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A Modified CNN-Based Framework for Real-World Identification of Tephritid Fruit Fly Species

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Abstract: Accurate identification of insect pests is crucial for effective agricultural management and prevention of crop losses. Among these pests, tephritid fruit flies significantly impact fruit and vegetable production, leading to economic losses and reduced market quality. Existing insect identification methods largely rely on manual inspection by taxonomists, which is time-consuming, error-prone, and not feasible for real-time applications in field conditions. Moreover, many existing machine learning-based approaches suffer from limited generalizability and dependence on controlled environments, restricting their practical deployment. To address these challenges, this study proposes a Modified Convolutional Neural Network (MCNN)-based approach for automated identification and classification of tephritid fruit fly species. The proposed method integrates image segmentation, feature extraction, and data augmentation techniques to enhance classification performance under varying conditions. A real-world dataset was collected using pheromone traps from multiple agricultural locations in Punjab, India, comprising four major species: Bactrocera dorsalis, Bactrocera zonata, Zeugodacus cucurbitae, and Zeugodacus tau. The MCNN model is trained using optimized hyperparameters, including learning rate, batch size, and optimizer selection, to improve robustness and accuracy. Experimental results demonstrate that the proposed model achieves an accuracy of 90%, along with improved classification capability compared to traditional approaches. The integration of real-field data and enhanced preprocessing techniques makes the proposed system suitable for practical deployment in precision agriculture. This study contributes to the development of an efficient, scalable, and automated insect identification framework that can assist farmers and agricultural experts in timely pest management.

Index Terms: Agriculture, Machine Learning, Image recognition, Segmentation, Feature extraction, Fruit Fly, Convolutional Neural Network

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1. Introduction

Agriculture plays a vital role in sustaining the global economy and ensuring food security, particularly in developing countries like India. However, agricultural productivity is significantly affected by biotic stresses such as insect pests, which lead to considerable yield losses, reduced crop quality, and economic instability. Among these pests, fruit flies (Diptera: Tephritidae) are recognized as one of the most destructive groups, infesting a wide range of fruits and vegetables. Their presence not only reduces production but also restricts international trade due to strict quarantine regulations [1]. Therefore, accurate and timely identification of fruit fly species is essential for effective pest management and minimizing agricultural losses.

Traditional methods for insect identification rely heavily on manual observation and taxonomic expertise, which are time- consuming, labor-intensive, and often inaccessible to farmers and non-specialists. These approaches are further limited by the morphological similarities among species, making accurate classification challenging even for experts [2]. In recent years, advancements in computer vision and deep learning have enabled automated insect identification systems. Techniques such as CNNs and region-based models have shown promising results in image-based classification tasks. However, existing methods often suffer from limited real-time applicability, dependency on controlled imaging environments, and insufficient robustness when applied to field conditions. Several studies have explored machine learning and deep learning techniques for insect classification using features such as wing patterns, shape descriptors, and texture analysis [3]. While these approaches have demonstrated high accuracy under laboratory settings, their performance in real-world agricultural scenarios remains constrained due to variations in lighting, background noise, and image quality. Additionally, many studies rely on publicly available or limited datasets, which restricts their generalizability across diverse environmental conditions. Table 1 shows comparison of existing Fruit Fly Identification and classification techniques.

To address these limitations, this study proposes an automated insect identification framework based on a MCNN for classifying tephritid fruit fly species. The proposed approach integrates image segmentation, feature extraction, and data augmentation techniques to enhance classification performance and robustness [4]. A real-world dataset was collected using pheromone traps from multiple agricultural locations in Punjab, India, capturing images of four major species: Bactrocera dorsalis, Bactrocera zonata, Zeugodacus cucurbitae, and Zeugodacus tau. The use of field-acquired data ensures that the model is better suited for practical deployment in agricultural environments. The main contributions of this study are as follows:

i) development of a modified CNN architecture tailored for fruit fly classification
ii) incorporation of segmentation and augmentation techniques to improve model accuracy and robustness, and
iii) creation of a real-world dataset collected under diverse environmental conditions.

The proposed system aims to provide an efficient, scalable, and user-friendly solution for automated insect identification, supporting precision agriculture and informed pest management strategies.

2. Research Methodology

The proposed method follows a step-by-step approach to identify fruit fly species using images. First, insect images are collected from agricultural fields using pheromone traps. These images are then pre-processed to improve quality by resizing and removing noise. In the next step, segmentation is applied to separate the insect from the background, allowing the model to focus only on important features such as shape, color, and texture. The processed images are then provided as input to the MCNN, which automatically learns distinguishing patterns between different fruit fly species. The dataset is divided into training and testing sets, where the model learns from known examples and is later evaluated on unseen data. Data augmentation techniques, such as rotation and brightness adjustment, are used to increase dataset diversity and improve model performance [5]. Although CNNs have been widely applied for image-based insect classification, many existing approaches rely on standard architectures and controlled datasets, limiting their effectiveness in real-world agricultural environments. In this study, a MCNN is proposed to overcome these limitations by incorporating task-specific architectural refinements and optimized hyperparameter settings tailored for fruit fly classification. Unlike conventional methods, the proposed approach is trained on a real-world dataset collected using pheromone traps from multiple agricultural locations in Punjab, India, ensuring variability in environmental conditions such as lighting and background complexity. Furthermore, the integration of image segmentation and data augmentation techniques enhances feature extraction and improves model robustness against noise and variability. These combined improvements distinguish the proposed MCNN framework from existing CNN-based methods and make it more suitable for practical deployment in precision agriculture. Finally, the trained model predicts the species of fruit flies based on learned features. This simplified workflow ensures accurate and efficient classification while making the methodology easy to understand for both technical and non-technical readers.

