A COMPARATIVE PERFORMANCE EVALUATION OF VARIOUS CLASSIFICATION MODELS FOR DETECTION AND CLASSIFICATION OF FLYING INSECTS

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ABSTRACT

Agriculture has long been a part of Indian culture. It is known as the Indian economy's backbone. Agriculture contributes to 17 % of the Indian GDP, but still, farmers confront several problems in growing their crops, one among them is insect pests. "Computational Entomology" is a branch of data mining that assists farmers in overcoming the challenges of damaging insect pests by utilizing appropriate sensors and methodologies for pest classification and application of the pesticides at the right time. The authors used various machine learning and deep learning algorithms to classify insects and examine the influence of classification performance on multiple classes of insects often found in Indian agricultural fields with varying numbers of data and classification models. The study found that proposed CNN based classification model performs better than other classification models in insect categorization, with a classification accuracy of 94,6 %**.** The research work done till now in the field of computational entomology deals with the insects grown in laboratory colonies or well-developed insects grown in the same geographic region and condition, but we have evaluated the performance of different classification models using random images available over the internet to select the well-suited classification model to classify flying insects**.** Applications with precise insect classification using machine learning and deep learning algorithms would have significant implications for entomological research. It is necessary to develop an automated insect classification techniques to provide a foundation for future research in the field of computational entomology.

KEY WORDS

computational entomology, insect pest, machine learning techniques, classification, deep learning techniques

CLASSIFICATION

JEL: C88

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INTRODUCTION

A key component of the Indian economy is agriculture due to India's geographical location, soil composition, climate, and other factors, all of which have played a role in making agriculture possible. The geographic position of our country has been highly conducive to the development of agricultural production. In agricultural production, insects are vital they aid in the reproduction of thousands of flowering plants, fruit trees and some crops [1, 2].The most beneficial insect to agriculture is bee, since it is responsible for all kinds of foods such as honey and almonds. The most harmful insect to agriculture is Bactrocera dorsalis(hendel), since it is responsible for destroying crops worth thousands of crores per year [3]. The insect borne diseases kill millions of people each year [4]. Meanwhile, beneficial insects pollinate most crop varieties, which constitutes our daily consumption [1]. The excessive use of chemical fertilizers to avoid harmful insects has led to the over-extraction of groundwater in the area. The research is needed to assess and design the best pest management strategies for the site. Despite the traditional Indian farmer's wisdom and scientific knowledge, modern technical opinion affirms its validity.

Unsurprisingly, computer science has a more significant impact in the field of entomology. Recent advances in sensor technology have changed this, spawning a new area known as "Computational Entomology".

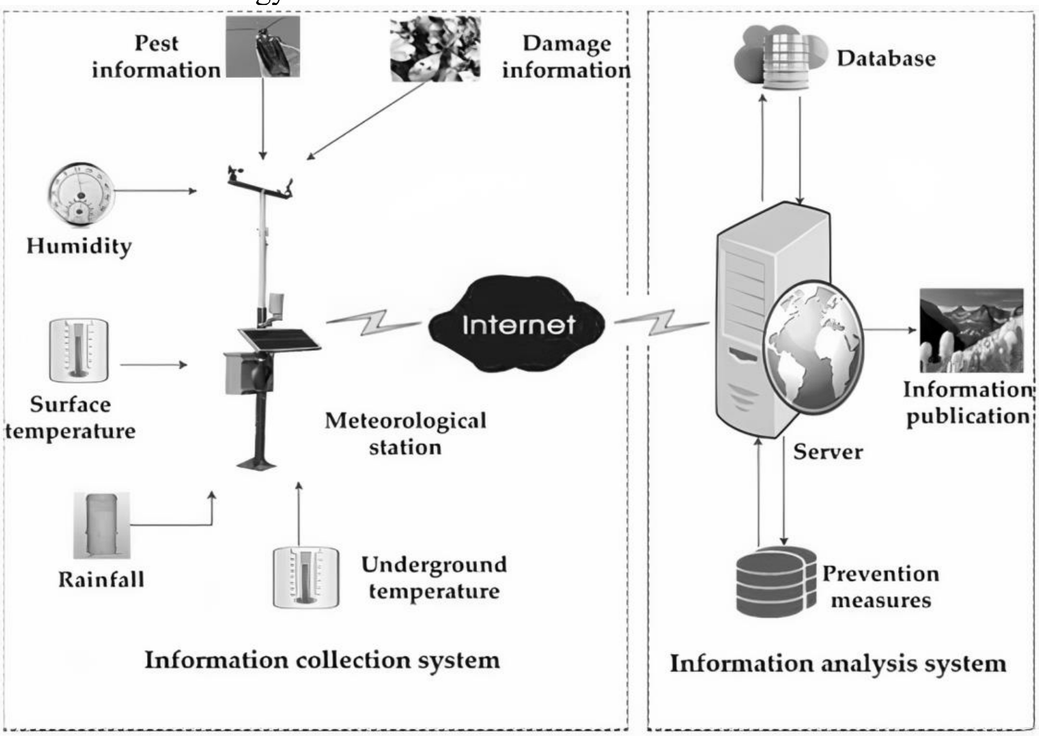


Figure 1. Computational Entomology.

As shown in Figure 1, recognizing harmful insect pests will help monitor the population dynamics of pests prior. The pest monitoring service platform will be an integrated platform the utilizes computer-based technologies, which can be categorized into two sections such as:

- Information Collection System
- Information Analysis System

INFORMATION COLLECTION SYSTEM

Technologies suitable for collecting data related to insects can be applied for data acquisition such as listed in subsubsections.

Internet of Things

Different types of sensors can be used for detection and classification based on different parameters. Acoustic sensors to detect the insect based on sound recorded, the recorded sound will be used as sound fingerprints for classification and bioacoustics recognition [5]. Image Sensors to detect the insect based on the captured image, using machine learning or deep learning models for classification [6-8]. Weather parameter sensors such as temperature and humidity sensors are used to measure the weather parameters to recognize the suitable environmental condition. Laser sensors/IR sensors can be used to identify insects based on wingbeat frequency, using signal processing techniques.

Computer Vision

Computer vision is used to detect the threat/damage, based on the image analysis using different algorithms such YOLO, SSD, SSP-net etc. [9-11]. The extent of threat or damage can be passed to the end-user to take necessary controlling measures.

INFORMATION ANALYSIS SYSTEM

Technologies suitable for analyzing the collected data related to insect pests can be applied to take necessary actions/decisions such as

Artificial Intelligence/ Machine Learning

The Artificial Intelligence (AI)/Machine Learning Algorithms can analyze the data. They check for patterns and will try to predict the behavior [6, 10]. The algorithm checks whether it is preparing to swarm. Once they are analyzed, the insights will be shared with the conservationists and Entomologists well in advance to take necessary actions.

Cloud

The data collected from the sensing device can be stored in the cloud, and the classification model can be deployed in the same cloud to get the data analysis results with very little delay. Once this data is shared to the cloud, we can monitor the continuous measurement of various parameters such as temperature and humidity, acoustics, weight, flight activity, etc.

