extremely rapidly which can infest more than two hundred species of crops. Whitefly infestation has resulted in damage to around 60% of total cotton crops during peaks of whitefly infestations. The whiteflies reproduce rapidly resulting an quick damage to crops if not cited and neutralized quickly. Being small in size, these flies may often go unnoticed during the initial stages of infestation. The lifecycle of the white fly consists of four major stages or instars. The whitefly bears a close resemblance with aphids and develops into a full grown fly after the completion of the fourth instar. The flies can multiply in abundance and damage crops in both farmlands and greenhouses.

II. Methodology

The different classification paradigms used in this work are explained subsequently.

Neural Networks: Artificial Neural Networks (ANN) have gained a lot of prominence recently due to the emergence of deep neural networks and deep learning. Artificial Neural Networks try to emulate the working of the human brain and its thought process. As the processing power of chips keeps increasing, it becomes possible to implement deeper neural networks with dense hidden layers on hardware.This has led to the popularization of neural networks and deep neural networks. Figure 2 depicts the structure of a single neuron.

A dense interconnection of such neurons is often termed as a neural network. Increasing the data processing or hidden layers of the network allows to make complex computations. This lays the foundation for a deep neural network and deep learning. Adjusting the parameters (often termed as Hyperparameters) of the network allows to tune the network to a given data set. The machine learning model is depicted in figure 2

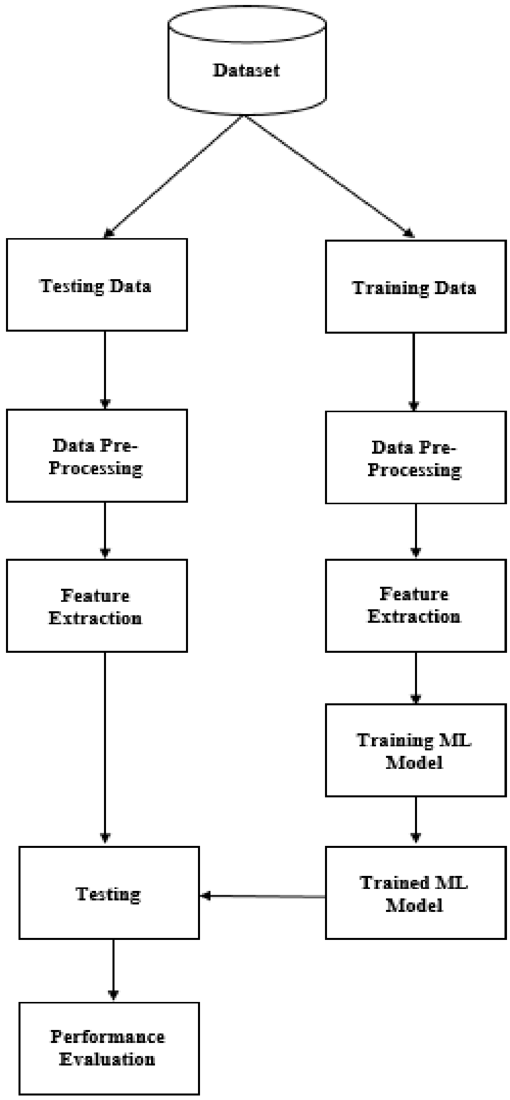

Figure 2 Architecture for Machine Learning Based Classification

Recurrent networks often use a cascading structure of applying the output of one layer to the input of another layer in loops. CNNs sometime encounter the problem of a vanishing gradient and overfitting. To overcome these limitations, residual networks (called ResNets) are sometimes employed which have skip connections among the hidden layers which do not directly connect the layers in cascade thereby decreasing the chances of overfitting. The hypothesis of any designed algorithm lies in the classification of partially overlapping datasets based on the deep probabilistic classifiers.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

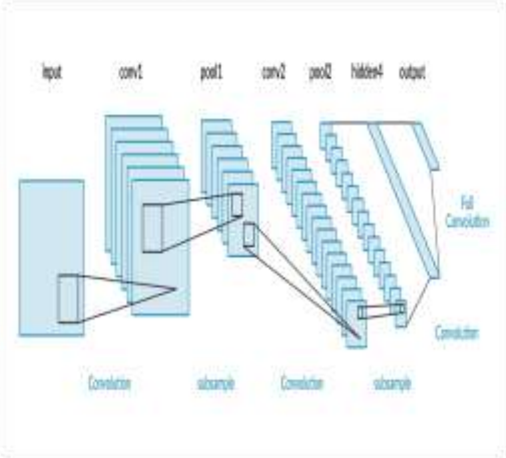

Figure 3 A Typical CNN structure

Another classifier employed in this work is the Residual Network which a modified version of the ubiquitous convolutional neural network (CNN) [32]. The ResNet has multiple convolution layers, but unlike typical convolutional networks, it has with skip connections between the layers. The architecture of the ResNet doesn't allow the direct cascade of the weights in the hidden layer. This serves two important purposes:

1) Reduces the chances of overfitting the network.
2) Avoiding the chances of vanishing gradient commonly encountered in conventional CNNs.