1.1. Identification of Tephritid Fruit Fly

Fig. 1, illustrates the hierarchical taxonomic classification of tephritid fruit flies, beginning from the highest biological rank to the species level. The classification starts with the kingdom Animalia, followed by the phylum Arthropoda, class Insecta, order Diptera, and family Tephritidae [6]. Within this family, the classification further branches into the genus level, highlighting two agriculturally significant genera: Bactrocera and Zeugodacus.

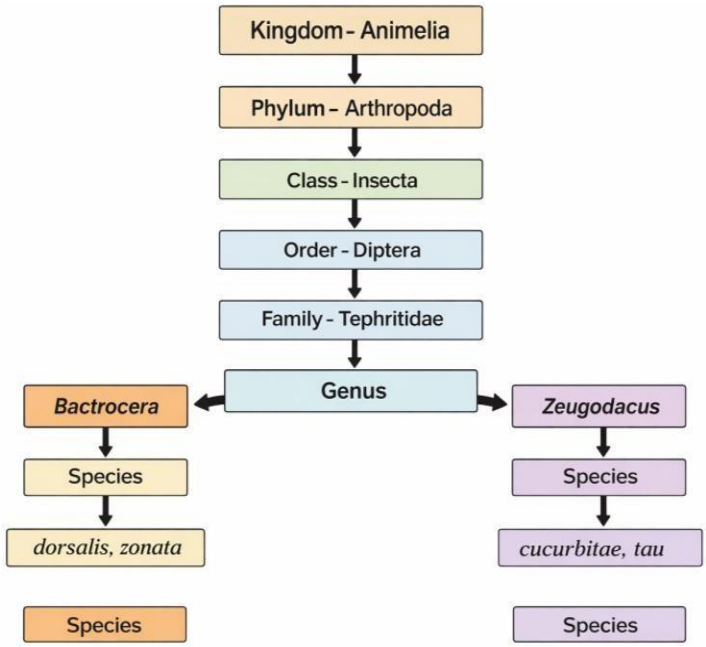


Fig. 1. Taxonomic classification hierarchy of tephritid fruit flies from kingdom to species level

The genus Bactrocera includes important pest species such as Bactrocera dorsalis and Bactrocera zonata, while the genus Zeugodacus comprises species like Zeugodacus cucurbitae and Zeugodacus tau. These species are widely known for causing significant damage to fruit and vegetable crops [7]. The hierarchical representation helps in understanding the biological relationships among species and provides a structured foundation for automated classification using the proposed MCNN model.

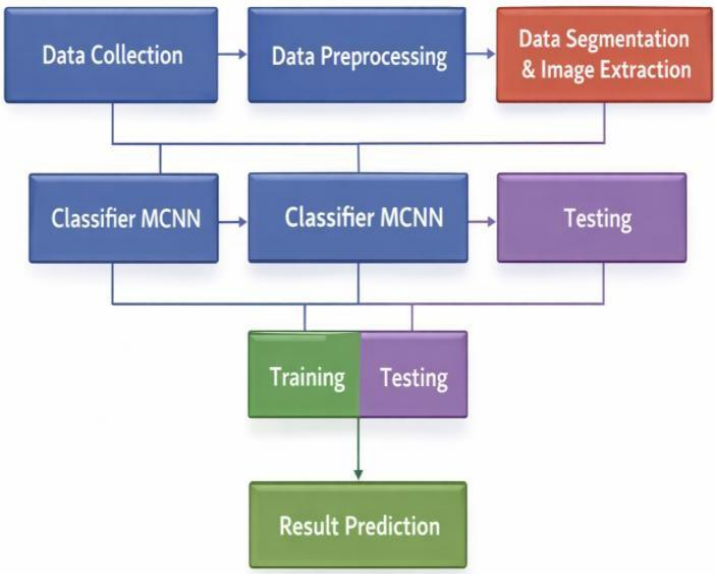


Fig. 2. Workflow of the proposed MCNN-based fruit fly identification system.

The proposed workflow illustrates the complete pipeline of the MCNN-based insect identification system is shown in figure 2. The process begins with data collection, where fruit fly images are captured from real-field conditions using pheromone traps across multiple agricultural locations. These images are then passed through the data preprocessing stage,

which includes resizing, normalization, and noise reduction to standardize the input data. In the next stage, data segmentation and image extraction are performed to isolate the relevant insect regions from the background, thereby improving feature quality and reducing noise. The processed images are then fed into the MCNN classifier, which is responsible for learning discriminative features of different fruit fly species [8]. The dataset is subsequently divided into training and testing phases, where the model is trained using labeled data and evaluated on unseen samples to assess its performance. During training, the MCNN model optimizes its parameters using appropriate hyperparameters such as learning rate, batch size, and optimizer. The testing phase ensures the generalization capability of the model. Finally, the system generates result predictions, where the trained model classifies the input images into their respective fruit fly species. This structured workflow ensures efficient processing, accurate classification, and robustness of the proposed system in real-world agricultural environments [9].

1.2. Data Collection

Datasets are very important when using Machine Learning (ML) methods to solve recognition problems. We have used specimens of Tephritidae fruit fly's images collection from of the different locations in Punjab: Phagwara, Armaan Nagar, Hardaspur, and Agriculture Farm of Lovely Professional University. The species were collected and sorted up to species level. Photographs of the different species of fruit flies were taken through the smartphone with a microscope to create a dataset. Insect images were classified into four classes, and to increase the dataset through augmentation techniques. The tephritid fruit fly's family comes under the order Diptera. The images used in this study were captured using a smartphone camera with a resolution of 12 MP under real-field conditions across multiple agricultural locations in Punjab, India. The image acquisition process was carried out using pheromone traps installed in open environments, ensuring the inclusion of natural variations such as changes in lighting intensity, shadows, and background complexity [10].