The main aim of presented work is to develop a good classification technique to classify harmful insects in the agriculture field. Deep learning and computer vision topics are related to a greater need for cost-effective pest management and pollinator monitoring. The Convolutional neural networks (CNNs) can be used to extract image features with deep learning models trained on real-world data, without the need for manual feature extraction, deep learning models can learn features by training on examples. Automatic detection and classification of insects using trained CNNs can be done automatically through video and time-lapse images, which can be used for monitoring [8, 12, 13]. A good classification algorithm will seek to minimize the difference between its prediction and the actual output. The excessive usage of pesticides to avoid the harmful pests in the agriculture sector increases the risk of cancer and other deadly diseases affecting human health worldwide. Computational entomology can address this issue by using advanced computer science technologies in entomology for the early detection and classification of harmful pests. The related work done in this field till now deals with the insects grown in laboratory colonies or well-developed insects grown in the same geographic region and condition [8, 11, 14].

Our article initially provides the pros and cons of various feature selection procedures and how to fix the parameters based on the region and genetics. Finally, we have evaluated the performance of different classification models using random images available over the internet to select the well-suited classification model to classify flying insects. The insect image classification has been done using different Deep learning and Machine learning algorithms such as CNN, MobileNet, Decision tree, and Support Vector Machine (SVM) and to come up with a conclusion on well suited classification model for computational entomology. The organization of this article is as follows: Section-I deals with introduction on the importance of entomology research in the field of agriculture, Section-II provides the insights on research works done in the field of entomology using the various computational methods, Section-III with the methods used in the conduction of experiments such as selecting suitable data for insect classification, insect image data preprocessing for the classification, and classification using various machine learning and deep learning algorithms. Section-IV deals with results of insect classification, followed by a discussion on comparison between various classification techniques used in our study and conclusions.

RELATED WORKS IN THE FIELD OF COMPUTATIONAL ENTOMOLOGY

The research work done in the field of entomology using different computation technologies are as follows:

MORPHOLOGY BASED APPROACH

In this kind of approach, image classification uses various machine learning or deep learning algorithms for handcrafted features that domain experts design [5, 15, 16]. One good example is the discriminative local soft coding (DLsoft) based approach for classifying insects by a hybrid approach [17]; a hybrid system can test the fruit fly, Tephritidae, with different species. Here initially, the dataset is trained, and then it is stretched to form a testing set. An image of Tephritidae is used as a sample used for both datasets. The calculation of local soft codes and discriminants is done. Subsequently, the overall max-pooling of the vectors in the same image is calculated. A spatial pyramid pooled vector is presented in an image sample that uses machine language or deep learning algorithms for classification.

CHARACTERISTICS BASED APPROACH

In this kind of approach, the experimental set-up consists of low powered laser source or any other form of the light-emitting source, which is placed side-by-side [18, 19]. An electronic board consists of a latter. The laser undergoes a total internal reflection after pointing to the inner reflector. It scatters the light back to the source, while some hits the phototransistor. In this process, counting of insects and classification takes place by recording high amplitude “beeps” of the signal [14, 20, 21].

BIOLOGY BASED APPROACHES

Medical Entomology focuses on the public health importance of insects, including mosquitoes that can transmit arboviruses and parasites that can cause lymphatic filariasis. The projects on medical entomology addresses pathogen-vector interactions with the organismal and molecular levels that mainly depended on factors such as control vector competence [22]. In “Pesticide toxicology,” specific laboratory educates and trains scientists in insect toxicology and environmental toxicology/chemistry of agrochemicals. It also contributes to the development of science in computational entomology by using natural products such as insect repellent and insecticides. Insect toxicology focuses on the environmental effects of agrichemicals and environmental toxicology. Pesticide toxicology mainly investigates on ecological effects of conventional pesticides, protein toxins, veterinary antibiotics, and vaccines that transgenic plants produce.

MATERIALS AND METHODS

SELECTION OF FEATURES FOR INSECT CLASSIFICATION

The only two measurable parameters used for detecting and classifying flying insects are "Morphological Features" or "Characteristic Features".

Morphological Features (Shape, Color, Size, Texture)

The experimental set-up should have an image-capturing sensor/device with night vision inside the trap to detect the morphological features such as Shape, Color, Size, etc. Collected morphological features are processed and analyzed to detect the flying insect class [5, 8, 15, 16, 23, 24]. In this kind of data collection, any image capturing sensor based on cost and functional requirements, preferably a "raspberry pi camera" that supports all revisions of the Pi, "5 megapixel OV5647 sensor in an adjustable-focus module" based on the size of the targeted class of insect, can be used along with technologies such as machine learning and deep learning algorithms to classify the insect-based on the captured image [17].

The pros of morphological feature-based insect classification are support for advanced tools along with detection, insects' classification can be easily done with the most advanced tools such as TensorFlow and AutoML. Classification accuracy, insects with any genetic and geographic background can be classified with less erroneous classification. Advanced learning techniques can give good results over image-based datasets than sound or waveform datasets. The only con of morphological feature-based insect classification is that there is no cost-effectiveness compared to characteristic behavior analysis because of the equipment's required for the experimental set-up.

Characteristic Feature (Wingbeat frequency, Sound)

Any light emitting or sound acquiring sensor should be placed inside the trap; once the insect enters the trap, its wingbeats intercept the light/sound source in the trap will be recorded and analyzed to detect the flying insect class [15, 25-27]. In this kind of data collection, sensors such as Opto-Electric Sensor (custom-made), LED with Phototransistor, IR Reflexive Sensor, Ultrasonic Sensor, Laser Sensor or LiDAR, Microphone can be used along with technologies such as signal processing to analyze the recorded characteristic features [14, 20, 21, 28].

The pros of characteristic feature-based insect classification are that it is cost-effective low-cost sensors can be used for data collection. Consumes less power as the experimental set-up records only sound/light interception. The cons of characteristic feature-based insect classification are that insect aerodynamics (wingbeat) is dependent on geographical region, genetics, and morphology (muscle weight), so it may vary based on the region where the insect is grown. Very minimal data means that the waveforms/frequency/sound recorded using a sensing device is minimal, which leads to erroneous in classification. Every class of insect needs to be reared in laboratory colonies with standard environmental parameters. Erroneous classification in the detection of insect pests due to similarity in the frequency/sound recorded.

Based on the above analysis related to characteristic features (wingbeat, Sound) and morphological features (Shape, Size, Color), if the experiment is done on insects grown in entomological research laboratories, then we can use characteristic features for classification because the insects will grow in uniform environmental parameters. Also, if the experiment is done on insects grown in agriculture fields, it's better to make use of morphological features to get accurate classification results, but experiment set-up for morphological analysis costs more compared to characteristic behavior analysis.

INSECT IMAGE DATASET AND PREPROCESSING FOR CLASSIFICATION

The image acquired by any image capturing setup cannot be directly used for classification; the raw image must go through preprocessing procedures before it is fed into any classification model to get results.