The number of convolution layers in the network are 48, with one Max-Pool layer. The activation function used is the ReLU, with a stride of 2. The addition of more hidden layers in conventional CNNs often leads to saturation in the performance with high chances of performance saturation, which is mitigated by the ResNet architecture with the skip connections and addition of identity layers [34]. The performance of the two training algorithms are evaluated subsequently in terms of classification accuracy. The concept of skip connections in the ResNet is depicted in figure 4.

The ResNet architecture used in the proposed work has an input size of 243x243x3 for the separate R,G and B channels of the image. A max pooling of 2x2 with a stride of 2 has been used. The feature layer of $Fc1000$ was employed with 1000 feature vectors.

Multi Instance Learning

Given a set of N samples, with a set of images being associated with each of the two categories—infested or non-infested, the data can be represented as:

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

Here,
y_i is the target vector for binary classification.
Thus:

$$y_i \epsilon \{0, 1\} \qquad (2)$$

In the standard MIL assumption each instance is considered to fall into one of the two categories—positive (1), or negative (0) Furthermore, the existence of one or more positive class instances in the bag renders the bag itself positive.

This, however, is quite a strong assumption for our problem. Firstly it requires knowledge of the instance-level class which is not available. To address this challenge, many algorithms arbitrarily assume that each instance inherits the class from the bag it belongs to. Broadly, we can classify aggregation approaches into two classes instance-level and embedding-level MIL.

1. Instance-level MIL. This approach aggregates instance-level predictions to give bag-level predictions. Thus, a model predicts y_i , which is followed by an aggregation function to yield an estimate of y_i. Examples of aggregation functions that fall into this category are the max and mean functions, logsum-exp, log-mean-exp, noisy-or, and noisy-and 2. Embedding-level MIL. In this approach, instead of aggregating predictions at the instance-level, a low-dimensional embedding of instances is learnt, and a bag-level classifier is trained on top of the aggregation of the embeddings of all instances in the bag. We shall refer to the vector resulting after the aggregation as the pooled feature vector, and the aggregation operation itself as pooling. A convolutional feature extractor is used to generate low-dimensional embeddings for each of the instances. The feature extractor is followed by a pooling operation in the embedding space, and a classifier which predicts the probability of disease trained on top of the pooled representations. We design the model so that it is end-to-end trainable, in that it learns the low-dimensional embedding as well as the classifier jointly The performance metrics commonly computed are:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (3)$$

$$Sensitivity\ or\ Recall = \frac{TP}{TP+FN} \qquad (4)$$

$$Specificity = \frac{TN}{TN+FP} \qquad (5)$$

$$Precisiosn = \frac{TP}{TP+FP} \qquad (6)$$

$$F - Measure = \frac{2.Precision.Recall}{Precision+Recall} \qquad (7)$$

III. Results

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 4000 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:

1) Whitefly infested.
2) Whitefly non-infested

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Figure 4 Leaf not infested (healthy)

Figure 5 Leaf infested by whitefly.

Figure 4 depicts a healthy image with no whitefly infestation. 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 flied are 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.

Figure 6 Classification of Infested

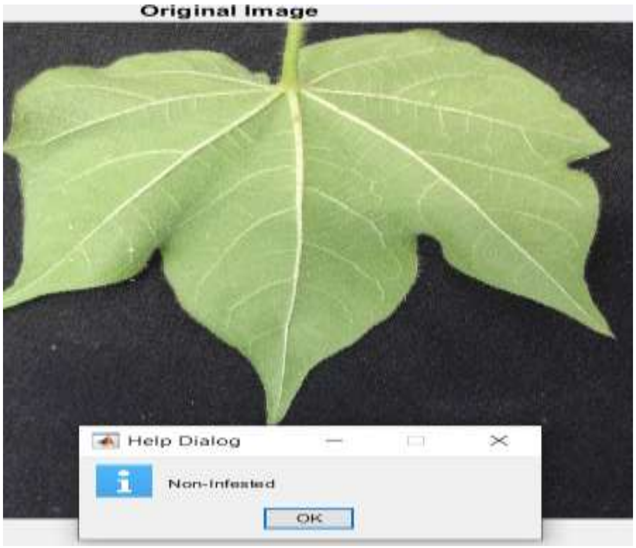

Figure 7 Classification of Non-Infested

Table. Statistical Features

Feature	Non-infested	Infested
Contrast	0.386363636363636	0.464772727272727
Correlation	0.128559776022824	0.103824624581877
Energy	0.746928589876033	0.720109762396694
Homogeneity	0.926780303030304	0.917196969696970
Mean	0.00313052599538983	0.00504692700090238
Standard Deviation	0.106583222637359	0.106509640802603
Entropy	3.51054724635011	2.97219490801144
rms	0.106600358177805	0.106600358177805
Variance	0.0112637421619560	0.0113468078433579
Inverse Difference	0.852620670631750	0.903163841596743
Kurtosis	8.83820302913425	9.47342974370778