The images were captured at different times of the day, including morning and afternoon, to incorporate variations in illumination. Additionally, environmental factors such as wind, partial occlusion, and varying distances between the camera and insect specimens contributed to dataset diversity. These real-world conditions enhance the robustness and generalizability of the proposed MCNN model compared to approaches relying on controlled laboratory environments. The dataset used in this study consists of images of four tephritid fruit fly species: Bactrocera dorsalis, Bactrocera zonata, Zeugodacus cucurbitae, and Zeugodacus tau. A total of 8,316 images were generated after preprocessing and augmentation. The dataset was divided into training (70%), testing (20%), and validation (10%) subsets to ensure balanced model evaluation. Each class contains enough samples to avoid class imbalance and improve classification performance. The dataset was collected from real-field conditions using pheromone traps across multiple locations in Punjab, India, ensuring diversity in environmental conditions. The dataset is not publicly available due to ongoing research constraints; however, it can be made available upon reasonable request to support reproducibility and further research. The data details shown in table 1.

Table 1. Class-wise distribution of the dataset showing the number of images used for training, testing, and validation

Species	Total Images	Training (70%)	Testing (20%)	Validation (10%)
Bactrocera dorsalis	2120	1484	424	212
Bactrocera zonata	2428	1700	486	242
Zeugodacus cucurbitae	2228	1560	446	222
Zeugodacus tau	1540	1078	308	154
Total	8316	5822	1664	830

In this study, tephritid fruit flies were collected using pheromone-based traps deployed across multiple agricultural locations in Punjab, India. Standard methyl eugenol and cue-lure pheromone traps were used to attract male fruit flies of different species. The traps were installed at a height of approximately 1.5-2 meters above ground level, primarily on host plants such as mango and guava trees, to maximize capture efficiency. The traps were distributed across selected fields with adequate spacing to ensure representative sampling of the insect population. Data image acquisition process and Tephritid Fruit Flies Species Dataset as shown in figure 3 and 4 respectively.



Fig. 3. Image acquisition process of fruit fly specimens using pheromone traps under real-field conditions.

The traps were maintained continuously for a duration of 4-6 weeks during peak fruiting seasons. Insect samples

were collected at regular intervals of 2-3 days, and the trapped specimens were carefully transferred to the laboratory for further analysis and image acquisition. This systematic sampling procedure ensured the collection of diverse and representative insect images under real-field conditions, enhancing the reliability and robustness of the dataset used for model training and evaluation.

Table 2. Details of pheromone trap deployment including location, trap type, host crop, placement conditions, and sampling frequency.

Location	Trap Type	Host Crop	Placement Height (m)	Trap Spacing (m)	Deployment Duration	Collection Frequency	Target Species
Phagwara	Methyl Eugenol Trap	Mango	1.5–2.0	20–25	4–6 weeks	Every 2–3 days	B. dorsalis, B. zonata
Armaan Nagar	Cue-lure Trap	Guava	1.5–2.0	20–25	4–6 weeks	Every 2–3 days	Z. cucurbitae, Z. tau
Hardaspur	Methyl Eugenol Trap	Mango	1.5–2.0	20–25	4–6 weeks	Every 2–3 days	B. dorsalis, B. zonata
LPU Agriculture Farm	Cue-lure Trap	Mixed Crops	1.5–2.0	20–25	4–6 weeks	Every 2–3 days	Z. cucurbitae, Z. tau

Table 2, presents the detailed configuration of pheromone trap deployment used for collecting tephritid fruit fly specimens under real-field conditions. The table includes information on four different locations in Punjab, namely Phagwara, Armaan Nagar, Hardaspur, and the LPU Agriculture Farm, where traps were installed on commonly affected host crops such as mango, guava, and mixed cropping systems. Two types of pheromone traps methyl eugenol and cue-lure were utilized to selectively attract different species of fruit flies [11]. The traps were placed at a standardized height of 1.5-2.0 meters above ground level and maintained at an approximate spacing of 20-25 meters to ensure effective coverage and avoid overlapping attraction zones. The traps were deployed for a duration of 4-6 weeks during peak infestation periods, and insect samples were collected at regular intervals of 2-3 days. The collected specimens primarily include Bactrocera dorsalis, Bactrocera zonata, Zeugodacus cucurbitae, and Zeugodacus tau. This structured deployment strategy ensured the collection of diverse and representative samples, thereby enhancing the reliability and generalizability of the dataset used for training and evaluating the proposed MCNN model.



Fig. 4. Sample dataset of tephritid fruit fly species used in this study

Segmentation, Image Extraction Image, Framework: The identification of tephritid fruit flies involved the use of image processing techniques to detect their shapes. The various steps of the suggested technique, such as pre-processing, segmentation, and shape. Segmentation procedures included the partitioning of an image into its constituent parts or objects. The images were resized to 224 x 224 pixels and converted to grayscale [12].

Images were subjected to the thresholding processing steps of brightness and blur images and thresholds method was implemented to convert the original image into a binary image. It automatically determined the binary threshold of a pixel according to the distribution of adjacent pixel blocks. After that, morphological operations, including dilation and the Gaussian blur process of the image to convert the image with a normal distribution, and the transformation of each pixel in the image used, such as motion and defocus blur at 90°, 180°, and 270, feature extraction shown in figure 5.