Dataset Description

In our work, we have considered five classes of insect species commonly available in the farms of India as dataset, the utilized classes of the insect species are Auchenorrhyncha, Diptera, Heteroptera, Hymenoptera, and Lepidoptera. Here we are trying to predict what class of insect does the image belongs to. For the chosen classes of the insects, we have considered a total of 151 images for each of the selected individual classes, and then finally, we have a total of 755 insect images in the dataset. The images required for the dataset were taken from Kaggle – Arthropod taxonomy orders object detection data set, which consists of images recorded from the agriculture fields.

Image Augmentation

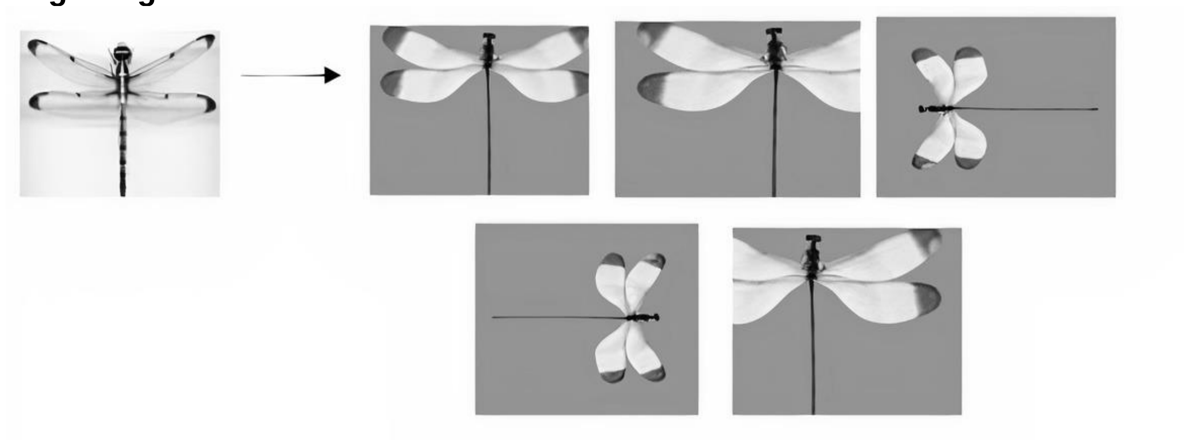


Figure 2. Augmentation of the original image using flipping, zooming, and rotation.

A total of 32 images from each of the five classes was downloaded from Kaggle and manually validated [29]. Data augmentation was used during the data preparation phase to increase the dataset size to 755 images. The original image set was split into two parts: training and testing. To learn effectively and avoid overfitting, classification models require a large corpus of training data. To increase the images in dataset, the dataset was artificially expanded by image augmentation using various processing methods or a combination of multiple processing methods, such as random rotation, shifts, and flips, as shown in Figure 2. The augmentation procedures used are as follows:

- Horizontal flipping
- Vertical flipping
- Zooming
- Rotate

Normalization and Feature Extraction

The selected raw images should be normalized, and the dimension of the image will be reduced as per the requirement so that it will be easy for preprocessing to extract the features and train them. The parameters which we have employed for the selected classes of the insect species in our project are as follows: Length of the insect, Size of the insect, Shape of the insect, Color of the insect and Texture of the insect species. We examined the performance across all data sets by employing a pooling strategy known as global max-pooling (which uses the maximum value for each filter layer) [28]. Other dimensionality reduction strategies could have been used, but this max-pooling strategy dominates current Image classification applications.

INSECT IMAGE CLASSIFICATION USING MACHINE LEARNING TECNIQUES

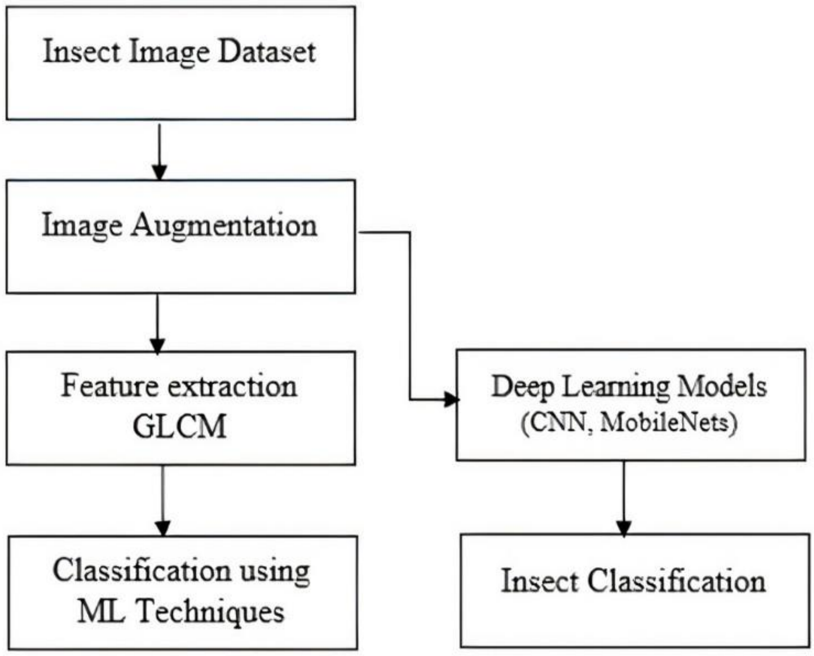


Figure 3. Insect image classifier framework.

Image classification on preprocessed images is applied as shown in Figure 3, classification models such as Support Vector Machine (SVM), MobileNet, Convolutional Neural Networks (CNN) is applied on preprocessed images.

Machine learning is a technique where a machine automatically learns to make accurate classifications or predictions based on past observations. Some good examples of classification using machine learning techniques are text categorization, fraud detection, natural language processing, bioinformatics, etc. [30]. here in our experiment same machine learning techniques, such as “Decision tree”, “Linear SVM”, “Quadratic SVM”, “Cubic SVM”, and “Fine Gaussian SVM”, are applied to the insect image dataset to check the classification accuracy. Unlike deep learning classification models for classification, the machine learning techniques require manual “feature extraction” to be applied on insect image datasets. Once after feature extraction, the extracted features from insect images will be fed into the machine learning algorithms for classification purposes mentioned in Table 1.

Gray-level co-occurrence matrix

Gray-level co-occurence matrix (GLCM) is a statistical method of examining an image’s texture that considers the spatial relationship of pixels in the gray-level co-occurrence matrix (GLCM) [31]. The GLCM functions characterize an image’s texture by calculating how often pairs of pixels with specific values and a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from the matrix [31]. Here in our experiment GLCM is applied to five classes of insects such as Auchenorrhyncha, Diptera, Heteroptera, Hymenoptera, and Lepidoptera. The list of statistics considered in GLCM feature extraction are as follows:

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2. \quad (1)$$

Table 1. Comparison of various machine learning algorithms used in the experimental study.

