Convolution Neural Network-based Mosquito Classification System

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Abstract. Many diseases caused on by mosquito bites have spread all over the world in recent decades. The most prevalent diseases are malaria, dengue, and chikungunya. Worldwide, diseases transmitted by mosquitoes are indeed a threat. Due to the extreme significant degree of similarity in appearance between different mosquito species, classifying mosquito is a particularly tough task. We focused on deep learnign using convolutional neural network. Classifying mosquitoes is a particularly difficult pursuit because different mosquito species have an extremely high level of visual analogy. In this paper, we offer a convolutional neural network-based (CNN) technique for classifying mosquito species. We have built mosquito image classification models using CNN on our own mosquito dataset of 1800 mosquito images from three different genera Aedes, Anopheles, Culex. We made use of data augmentation. Results prior to and following augmentation were compared. After augmentation, we obtained accuracy of 84.51%.

Keywords: CNN, Mosquito, Aedes, Anopheles, Culex

1 Introduction

The task of classifying and assigning names to groups of pixels or matrices within an image based on specific rules is known as image classification. One or more spectral or textural characteristics can be used to apply the classification principle.[1]

Classifying flying insect species is particularly difficult due to the tremendous degree of resemblance in appearance between various species. Because of the visual similarities between distinct species, flying insect categorization presents a wonderful chance to utilize new Deep CNN algorithms. Academics are now able to construct increasingly automated algorithms capable of reliably detecting every type of object due to advances in image categorization. We

[1] Boesch, G. A Complete Guide to Image Classification in. Retrieved from viso.ai: https://viso.ai/computer-vision/image-classification/(2022)

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provide a new convolutional neural network-based technique for classifying mosquito species in this paper (CNN). The effectiveness of identifying distinct sorts of images of mosquito images from three different species is investigated in this study. Once planned, constructed, and trained, our prediction system may be utilised as a prototype "back-end" for a scalable mosquito classification application.We built an image dataset with 1800 images of three different mosquito species: Aedes, Anopheles, and Culex. On 20% of the test images and 80% of the training images, CNN correctly identified species levels. With the help of computer vision, the study will categorise several mosquito species. Two datasets were used to compare the performances of deep learning algorithms on a dataset before and after augmentation. Images are pre-processed using image processing techniques. A 16 GB RAM and 2.4 GHz Intel Core i5 processor were used for the experiments. Python is used in the work's implementation, together with additional supporting frameworks like Keras and TensorFlow, for the study of mosquito species images recognition and categorization.

2 Problem Statement

More than 17% of all infectious diseases are vector-borne, and they account for more than 700,000 annual fatalities. They may be brought on by viruses, bacteria, or parasites. [2].

According to the Centers for Disease Control and Prevention (CDC), only three main mosquito species—Aedes, Culex, and Anopheles—are responsible for the majority of mosquito-borne illnesses in the United States. According to a tropical medicine specialist, blood-sucking mosquito species include the Aedes, Anopheles, and Culex species [3]. Blood-sucking mosquitoes include the Aedes, Anopheles, and Culex species, as shown in a tropical medicine expert.

Mosquitoes have diverse things according on their time zones, behaviour patterns, and mediated infections. Because the prevention and eradication of infectious diseases varies depending on the species, species classification is essential. It is difficult for a novice to differentiate between mosquito species[4]. Some recent studies have proposed techniques for identifying, such as methods based on DNA sequences[5] or image recognition[6]. Due to the general visual similarities between distinct mosquito species, mosquito categorization presents a wonderful opportunity to apply new Deep CNN algorithms

[2] WHO Report Vector-borne diseases https://www.who.int/news-room/fact-sheets/detail/vector-borne-diseases (2020)
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3 Deep Learning

Deep learning is a subfield of machine learning that focuses on building and training artificial neural networks with many layers. Deep learning models are capable of learning and making predictions from large and complex datasets [7].

3.1. Convolutional Neural Network:

A Convolutional Neural Network (CNN) is a type of deep learning neural network that is widely used for image and video analysis, processing and classification. CNNs are one of the most famous and commonly employed algorithms in the field of deep learning, especially in the area of computer vision[89]. One of the main benefits of CNNs compared to its predecessors, such as traditional machine learning algorithms and manually designed feature extractors, is that they can automatically identify the relevant features in an image without any human supervision [10]. Many diverse domains, such as computer vision[11],, audio processing[12], face recognition[13], etc., have made substantial use of CNNs. the structure of CNNs was inspired by the organization of the visual cortex in human and animal brains[14]. Three key benefits of the CNN: equivalent representations, sparse interactions, and parameter sharing. The combination of equivalent representations, sparse interactions, and parameter sharing leads to highly efficient and effective networks for image processing and computer vision tasks. By reducing the number of parameters needed to train the network and increasing the network's ability to generalize to new images, CNNs have achieved state-of-the-art performance in a wide range of applications, from image classification to object detection and segmentation. Unlike conventional fully connected (FC) networks, shared weights and local connections in the CNN are employed to make full use of 2D input-data structures like image signals[15]. The use of local filters in CNNs is inspired by the function of neurons in the visual cortex, which are specialized for processing small regions of the visual field. the use of local filters in CNNs is an important design feature that allows the network to effectively process images and other high-dimensional inputs, while also reducing the number of parameters and improving its computational efficiency.[16]