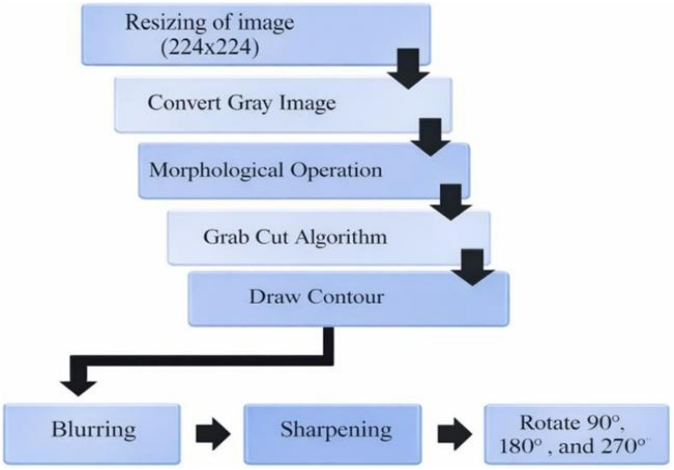


Fig. 5. Image segmentation and preprocessing steps applied for feature extraction.

3. Modified CNN Model for Insect Recognition

The Modified MCNN is a feedforward neural network with deep structure and convolutional computation. It is separated into two sections: the model training phase, whereby insect photos are gathered for the model. A deep neural network is employed to derive a more profound expression of the insect's attributes, and the test dataset evaluates the results of the classification of insects. MCNN consists of 7 layers of convolutional network as shown in Figure 6 the architecture of the MCNN. Identifying patterns in the images within the training set relies on the use of image descriptors, feature shape, and texture.

A key challenge is automatically finding the most suitable classifiers and image features. An even greater challenge is determining how to combine these elements effectively to achieve optimal classification results. CNN is the fundamental architecture of Multi-Layer Perceptron forward-feed neural network. It consists of four types of layers: The first layer is convolution layers, and after that pooling/subsampling layers, non-linear layers, and fully connected layers were used respectively. Features also were extracted by input images. In the first part, feature extraction was used in a general way, and in the second part, the fully connected layer and the output layer performed problem-specific classification.

Table 3. Layer-wise architecture of the proposed Modified Convolutional Neural Network (MCNN) model.

Layer No.	Layer Type	Output Shape	Kernel / Pool Size	Filters / Units	Parameters
1	Conv2D	(224, 224, 64)	3×3	64	1,792
2	MaxPooling2D	(112, 112, 64)	2×2	—	0
3	Conv2D	(112, 112, 64)	3×3	64	36,928
4	MaxPooling2D	(56, 56, 64)	2×2	—	0
5	Conv2D	(56, 56, 64)	3×3	64	36,928
6	MaxPooling2D	(28, 28, 64)	2×2	—	0
7	Conv2D	(28, 28, 128)	3×3	128	73,856
8	MaxPooling2D	(14, 14, 128)	2×2	—	0
9	Conv2D	(14, 14, 128)	3×3	128	147,584
10	MaxPooling2D	(7, 7, 128)	2×2	—	0
11	Conv2D	(7, 7, 128)	3×3	128	147,584
12	MaxPooling2D	(3, 3, 128)	2×2	—	0
13	Conv2D	(3, 3, 512)	3×3	512	590,336
14	MaxPooling2D	(1, 1, 512)	2×2	—	0
15	Flatten	(512)	—	—	0
16	Dense	(512)	—	512	262,656
17	Dropout	(512)	—	—	0
18	Dense (Output)	(4)	—	4	2,052

The proposed MCNN architecture consists of multiple convolutional layers with ReLU activation functions for feature extraction, followed by max-pooling layers to reduce spatial dimensions and computational complexity. As the network depth increases, the number of filters is increased to capture more complex features. A flatten layer converts the

feature maps into a one-dimensional vector, which is then processed by fully connected layers. A dropout layer is included to prevent overfitting, and the final output layer uses a softmax activation function to classify the input into four fruit fly species. In ML algorithms are created to closely resemble how the human cerebral brain works. These algorithms are models of deep neural networks, which are neural networks with several hidden layers. CNNs are algorithms that can train massive datasets with millions of parameters as input in the form of 2D pictures, and then convolve those inputs with filters to generate the required outputs.