Classification Model	Interpretability	Model Flexibility
Decision Tree	Easy	It makes many leaves to provide fine distinctions between classes.
Linear SVM	Easy	Provides a simple linear separation between classes used for classification.
Quadratic SVM	Hard	The quadratic decision function can separate the data non-linearly.
Cubic SVM	Hard	Cubic refers to the way the Gram matrix $G(x_i,x_j)$ is created for classification.
Fine Gaussian SVM	Hard	Provides finely detailed distinctions between classes, with kernel range set to $(p/4)^{1/2}$

Equation (1) defines how the **contrast** is used to measure the local variations in the GLCM co-occurrence matrix.

$$\sum_{i,j=0}^{N-1} \frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i)(\sigma_j)}}. \quad (2)$$

Equation (2) represents the **correlation** is used to measure the join probability among pair of pixels.

$$\sum_{i,j=0}^{N-1} P^2{}_{i,j}. \quad (3)$$

Equation (3) represents the **energy** is used to measure the uniformity using squared sum in GLCM.

$$\sum_i \sum_j \frac{1}{1+(i-j)^2} P_{i,j}. \quad (4)$$

Equation (4) represents the **homogeneity** is used to compare the elements between GLCM and GLCM diagonal.

INSECTS IMAGE CLASSIFICATION USING MOBILENETS

MobileNets are based on a streamlined architecture that builds lightweight deep neural networks using depth wise separable convolutions [32]. In this experimental study, we used the pretrained tool Teachable-Machine, a web-based tool for quickly and easily creating deep learning models. MobileNets is a classification model is composed of separable convolutions of two layers, such as “Depth wise convolutions” and “Pointwise convolutions”. Depth wise convolutions for the input depth is written as follows:

$$\widehat{\boldsymbol{G}}_{k,l,m} = \sum_{\boldsymbol{i},\boldsymbol{j}} \widehat{\boldsymbol{K}}_{i,\,j,\,n} * F_{k+i-1,\,l+j-1,\,m}. \quad (5)$$

In the equation (5), $\widehat{\boldsymbol{K}}$ indicates depth-wise convolutional kernel size is applied to the mth channel in F to produce filtered output feature map $\widehat{\boldsymbol{G}}$. Pointwise convolutions are the sum of depth-wise is written as follows:

$$\mathbf{D_K * D_K * M * D_F * D_F + M * N * D_F * D_F}. \quad (6)$$

MobileNet employs 3 · 3 depth-wise separable convolutions, which consume 8 to 9 times less computation energy than standard convolutions while sacrificing only a minor amount of accuracy [32]. The experiment was done with five classes of insects, such as Auchenorrhyncha, Diptera, Heteroptera, Hymenoptera and Lepidoptera.

MobileNets based Image Classification Model

The MobileNets makes use of the transfer learning-based algorithm to classify the given insect images as shown:

Algorithm: MobileNets Classification Model

Input - set of insect images with the class label **Output** - classification of detected insects

Step-1: Give different class labels for training data
Step-2: Load the label to the dictionary
Step-3: Provide Training images from any source or a path you choose
Step-4: Load and format your image for use with TM2 model
Step-5: Image is reformatted to a square
Step-6: Return output inference
Step-7: Load the model to any edge device
Step-8: Record image from any source, Resize and flip the image so it's a square and matches training
Step-9: Classify and display the result.

INSECT IMAGE CLASSIFICATION USING CNN

Convolutional neural networks (CNNs) can be used to extract image features with deep learning models trained on real-world data. Without the need for manual feature extraction, deep learning models can learn features by training on examples. They reduce the number of network units. This means that there are fewer parameters to learn, which reduces the likelihood of overfitting because the model is less complex and produces more accurate results [6]. there are two essential processes involved in the training of any neural network: "Forward Propagation – Receive input data, process the information, and generate output" and "Backward Propagation – Calculate error and update the parameters of the network".

Algorithm: CNN based classifier

Input - set of insect images with the class label
Output - classification of detected insects
Step-1: Load the input images from the insect dataset.
Step-2: Define filter matrix $\mathbf{Z_1 = X * f}$ for image convolution.
Step-3: Apply "Activation function" on the result

$$\mathbf{A = sigmoid(Z_1)}$$

Step-4: Initialize weight and bias matrix and apply a linear transformation $\mathbf{Z_2 = W^T.A + b}$
Step-5: Apply sigmoid function to get final output

$$\mathbf{O = sigmoid(Z_2)}$$

Step-6: Change in $\mathbf{Z_2}$ with respect to Weight W

$$\mathbf{Z_2 = W^T.A^1 + b} \text{ Where } \mathbf{A^1 = \partial Z_2/\partial W}$$

Using trained CNNs, automatic detection and classification of insects can be done automatically through video and time-lapse images, which can be used for monitoring. Due to the automated detection process of pests and pollinators employed by utilizing the CNN image classification model, farmers can detect pests at an early stage and take necessary steps to avoid crop loss.

In our experiment, we have considered five classes of insect species for the datasets. We have considered 151 images for each of the selected individual classes, and then finally, we have a total of 755 images in the dataset of insect species. The image dataset for our project has been taken from Kaggle, an online community for finding and publishing datasets. The characteristic parameters which we have employed for the selected classes of the insect species in our experiment are as follows: Length of the insect, Breadth of the insect, Height of the insect, Size of the insect, Shape of the insect, Color of the insect and finally the texture of the insect species. The selected species of the insects are then fed into the convolution neural network where they would undergo through the several layers of the network and are then filtered accordingly based on the parameters that we have defined and finally, we get the desired result, in other words, the specific class of the insect that was after.

RESULTS AND DISCUSSIONS

The classification results obtained by applying the methods discussed in the previous section on the insect images mentioned in Table 2.

Table 2. Different classes of insect species data set considered in the experimental study.

Insect Class	Number of Insects
Auchenorrhyncha	151
Diptera	151
Heteroptera	151
Hymenoptera	151
Lepidoptera	151

CLASSIFICATION RESULTS OF MACHINE LEARNING TECHNIQUES

The experiment was conducted on five classes of insects such as Auchenorrhyncha, Diptera, Heteroptera, Hymenoptera and Lepidoptera. The results are represented using a confusion matrix.