Skewness	0.822684013647488	0.896207776217934

Table.2 Classification Results

Class	Accuracy	Sensitivity	Specificity	Precision
Infested	98.72	99.42	98.04	98.02
Non-Infested	98.38	98.30	98.46	98.44

Table.3 Comparison with Previous Work

Work	Approach	Accuracy%
Previous [1]	YOLO	95%
Proposed	MIL-CNN	98.5%

Different pooling operators, network parameters (number of channels K), configurations (using images and clinical attributes) and training strategies are reported in this study in order to show the behaviour of our proposed method.

Starting with the pooling operators, f_{max} and f_{LSE} show comparatively poor performance over the tested values of K. We postulate that the f_{max} operator is too strong for the problem at hand, while the f_{LSE} operator—being a smooth approximation to the maximum—performs better than f_{max}. However, both f_{max} and ff_{LSE} fail to capture the relationship between the instance and the bags unlike f_{mean}, which reports the best performance for all the configurations. Our experiments further indicate that the models work better when an MIL-CNN is used, i.e., a higher value of convolution layers. In particular, narrower networks seem not powerful enough to capture all the available information and learn enough features from the data, both ResNet and MIL-CNN perform similarly with both values reporting very close performance. This result also alleviates overfitting concerns with wider models.

Conclusion:

This paper presents a machine learning and deep learning model for detection of white fly infestation. The proposed scheme presents two network architectures v.i.z. the Deep Bayes Net, the convolutional neural network, the ResNet and the MIL-CNN for the classification of images. The proposed model presents a rigorous image pre-processing paradigm prior to feature computation, which makes the system more robust and immune to noise effects. The statistical feature extraction presented in this paper would be applicable to a wide range of images thereby rendering flexibility to the choice of data source and image formats. The performance metrics of the proposed system have been chosen as accuracy, sensitivity, specificity and precision. The proposed MIL-CNN outperforms the other models in terms of accuracy.

As manual labelling the data for large datasets is extremely cumbersome and prone to errors, hence further directions of research can be exploring self supervised learning (SSL) models and techniques to reduce the complexity in labelling large datasets.

Future directions of research in the domain can explore the utility and efficacy of transfer learning. This would allow pre-trained models to be tested on new diverse datasets which may reduce the time spent in labelling of new datasets and make use of the existing pre-trained models for time critical applications of machine learning in the medical field.

REFERENCES

[1] Sujaritha, M., Kavitha, M., Roobini, S. (2023). Pest Detection Using Improvised YOLO Architecture. In: Kannan, R.J., Thampi, S.M., Wang, SH. (eds) Computer Vision and Machine Intelligence Paradigms for SDGs. Lecture Notes in Electrical Engineering, vol 967. Springer[2] J. Treboux and D. Genoud, "Improved Machine Learning Methodology for High Precision Agriculture," 2018 Global Internet of Things Summit (GIoTS), 2018, pp. 1-6

[2] AI Jajja, A Abbas, HA Khattak, G Niedbała, A Khalid, HT Rauf, S Kujawa, "Compact convolutional transformer (CCT)-Based approach for whitefly attack detection in cotton crops", MDPI, vol.12, 1529.

[3] D. Brunelli, A. Albanese, D. d'Acunto and M. Nardello, "Energy Neutral Machine Learning Based IoT Device for Pest Detection in Precision Agriculture," in IEEE Internet of Things Magazine, December 2019., vol. 2, no. 4, pp. 10-13,

[4] S,M, Pedersen and K.M. Lind, K.M., "Precision Agriculture—From Mapping to Site-Specific Application. In Precision Agriculture", Technology and Economic Perspectives, 1st ed.; Springer Nature: Basel, Switzerland, 2017; pp. 1–20.

[5] Jeremy Francis Tusubira, Solomon Nsumba, Flavia Ninsiima, Benjamin Akera, Guy Acellam, Joyce Nakatumba, Ernest Mwebaze, John Quinn, Tonny Oyana; Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, 2020, pp. 68-69.

[6] Rana Muhammad Saleem, Rafaqat Kazmi , Imran Sarwar Bajwa , Amna Ashraf , Shabana Ramzan and Waheed Anwar, "IOT-Based Cotton Whitefly Prediction Using Deep Learning", Scientific Programming, Hinndawi, vol. 2021, , pp.1-17.