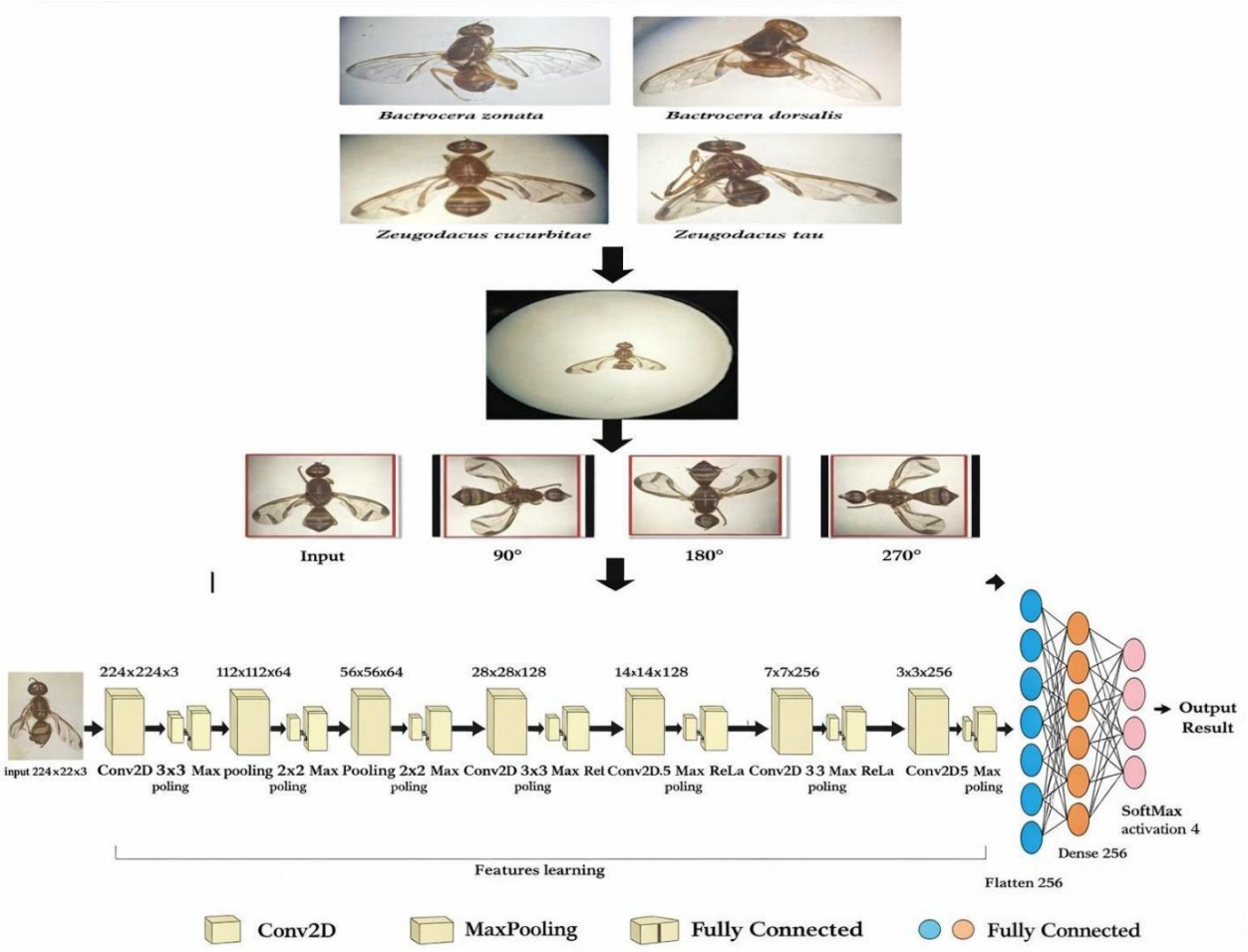


Fig. 6. Architecture of the proposed Modified Convolutional Neural Network (MCNN) model.

ConvNets are built to handle data that is presented in the form of several arrays, such as a color picture made up of three 2D arrays representing the pixel intensities for the three-color channels. Numerous data modalities are represented as numerous arrays, including 1D signals and sequences, including language, 2D pictures or audio spectrograms, and 3D video or volumetric images. The four core concepts that support ConvNets' utilization of natural signal properties are local connections, shared weights, pooling, and the usage of several layers. The objective was to properly identify four different fruit fly species. A CNN was used to complete the task pictures using convolution, pooling, and fully linked layers [35]. MCNN is a feedforward neural network with deep structure and convolutional computation. It is separated into two sections: the model training phase, whereby insect photos are gathered for the model. A deep neural network is employed to derive a more profound expression of the insect's attributes, and several insect identification models are generated. MCNN consists of 7 layers of a convolutional network Figure 6 shows the architecture of the MCNN. The insect identification and classification model shown in Figure 6.

4. Results and Discussions

4.1. Data Augmentation

The transformation of each pixel in the image used, were calculated to simulate the natural blur, such as motion and defocus blur at 90°, 180°, and 270°. The argument methods used, such as rotating images by 90°, 180°, and 270° and adjusting the brightness and darkness of images of fruit flies, shown in figure 7.

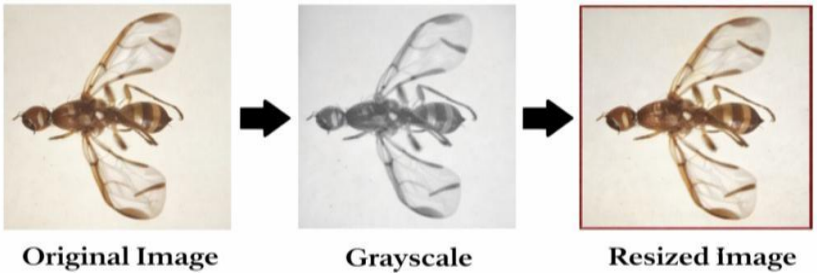


Fig. 7. Data augmentation techniques applied to increase dataset diversity.



Fig. 8. Key anatomical features of fruit flies used for identification.