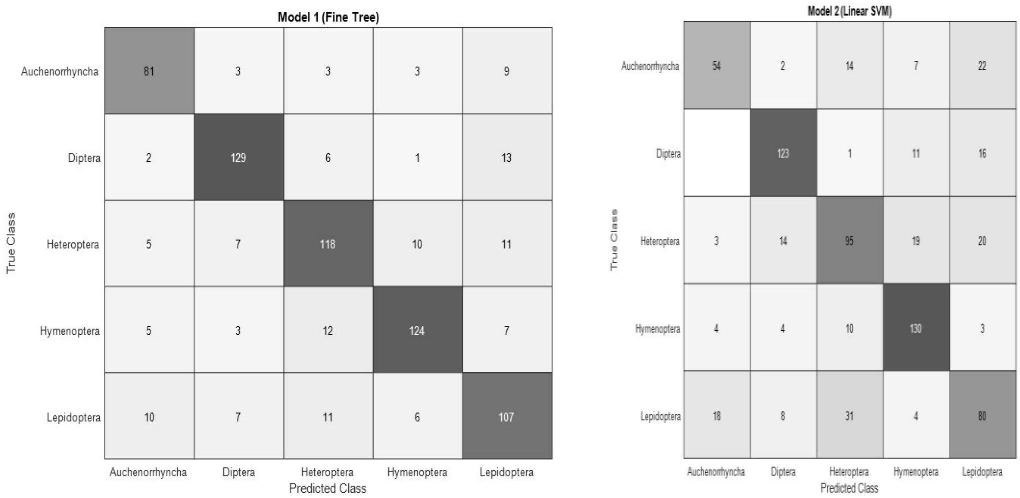
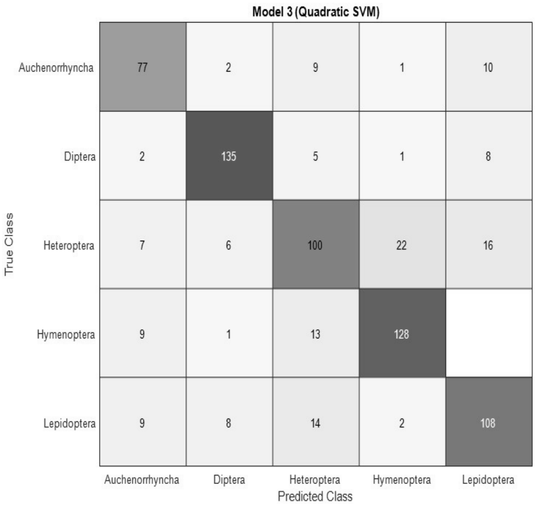


Figure 4. (left) Output-based confusion matrix after applying decision tree technique on the insect image dataset, (right) output-based confusion matrix after applying linear SVM technique on the insect image dataset.

CLASSIFICATION RESULTS OF MOBILENET'S

The MobileNets classification model is applied on insect images captured in smartphone for classification, as shown in Figure 7.



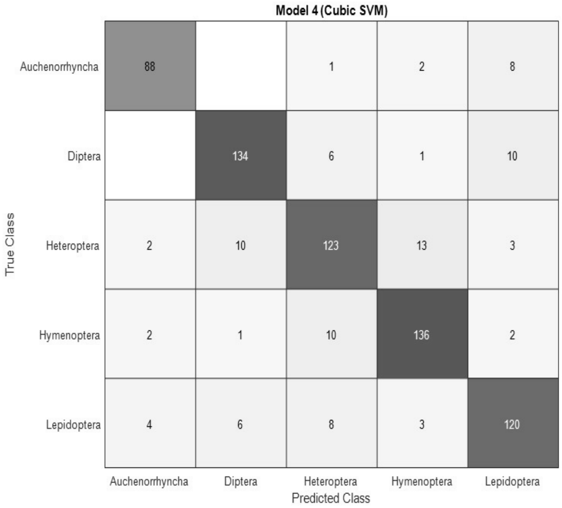


Figure 5. (left) Output-based confusion matrix after applying quadratic SVM technique on the insect image dataset, (right) output-based confusion matrix after applying cubic SVM technique on the insect image dataset.

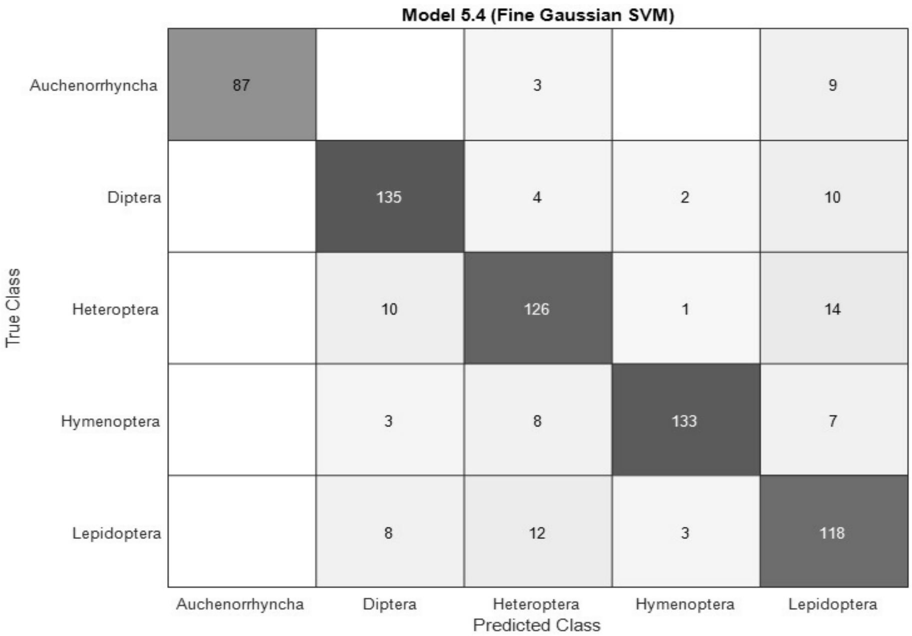


Figure 6. Output-based confusion matrix after applying fine gaussian SVM technique on the insect image dataset.

The classification model was tested using 150 images consisting of all five insects considered in the experimental study. Out of 150 images considered for validation, the MobileNet-based classifier classifies 135 images to their valid class, so the MobileNet based classification model gives more accurate classification results up to 90 % compared to machine learning models discussed in the previous section.

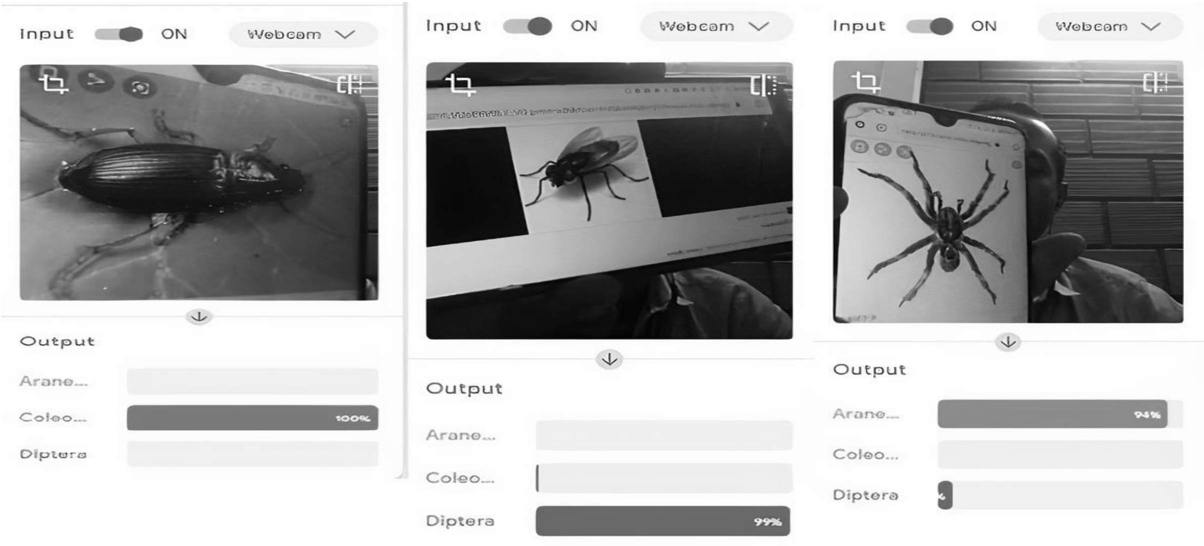


Figure 7. Simulation of insect classification in edge devices using MobileNet-Transfer learning technique: (left) classification of Coleoptera class insects; (middle) classification of Diptera class insects; (right) classification of Arena class insects.