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3.1.1.CNN working

A notable CNN version, which is related to the multi-layer perceptron (MLP), has many convolution layers that come before sub-sampling (pooling) layers and FC layers at the end[17]. At a high level, a CNN works by taking an input image and passing it through a series of convolutional layers, which extract features from the image at different levels of abstraction. Without any image pre-processing, convolutional neural networks (CNN) can use the original image as input. CNN has demonstrated the highest accuracy in large-scale image classification and recognition since it was integrated with deep learning[18]. To improve the CNN model structure's accuracy, scientists use parameters. Most improved models require additional time to train and assess. [19]

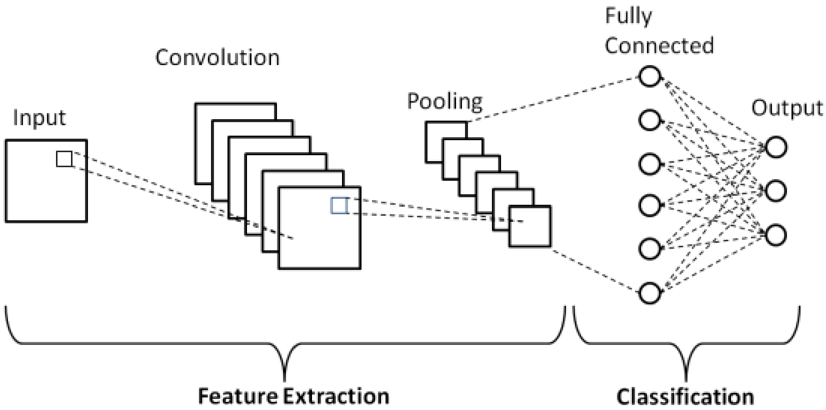

Fig 1 Classification using CNN

4. Proposed system

Flow chart of the recognition system is shown in Figure. The main process is composed of image collection, image pre-processing, feature extraction, train pattern, mosquito detection, classification of mosquito types.

4.1.Mosquito classification with CNN model

It's important to note that accurate identification of adult mosquito species is essential for identifying disease vectors and designing disease control strategies[20]. Due to their outstanding capacity to detect patterns from images, CNNs are one of the most prominent deep learning network architectures used in computer vision [21]. New models for the automatic classification of mosquitoes have recently been proposed. The frequency and harmonics of mosquito

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[17] Tianming Liang, X. X. A new image classification method based on modified condensed nearest neighbor and convolutional neural networks. *Pattern Recognition Letters, vol. 94, ,,* pp-105-111, (July 2017).

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wingbeats have been used in several studies to classify mosquito species[22]. Techniques based on image feature analysis have also been used as a classification method. In addition, Machine Learning and Deep Learning techniques have been used for mosquito classification[23]. A feature extractor and a classifier that are trained end-to-end can describe the architecture of such networks. Many convolutional and pooling layers make up the feature extractor. Between their inputs and their learnable weights, convolutional layers perform weighted convolutions. As a result, they identify local patterns in the data. Non-trainable pooling layers reduce the dimensionality of their input by mapping a single layer in the input to a single number locally. One or more fully connected layers and a SoftMax function are commonly used to create the classifier[24]. Deep learning methods are essential for the processes underlying general object recognition[25]

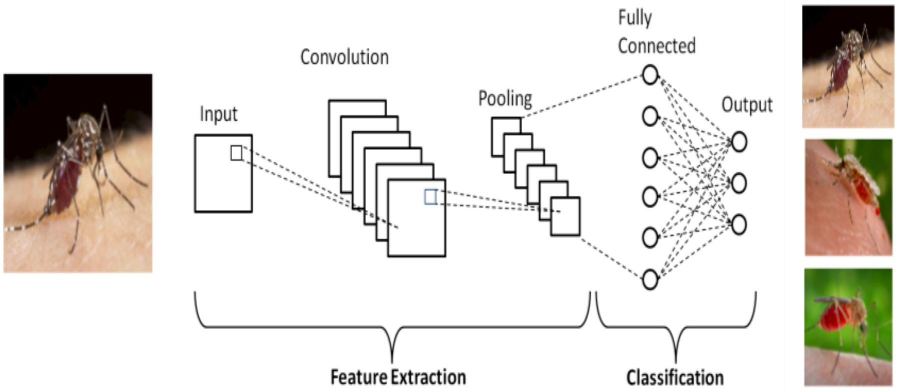

Fig. 2 Proposed Mosquito classification system

4.2.Image sources

Images were collected from websites/blogs.