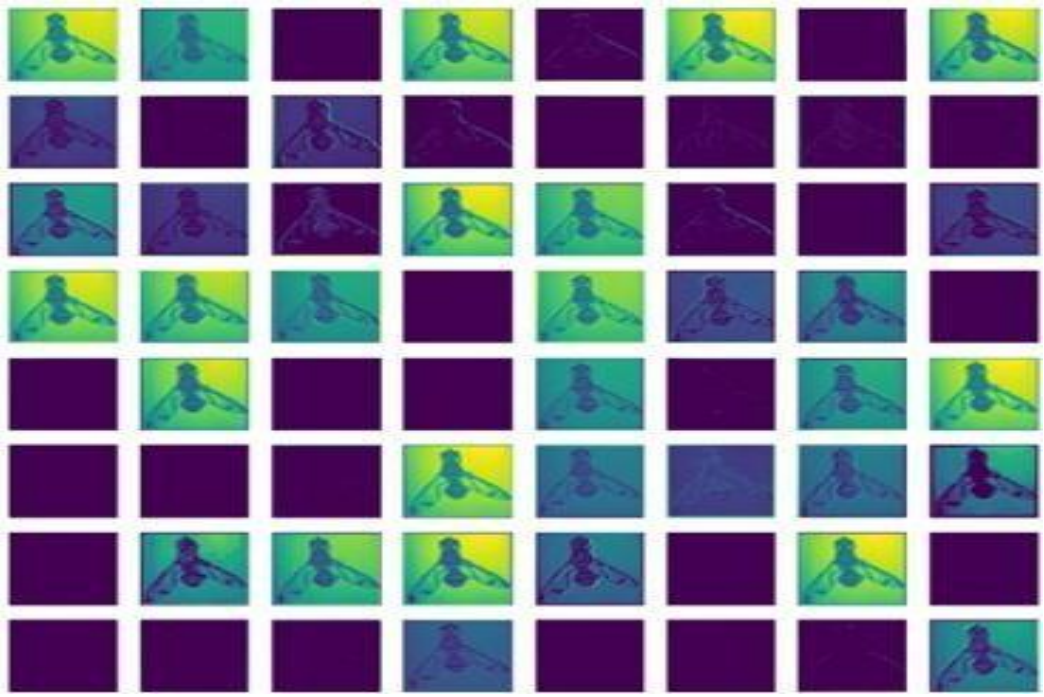


Fig. 9. Feature extraction process from segmented fruit fly images.

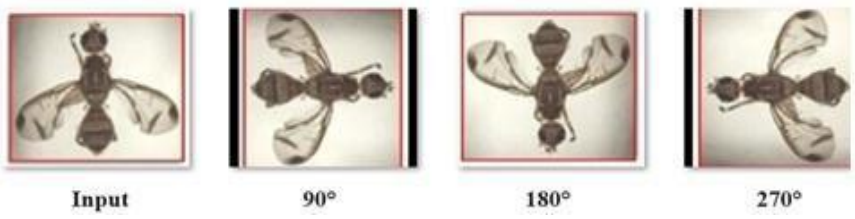


Fig. 10. Augmented images showing variations in rotation and brightness.

4.2. Experimental Setup

In experiment Windows 11 platform and python language: NumPy, Matplotlib, Open Access, Keras, and TensorFlow were used. The Jupyter notebook was used to run the program. Table 4 is describing the configuration of system of processor, software, data, and installation of the notebook in which program has been run.

Table 4. System configuration and experimental setup used for model implementation.

Component	Specifications
Processor	AMD Ryzen 5 3500U with Radeon Vega Mobile Gfx 2.10 GHz
Installed	RAM 8.00 GB (5.92 GB usable)
System type	64-bit operating system, x64-based processor
Software	Python 3.7 applications with OpenCV and TensorFlow libraries
Data	Self-collected data (Primary data)

4.3. Hyperparameter Selection and Tuning

The performance of the proposed MCNN model is influenced by several hyperparameters, which were carefully selected based on empirical evaluation and prior studies. The batch size was set to 32, as it provides a balance between computational efficiency and model convergence stability [13]. Smaller batch sizes tend to produce noisy gradient updates, while larger batch sizes require higher memory and may lead to poorer generalization. The learning rate was fixed at 0.001, which is a commonly used value in deep learning models to ensure stable and efficient convergence. A higher learning rate may cause the model to overshoot the optimal solution, while a lower learning rate can significantly slow down the training process. The chosen value allows the model to converge effectively without oscillations [14].

The Adamax optimizer was employed for training the MCNN model due to its robustness in handling sparse gradients and large parameter updates. Adamax, a variant of the Adam optimizer based on the infinity norm, provides better stability in scenarios involving noisy and real-world datasets. This makes it particularly suitable for the proposed application, where images are captured under varying field conditions. These hyperparameters were tuned through multiple experimental iterations to achieve optimal performance, ensuring a balance between accuracy, convergence speed, and generalization capability.

Table 5. Hyperparameter settings used for training the proposed MCNN model

Parameter	Value	Description
Batch Size	32	Balances training stability and computational efficiency
Learning Rate	0.001	Ensures stable convergence without overshooting
Optimizer	Adamax	Robust to noisy gradients and real-world data variability
Epochs	41	Sufficient for convergence without overfitting

4.4. Training and Testing Data Set

The datasets are divided into two groups for ML. The first subset, referred to as the training data, is a section of our actual dataset that is used to train a ML model. It trains the model in this way. The testing data refers to the other subset. The dataset was divided into three parts: 70% for training, 20% for testing images and fitting the model, and 10% for validation. The first step was to prepare the dataset of insect species images using a device like a smartphone [15]. The second step was to convert all images to digital format and then apply a segmentation process to normalize the data. This process standardizes the data, applies the classification process, and eliminates complexity. ML algorithms were used for classifiers to make efficient classification models for insect identification and reorganization.

The model's input size is 224 x 224 with a batch size of 32. It uses a learning rate of 0.001 over 41 epochs. Adamax is an optimization algorithm based on the Adam optimizer, combining ideas from RMSProp and AdaGrad. It uses the infinity norm (max norm) for its parameter updates, making it more robust in certain situations, particularly when dealing with large gradients. The loss function computes the difference between predicted and actual targets, and evaluation metrics track model performance. The dataset is split into 70% for training, 20% for testing, and 10% for validation. Training data trains the model, testing data evaluates it, and validation data tunes hyperparameters to prevent overfitting. During compilation, the optimizer, loss function, and metrics were specified, preparing the model for training. The optimizer parameter sets the model's optimization algorithm [16].