CLASSIFICATION RESULTS OF CNN

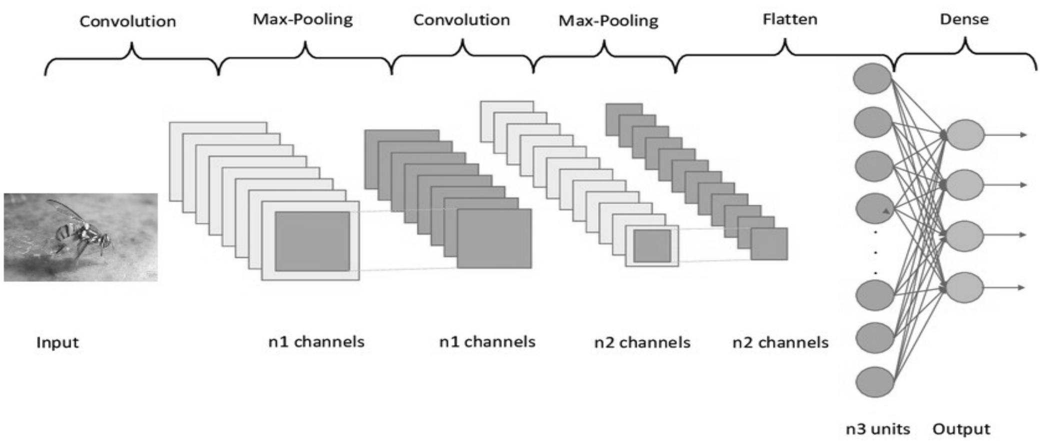


Figure 8. Layer wise output from proposed CNN model for insect classification.

The algorithm takes images as the input and assigns importance to various parameters in the image and differentiates one image from another. The processing of images undergoes through different types of layers present in the Convolution Neural Network, which are Convolution Layer, Max Pooling Layer, ReLU layer, Flattening Layer, and Softmax Layer as shown in Figure 8. An image is selected from the dataset and is set for preprocessing. The image is used for Normalization. Here the dimension of the image is reduced as per the requirement so that it will be easy for preprocessing to extract the features and train them. The images are trained iteratively in terms of epochs.

An epoch represents the number of passes the machine learning algorithm has made through the entire training dataset. Typically, datasets are organized into batches. The dataset's internal model parameters are updated with each epoch as shown in Figure 9.

In the testing process, the selected image will be compared with the 755 trained images from 5 different classes of insects and matches with a particular class of insect. Here, re-training is not required once training is done.

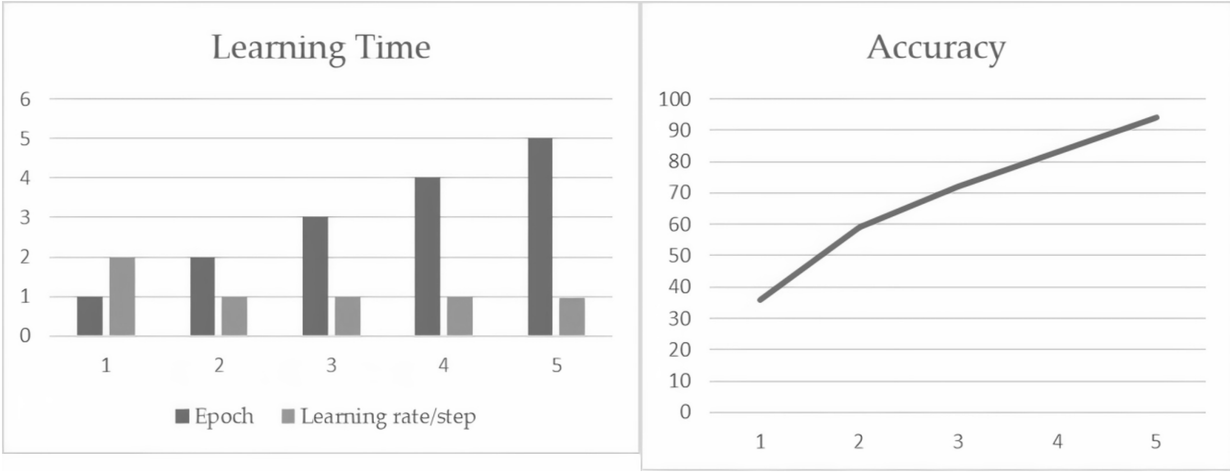


Figure 9. (left) epoch wise Learning rate, (right) accuracy achieved in each Epoch by Deep Learning based Classification model.

As shown in Figure 10, The classification model was tested using 150 images consisting of all five insects considered in the experimental study. Out of 150 images considered for validation, the CNN-based classifier classifies 142 images to their valid class, with a classification accuracy of 94,6 %.