[7] DN Byrne and TS Bellows Jr, "Whitefly biology", Annual review of entomology, 1991, vol.36, pp.431-457.

[8] T. Moranduzzo and F. Melgani, "A SIFT-SVM method for detecting cars in UAV images," 2012 IEEE International Geoscience and Remote Sensing Symposium, 2012, pp. 6868-6871.

[9] S.L. Olsen, "Estimation of Noise in Images: An Evaluation", CVGIP: Graphical Models and Image Processing, Elsevier, 1993, vol.55, no.4, pp.319-323.

[10] E. Abreu, M. Lightstone, S. K. Mitra and K. Arakawa, "A new efficient approach for the removal of impulse noise from highly corrupted images," in IEEE Transactions on Image Processing, vol. 5, no. 6, pp. 1012-1025, June 1996.

[11] S.A. Khmag, R. Al Haddad, R.A. Ramlee, K. Noraziahtulhidayu and F. Malallah, "Natural image noise removal using nonlocal means and hidden Markov models in transform domain", The Visual Computer, Springer, 2018, vol.34, pp.1661–1675.

[12] S. Ruikar and D. D. Doye, "Image denoising using wavelet transform," 2010 International Conference on Mechanical and Electrical Technology, 2010, pp. 509-515.

[13] 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," 2019 International Conference on Advanced Science and Engineering (ICOASE), 2019, pp. 100-105.

[14] D. Gunawan, "Denoising images using wavelet transform," 1999 IEEE Pacific Rim Conference on Communications, Computers and Signal Processing (PACRIM 1999). Conference Proceedings (Cat. No.99CH36368), 1999, pp. 83-85.

[15] A. Rasheed and S Shihab, “The Analytic of image processing smoothing spaces using wavelet”, Journal of Physics: Conference Series, 2021, IOP Science, J. Phys.: Conf. Ser. 1879 022118.

[16] M. HemaLatha, S. Varadarajan and Y. M. M. Babu, "Comparison of DWT, DWT-SWT, and DT-CWT for low resolution satellite images enhancement," 2017 International Conference on Algorithms, Methodology, Models and Applications in Emerging Technologies (ICAMMAET), 2017, pp. 1-5.

[17] MMI Ch, MM Riaz, N Iltaf, A Ghafoor and SS Ali, “A multifocus image fusion using highlevel DWT components and guided filter”, Multimedia Tools and Applications, Springer 2020, vol.79, pp.12817–12828

[18] J. Kovacevic and W. Sweldens, "Wavelet families of increasing order in arbitrary dimensions," in IEEE Transactions on Image Processing, vol. 9, no. 3, pp. 480-496, March 2000.

[19] A Aldroubi and M Unser, “amilies of multiresolution and wavelet spaces with optimal properties”,Numerical Functional Analysis and Optimization, Taylor and Francis, 1993, vol.14, no. 5-6., pp. 417-446.

[20] J. Starck, J. Fadili and F. Murtagh, "The Undecimated Wavelet Decomposition and its Reconstruction," in IEEE Transactions on Image Processing, vol. 16, no. 2, pp. 297-309, Feb. 2007.

[21] M. D. Swanson and A. H. Tewfik, "A binary wavelet decomposition of binary images," in IEEE Transactions on Image Processing, vol. 5, no. 12, pp. 1637-1650, Dec. 1996.

[22] Yining Deng, B. S. Manjunath and H. Shin, "Color image segmentation," Proceedings. 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No PR00149), 1999, pp. 446-451.

[23] S. B. Chaabane, M. Sayadi, F. Fnaiech and E. Brassart, "Color image segmentation using automatic thresholding and the fuzzy C-means techniques," MELECON 2008 - The 14th IEEE Mediterranean Electrotechnical Conference, 2008, pp. 857-861.

[24] V. Sivakumar and V. Murugesh, "A brief study of image segmentation using Thresholding Technique on a Noisy Image," International Conference on Information Communication and Embedded Systems (ICICES2014), 2014, pp. 1-6.

[25] K. V. Mardia and T. J. Hainsworth, "A spatial thresholding method for image segmentation," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 10, no. 6, pp. 919-927, Nov. 1988.

[26] J Daugman, “The importance of being random: statistical principles of iris recognition”, Pattern Recognition, Elsevier 2003, vol.23, no. 2, pp. 279-291.

[27] J. Carreira and C. Sminchisescu, "Constrained parametric min-cuts for automatic object segmentation," 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2010, pp. 3241-3248.

[28] AL Barbieri, GF De Arruda, FA Rodrigues, Odemir and M.Brunoa, L. FontouraCostaab, “An entropy-based approach to automatic image segmentation of satellite images”, Physica A: Statistical Mechanics and its Applications, Elsevier, 2011, vol.390, no.3, 1 pp.512-518.