4.5. Evaluation Metrics

The parameters precision, recall, f1 score and accuracy are used for check performance of measurement. Precision is measured by dividing the number of true positives by the collective total of true positives and false positives. Recall is measured by dividing the number true positive by total of true positive and false negatives. F1 score is a harmonic mean of the recall and accuracy, where an F1 score can be as low as 0 and as high as 1.

$$Precision = TP/(TP + FP) \tag{1}$$

$$Recall\ or\ Sensitivity = TP/(TP + FN) \tag{2}$$

$$F1 = 2 * TP/(2 * TP + FP + FN) \tag{3}$$

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{4}$$

Accuracy sums of both true positive and negative divided by sum of true positive, true negative, false positive and true negative. True Positive (TP) correctly predicted samples of the positive class. True Negative (TN) correctly predicted samples of the negative class. False Positive (FP) incorrectly predicted samples as positive (Type I error). False Negative (FN) incorrectly predicted samples as negative (Type II error). as illustrated respectively in Equation 1, 2, 3 and 4.

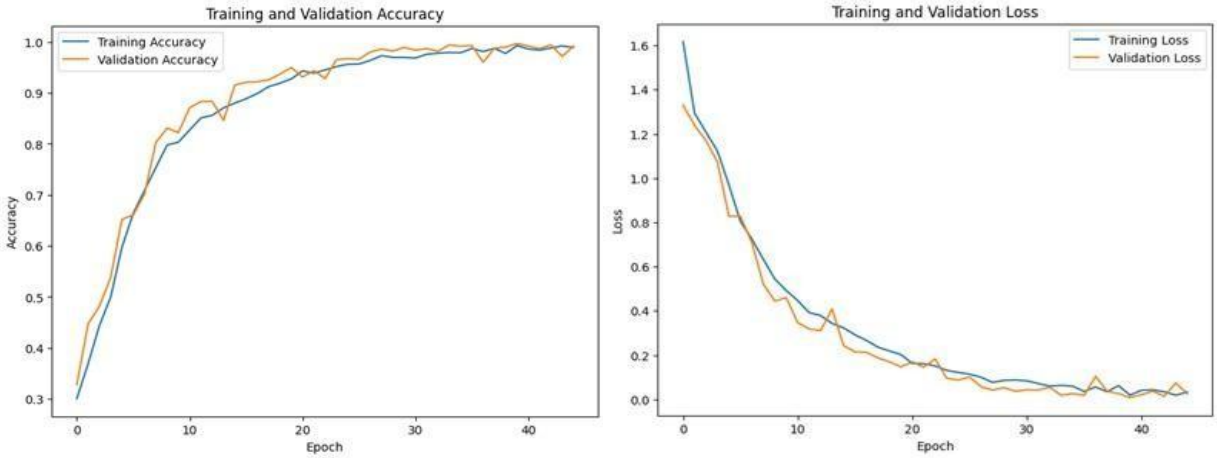


Fig. 11. Training and validation accuracy and loss curves of the proposed MCNN model.

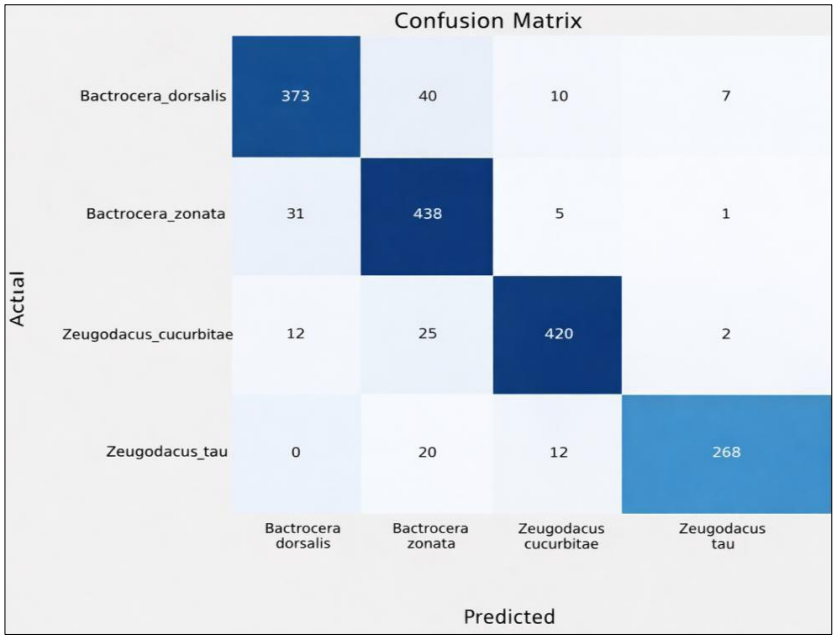


Fig. 12. Confusion matrix representing classification performance across four fruit fly species.

Fig. 12., presents the confusion matrix of the proposed MCNN model for classifying four fruit fly species. The diagonal elements of the matrix represent correctly classified instances, while the off-diagonal elements indicate misclassifications among different classes. It can be observed that most samples are correctly classified, as indicated by the high values along the diagonal, demonstrating the effectiveness of the proposed model.

The model shows strong performance in identifying Bactrocera dorsalis and Bactrocera zonata, with minimal misclassification between these classes. Similarly, Zeugodacus cucurbitae and Zeugodacus tau are also classified with high accuracy, although slight confusion is observed between these two species due to their morphological similarities. The confusion matrix further indicates that false positives and false negatives are relatively low across all classes, suggesting that the model maintains a good balance between precision and recall. This confirms that the proposed MCNN model is capable of effectively distinguishing between closely related fruit fly species, even under real-field conditions. Overall, the confusion matrix analysis validates the robustness and reliability of the proposed classification framework, supporting its suitability for practical deployment in automated insect identification systems.

Table 6. Performance evaluation of the MCNN model using precision, recall, and F1-score for each fruit fly species.