4.2.1.Data: Dataset of 1800 images is created. Images of three different types of mosquito species are collected. Dataset consists of Images of Aedes, Anopheles and Culex

4.2.2. **Pre-processing.** Total 120 images of each type of mosquito were acquired using web scraping from various websites.Images were then resized to a standard size.All mosquito images were changed to a standard JPEG format.

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[22] Loris Nannia, G. M. (n.d.). Insect pest image detection and recognition based on bio-inspired methods, University of Padova, via Gradenigo 6, Padova 35131, Italy.

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Also, all image sizes have been altered to be uniform.The images were rescaled to improve accuracy. Every image is changed to the.jpg format. Data augmentation is used to create an image dataset, for improving image data, rotation, flipping, and cropping are employed to expand the training set in order to improve accuracy. A dataset of 120 images of each variety of mosquito is converted into multiple images in the augmented dataset by using eight distinct operators, as illustrated in Fig.The files contain 360 and 1440 augmented training mosquito species images, respectively, after augmentation on the training set.
The information is provided in additional data Tables 3.

Table 1. Mosquito classification

Mosquito	classification
Kingdom	Animalia (Animals)
Phylum	Arthropoda (Arthropods)
Subphylum	Hexapoda (Hexapods)
class	Insecta (Insects)
Order	Diptera (Flies)

[Table source[26]]

4.Mosquito((*Culicidae*)

4.1.Taxonomy

The name "Culicidae" is derived from the Latin word "culex," which means "gnat." Mosquitoes belong to the infraorder Culicomorpha within the suborder Nematocera, which also includes other biting insects like midges and black flies. There are approximately 3,200 species of mosquitoes that have been described and recognized within the family Culicidae, although new species are still being discovered [27].

Mosquitoes are notorious for spreading diseases that can be transmitted to humans and other animals through their bites. Some of the most common mosquito-borne diseases include:

1. Malaria: A life-threatening disease caused by a parasite that is transmitted to humans through the bites of infected Anopheles mosquitoes. Malaria can cause fever, chills, and flu-like symptoms, and can be fatal if left untreated.
2. Dengue fever: A viral infection that causes high fever, severe headache, joint and muscle pain, and a rash. Dengue fever is spread by Aedes mosquitoes and can be fatal in some cases.
3. Zika virus: A viral infection that is primarily spread by Aedes mosquitoes. Zika virus can cause fever, rash, joint pain, and red eyes, and can also be transmitted from mother to fetus during pregnancy, which can lead to birth defects.

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[27] D.WALKER, W. A. MOSQUITOES (Culicidae). In W. A. D.WALKER, *Medical and Veterinary Entomology* (pp. Pages 203-262). Sciencedirect, (2002).

4. Chikungunya: A viral infection that causes fever, joint pain, and muscle aches. Chikungunya is spread by Aedes mosquitoes and can cause long-term joint pain in some cases.
5. Yellow fever: A viral infection that can cause fever, chills, headache, and muscle aches, and can progress to more severe symptoms such as liver failure and bleeding. Yellow fever is spread by Aedes mosquitoes and can be prevented by vaccination.

Table 2. Diseases transmitted by mosquitos

Species	Details of diseases spread by them
Aedes	Dengue, lymphatic filariasis, Yellow fever
Anopheles	Malaria
Culex	Japanese encephalitis , Lymphatic filariasis, other viral diseases

[Table source[28]]

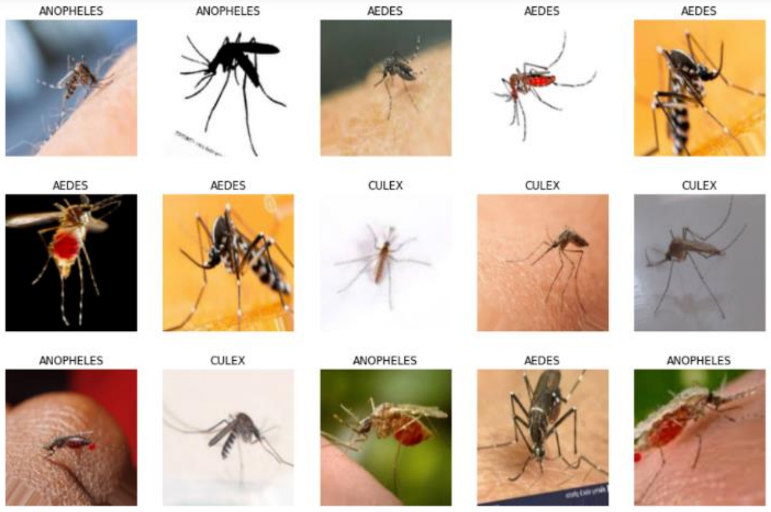


Fig 3.Images from dataset

5. Experiments, Results and Analysis

Mosquito classification is done with the help of convolution neural network. The dataset of 360 images were created by downloading images from differnt websites using webscrapping. Then all images were rescaled in uniform size and type. Using augmentation dataset of 1800 images was created. Details of images in dataset is given in table.