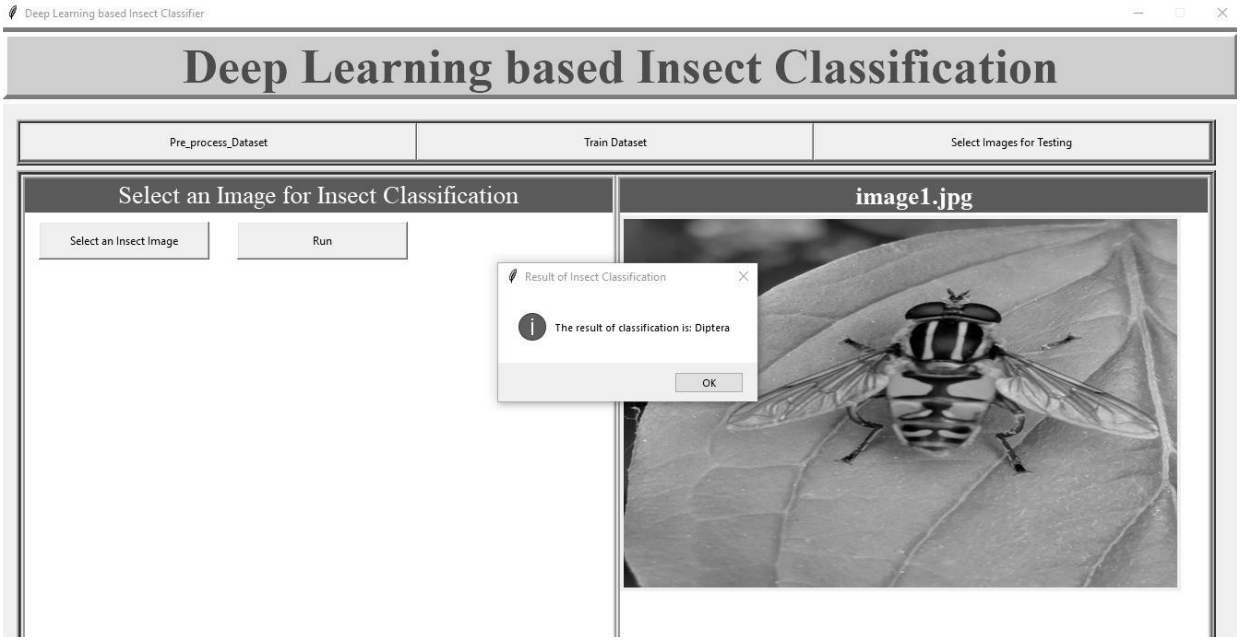


Figure 10. Sample output of proposed CNN based insect classifier on Diptera class insect.

The misclassification was only when classifying the Diptera class of insects due to their resemblance in morphological features with other classes of insects used in our experimental study. The classification model's accuracy is calculated by using the following equation (7):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP}. \tag{7}$$

The denominators TP, TN, FN, and FP represent "True-positive", "True-negative", "False-negative", and "False-positive", respectively, indicating the total number of classifications done by the model. The numerators TP and TN represent "True-positive" and "True-negative", respectively, indicating the total number of correct classifications done by the model.

The experiment for insect image classification was conducted using Machine learning techniques and Deep Learning techniques on commonly found insects in indian region to analyze the performance of various classification models on insect image classification as shown in Figure 11.

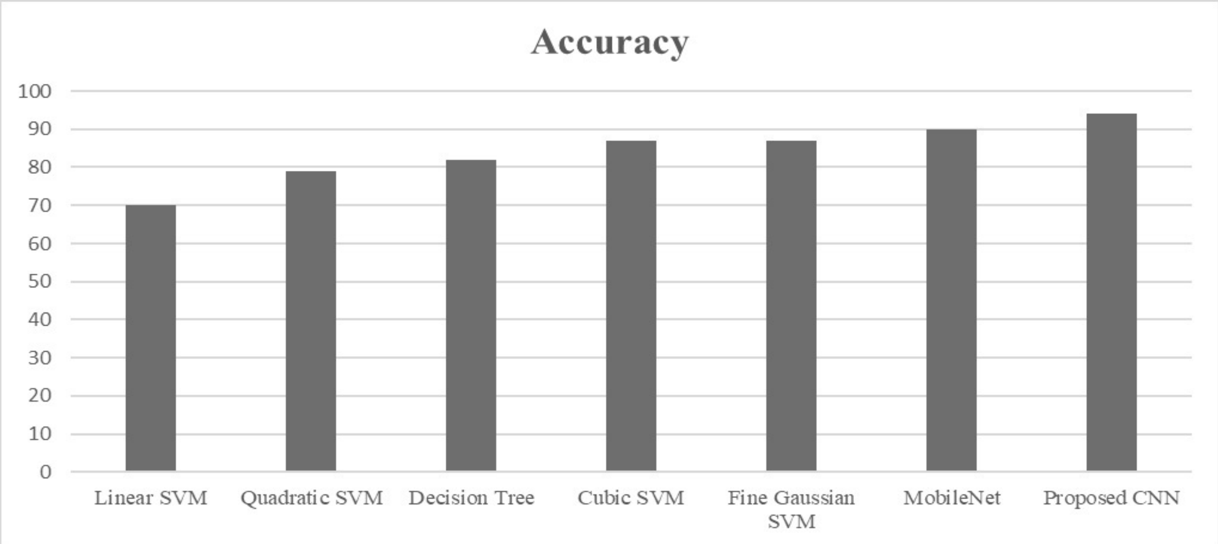


Figure 11. Comparison on Classification accuracy of various models used in the experimental study.

CONCLUSION

In this article, the insects generally present in the agriculture fields of India such as Auchenorrhyncha, Diptera, Heteroptera, Hymenoptera and Lepidoptera were classified and detected by applying various machine learning and deep learning algorithms, and the results were compared. All the insect images obtained from the agriculture field-based dataset were rescaled, preprocessed, and augmented to improve the accuracy of classification models. In the agricultural field, achieving the highest accuracy in real-time is a major challenge in the presence and absence of sunlight, dirt such as fallen leaves and flowers, etc. The classification accuracy of various machine learning and deep learning algorithms is compared, including Fine Tree, Linear SVM, Cubic SVM, Fine Gaussian SVM, MobileNet Model, and CNN model. The results demonstrated that the deep learning-based CNN model has the highest classification accuracy of 94.6 percent when compared to all other classification models tested in the study. The pest detection algorithm (CNN) based on Deep Learning outperforms other learning techniques in detecting insects with class labels for larger insect datasets. The proposed classification methods will be more beneficial to farmers in terms of early detection and classification of insects in agricultural fields and making necessary decisions in advance to improve crop quality while using fewer pesticides to control harmful insect pests and reduce the threat to the environment and pollinators.

REFERENCES

[1] Yang, L.H. Gratton, C.: *Insects as drivers of ecosystem processes*. Current Opinion in Insect Science **2**, 26-32, 2014, http://dx.doi.org/10.1016/j.cois.2014.06.004,

[2] Lushchak, V.I., et al.: *Pesticide toxicity: a mechanistic approach*. EXCLI journal **17**, 1101-1136, 2018, http://dx.doi.org/10.17179/excli2018-1710,