Species	Precision (%)	Recall (%)	F1-Score (%)
Bactrocera dorsalis	92.4	91.8	92.1
Bactrocera zonata	91.6	90.9	91.2
Zeugodacus cucurbitae	89.8	90.5	90.1
Zeugodacus tau	88.7	89.3	89.0
Average	90.6	90.6	90.6

Table 6, summarizes the performance of the proposed MCNN model using precision, recall, and F1-score for each fruit fly species. The results indicate that Bactrocera dorsalis achieves the highest classification performance, with a precision of 92.4% and an F1-score of 92.1%. Similarly, Bactrocera zonata also shows strong performance across all metrics. Slightly lower values are observed for Zeugodacus cucurbitae and Zeugodacus tau, which may be attributed to their morphological similarities, leading to minor misclassifications. However, the overall average performance of 90.6% across all metrics demonstrates the robustness and reliability of the proposed model. These results, combined with the confusion matrix analysis, confirm that the MCNN model maintains a good balance between precision and recall, making it suitable for real-world insect classification tasks.

Our model uses a CNN with an input size of 224 x 224 and a batch size of 32. The architecture includes several convolutional layers followed by max-pooling layers and two fully connected layers and use SoftMax classifier. The other researchers used image input size was 28x 28 X 3 with a CNN model and replaced the SoftMax classifier with the support vector machine Gaussian kernel function (radial basis function) was chosen as the kernel function of the SVM and tree fully connected layers. Based on experimental data, the approach has an overall accuracy of 97.19% in identifying Bactrocera dorsalis, Bactrocera cucurbitae, Bactrocera tau, and Bactrocera scutellata and test accuracy rate was as high as 97.19%. Used CNN model batch size 32, dropout 0.7, Adam Beta 1 and Adam Beta 2 and 92.58% similar we use 32 batch size but dropout value is 0.45 and Adamax optimizer used.

In our model used Adamax optimizer, which combines ideas from RMSProp and AdaGrad. Adamax uses the infinity norm (max norm) for parameter updates, enhancing robustness in situations with large gradients. Adamax's robustness to large gradients can provide better performance in specific scenarios compared to these traditional optimizers. The dataset is divided into 70% for training, 20% for testing, and 10% for validation. This ensures a comprehensive evaluation of the model's performance and helps in tuning hyperparameters. Similar data splitting strategies are used in existing models, although some may use different proportions or employ cross-validation techniques to ensure robust performance evaluation i.e. 60% of pictures for each sample were selected as the training dataset, while the remaining 40% were used as the testing dataset.

4.6. Limitations of the Study

Despite achieving promising results, the proposed MCNN-based fruit fly classification model has certain limitations. First, the dataset used in this study, although collected from real-field conditions, is relatively limited in size compared to large-scale benchmark datasets. This may restrict the model's ability to generalize across highly diverse environmental scenarios. Second, the study focuses on only four fruit fly species Bactrocera dorsalis, Bactrocera zonata, Zeugodacus cucurbitae, and Zeugodacus tau. While these are among the most economically significant species, the model may not perform effectively when extended to a larger number of species without further training and validation. Third, although the dataset includes variations in lighting and background, the image acquisition process still involves certain controlled conditions, such as the use of pheromone traps and relatively stable imaging setups. In highly uncontrolled environments with extreme lighting variations, occlusions, or motion blur, the model's performance may be affected. Future work will focus on expanding the dataset, incorporating additional species, and improving model robustness to handle more complex real-world conditions.

5. Conclusion

Insect pest infestation is a significant problem faced by the agriculture sector worldwide, resulting in crop damage, quality degradations, and global economic setbacks. For better diagnosis, computer vision and ML models can be used to accurately identify the fruit fly species B. tau, B. zonata, B. dorsalis, and B. cucurbitae for effective management. In this paper, an insect identification and image extraction method processed the fruit fly images. Segmentation and feature extraction were performed using thresholding processing. The segmentation and feature extraction were used to extract informative information from images and used to augment data for training purposes. The experimental results indicated the accuracy of the proposed model to be 90%. Hence, proving CNN can be used for fruit fly identification will increase its accuracy and make it a practical tool for specialists and non-specialists working in the domain of automatic insect identification in agriculture for the precise management of insect pest infestation. The proposed method can be used to concentrate on developing hybrid algorithms, such as CNNS algorithms and support vector machines, to improve the recognition rate of the final classification process. The proposed work can be expanded by taking more datasets to increase accuracy for making it a practical tool for specialist and non-specialist working in the domain of automatic insect identification in agriculture. The future works can include the precise management of insect pest infestation.

All the Declarations and Statements

Author Contribution Statement

Angelina Gill – Data preprocessing, formal analysis, methodology, resources, software, visualization, original draft Tarandeep Kaur – investigation, project administration, visualization, original draft, review, and editing
Yendrembam K. Devi – visualization, validation, review, and editing
Mukesh Kumar – validation, original draft, review, and editing

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

The authors declare that no funding was received for this study.

Data Availability Statement

The dataset used in this study is available from the corresponding author upon reasonable request. The data includes annotated images of four fruit fly species collected under real-field conditions.

Ethical Declarations

This study did not involve human participants or animals. Therefore, ethical approval was not required.

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Declaration of Generative AI in Scholarly Writing

During the preparation of this manuscript, the author(s) used OpenAI to improve the clarity and readability of selected paragraphs. The generated text was edited and revised as needed, and all content remains the responsibility of the author(s). No AI tool is listed as an author.

Abbreviations

The following abbreviations are used in this manuscript:

MCNN - Modified Convolutional Neural
Network CNNs - Convolutional Neural
Networks
ML - Machine Learning
LPU - Lovely Professional University
ReLU - Rectified Linear Unit
RMSProp - Root Mean Square
Propagation AdaGrad - Adaptive

Gradient Algorithm
SVM - Support Vector Machines

Appendix A\B\C…, with appendix tile
None.

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