[3] Verghese, A.; Madhura, H.S.; Jayanthi, P.D.K. and Stonehouse, J.M.: *Fruit flies of economic significance in India with special reference to Bactrocera dorsalis (Hendel).* Proceedings of the 6th International Symposium on fruit flies of economic importance. Stellenbosch, pp.317-324, 2002,
[4] Laroche, M., et al.: *Medical Entomology: A Reemerging Field of Research to Better Understand Vector-Borne Infectious Diseases.* Clinical Infectious Diseases **65**(suppl_1), S30-S38, 2017, http://dx.doi.org/10.1093/cid/cix463,
[5] Liu, Y., et al.: *Towards continuous surveillance of fruit flies using sensor networks and machine vision.* The 5th International Conference on Wireless Communications, Networking and Mobile Computing. Beijing, pp.1-5, 2009, http:/dx./doi.org/10.1109/wicom.2009.5303034,
[6] Sharma, P; Berwal, Y.P.S. and Ghai, W.: *Performance analysis of deep learning CNN models for disease detection in plants using image segmentation.* Information Processing in Agriculture **7**(4), 566-574, 2020, http://dx.doi.org/10.1016/j.inpa.2019.11.001,
[7] Saranya, K; Uva Dharini, P.; Uva Darshni, P. and Monisha, S.: *IoT Based Pest Controlling System for Smart Agriculture.* International Conference on Communication and Electronics Systems. pp.1548-1552, 2019, http://dx.doi.org/10.1109/ICCES45898.2019.9002046,
[8] Xiao, Z., et al.: *Pest identification via hyperspectral image and deep learning*. Signal, Image and Video Processing **16**, 873-880, 2022, http://dx.doi.org/10.1007/s11760-021-02029-7,
[9] Fuchida, M., et al.: *Vision-Based Perception and Classification of Mosquitoes Using Support Vector Machine*. Applied Science **7**(1), No.51, 2017, http://dx.doi.org/10.3390/app7010051,
[10] Valan, M., et al.: *Automated Taxonomic Identification of Insects with Expert-Level Accuracy Using Effective Feature Transfer from Convolutional Networks*. Systematic Biology **68**(6), 876-895, 2019, http://dx.doi.org/10.1093/sysbio/syz014,
[11] Mamdouh, N. and Khattab, A.: *YOLO-Based Deep Learning Framework for Olive Fruit Fly Detection and Counting*. IEEE Access **9**, 84252-84262, 2021, http://dx.doi.org/10.1109/ACCESS.2021.3088075,
[12] Lim, S; Kim, S.; Park, S. and Kim. D.: *Development of Application for Forest Insect Classification using CNN.* 15th International Conference on Control, Automation, Robotics and Vision (ICARCV). Singapore, pp.1128-1131, 2018, http://dx.doi.org/10.1109/ICARCV.2018.8581103,
[13] Høye, T.T., et al.: *Deep learning and computer vision will transform entomology.* Proceedings of the National Academy of Sciences **118**(2), No.e2002545117, 2021, http://dx.doi.org/10.1073/pnas.2002545117,
[14] Potamitis, I.; Rigakis, I.; Tatlas, N.-A.: *Automated Surveillance of Fruit Flies.* Sensors **17**(1), No.110, 2017, http://dx.doi.org/10.3390/s17010110,
[15] López, O., et al.: *Monitoring Pest Insect Traps by Means of Low-Power Image Sensor Technologies*. Sensors **12**(11), 15801-15819, 2012, http://dx.doi.org/10.3390/s121115801,

[16] Rehman, M.Z.U., et al.: *Classification of citrus plant diseases using deep transfer learning*. Computers, Materials & Continua **70**(1), 1401-1417, 2022, http://dx.doi.org/10.32604/cmc.2022.019046.

[17] Lu, A.; Hou, X.; Liu, C.-L. and Chen, X.: *Insect species recognition using discriminative local soft coding*. Proceedings of the 21th ICPR. Tsukuba, pp.1221-1224, 2012,

[18] Qazi, S.; Khawaja, B.A. and Farooq, Q.U.: *IoT-Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review, Current Challenges and Future Trends.* IEEE Access **10**, 21219-21235, 2022, http://dx.doi.org/10.1109/ACCESS.2022.3152544,

[19] Seesaard, T.; Goel, N.; Kumar, M. and Wongchoosuk, C.: *Advances in gas sensors and electronic nose technologies for agricultural cycle applications.* Computers and Electronics in Agriculture **193**, No.106673, 2022, http://dx.doi.org/10.1016/j.compag.2021.106673,

[20] Sandrini Moraes, F.; Edson Nava, D.; Scheunemann, T.; Santos da Rosa, V.: *Development of an Optoelectronic Sensor for Detecting and Classifying Fruit Fly (Diptera: Tephritidae) for Use in Real-Time Intelligent Traps.* Sensors **19**(5), No.1254, 2019, http://dx.doi.org/10.3390/s19051254,

[21] Kumar, N. and Nagarathna: *Survey on Computational Entomology: Sensors based Approaches to Detect and Classify the Fruit Flies*. 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT). pp.1-6, 2020, http://dx.doi.org/10.1109/ICCCNT49239.2020.9225582,

[22] Zettle, M.; Anderson, E. and LaDeau, S.L.: *Changes in Container-Breeding Mosquito Diversity and Abundance Along an Urbanization Gradient are Associated With Dominance of Arboviral Vectors*. Journal of Medical Entomology **59**(3), 843-854, 2022, http://dx.doi.org/10.1093/jme/tjac023,

[23] Lim, S.; Kim, S. and Kim, D.: *Performance effect analysis for insect classification using convolutional neural network.* 7th IEEE International Conference on Control System, Computing and Engineering (ICCSCE). pp.210-215, 2017, http://dx.doi.org/10.1109/ICCSCE.2017.8284406,

[24] Reza, M.T; Mehedi, N.; Tasneem, N.A. and Ashraful Alam, M.: *Identification of Crop Consuming Insect Pest from Visual Imagery Using Transfer Learning and Data Augmentation on Deep Neural Network.* 22nd International Conference on Computer and Information Technology (ICCIT). Dhaka, pp.1-6, 2019, http://dx.doi.org/10.1109/ICCIT48885.2019.9038450,

[25] Batista, G.E.A.P.A.; Hao, Y.; Keogh, E. and Mafra-Neto, A.: *Towards Automatic Classification on Flying Insects Using Inexpensive Sensors*. 10th International Conference on Machine Learning and Applications and Workshops. Washington, pp.364-369, 2011, http://dx.doi.org/10.1109/ICMLA.2011.145,

[26] Nangai, V.L. and Martin, B.: *Interpreting the Acoustic Characteristics of Rpw Towards Its Detection - A Review.* IOP Conference Series: Materials Science and Engineering **225**, No.012178, 2017, http://dx.doi.org/10.1088/1757-899x/225/1/012178,

[27] Potamitis, I; Rigakis, I. and Fysarakis, K.: *Insect Biometrics: Optoacoustic Singal Processing and Its Applications to Remote Monitoring of McPhail Type Traps.* PLoS ONE **10**(11), No.e0140474, 2015, http://dx.doi.org/10.1371/journal.pone.0140474,

[28] Nanni, L; Maguolo, G. and Pancino, F.: *Insect pest image detection and recognition based on bio-inspired methods.*
Ecological Informatics **57**, No.101089, 2020,
http://dx.doi.org/10.1016/j.ecoinf.2020.101089,

[29] –: *Arthropod Taxonomy Orders Object Detection Dataset*.
https://www.kaggle.com/mistag/arthropod-taxonomy-orders-object-detection-dataset,

[30] Sarker, I.H.: *Machine Learning: Algorithms, Real-World Applications and Research Directions.*
SN Computer Science **2**, No.160, 2021,
http://dx.doi.org/10.1007/s42979-021-00592-x,

[31] Bino, S.V.; Unnikrishnan, A. and Balakrishnan, K.: *Gray Level Co-Occurrence Matrices: Generalisation and Some New Features*.
Preprint arXiv:1205.4831 [cs.CV], 2012,
http://dx.doi.org/10.48550/arXiv.1205.4831,

[32] Howard, A.G., et al.: *MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications*.
preprint arXiv:1704.04861 [cs.CV],
http://dx.doi.org/10.48550/arXiv.1704.04861.