[28] WHO Report Vector-borne diseases https://www.who.int/news-room/fact-sheets/detail/vector-borne-diseases (2020)

Table 3. Dataset details

Mosquito species	Number of mosquitos Before Augmentation	Number of mosquitos After Aumentation
Aedes	120	600
Anopheles	120	600
Culex	120	600

After applying augmentation dataset of total 1800 images are created. Coevolution neural network is applied to both dataset and compared the result. Epoch size is 100 for both the CNN module.

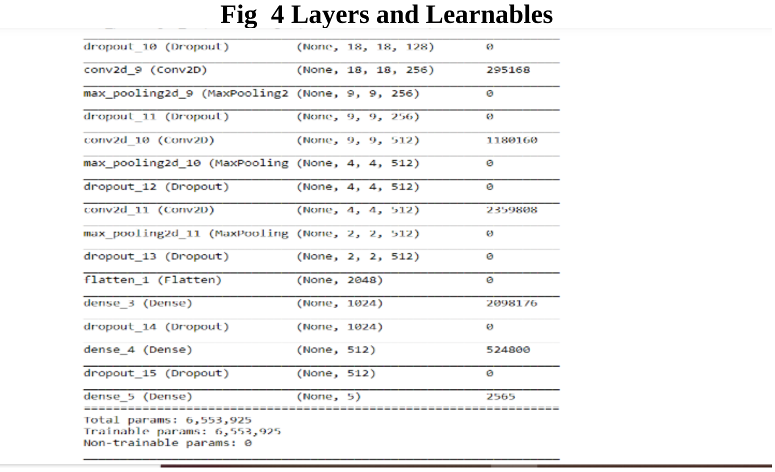
Table .4 Hyper Parameters of CNN

Parameter	Before Augmentation Value	After Aumentation Value
No of Epoch	100	100
Batch size	100	200
Training sample	288	1440
Testing sample	72	360
Optimizer	Adam	Adam

5.1. Disscussions : Comparison of CNNs

The feature from the first layer is transferred over to the second layer, and the outcome is then sent to CNN's hidden layers.Even until the last layer's final output is produced, the process is repeated.The screenshot in Fig. displays the many layers employed as well as the output shapes and learnable items.

Fig 4 Layers and Learnables



dropout_10 (Dropout)	(None, 18, 18, 128)	0
conv2d_9 (Conv2D)	(None, 18, 18, 256)	295168
max_pooling2d_9 (MaxPooling2	(None, 9, 9, 256)	0
dropout_11 (Dropout)	(None, 9, 9, 256)	0
conv2d_10 (Conv2D)	(None, 9, 9, 512)	1180160
max_pooling2d_10 (MaxPooling	(None, 4, 4, 512)	0
dropout_12 (Dropout)	(None, 4, 4, 512)	0
conv2d_11 (Conv2D)	(None, 4, 4, 512)	2359808
max_pooling2d_11 (MaxPooling	(None, 2, 2, 512)	0
dropout_13 (Dropout)	(None, 2, 2, 512)	0
flatten_1 (Flatten)	(None, 2048)	0
dense_3 (Dense)	(None, 1024)	2098176
dropout_14 (Dropout)	(None, 1024)	0
dense_4 (Dense)	(None, 512)	524800
dropout_15 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 5)	2565

Total params: 6,553,925
Trainable params: 6,553,925
Non-trainable params: 0

The maximum number of epochs evaluated for experimentation is set to 100, resulting in an increase in the number of iterations needed to complete the procedure and an increase in image accuracy with each iteration. Table 4 displays the main parameter settings used to train the network, and Figures 5 and 6 provide a screenshot of the classification output from CNN using the training parameter values, number of epochs, number of data, batch size, and optimizer. In order to assess the convolutional neural network's accuracy, predictions are made, compared to test results, and the accuracy is then calculated using the mean. The training network is given t he class labels image as an input in the form of a jpg image. The input information, which is sp ecified as a jpg file and is supplied for testing . To determine the accuracy level, the modelled d ata is compared to the testing data, which acts as the benchmark.

Fig. 5. Classification report before augmentation

```
6
Epoch 95/100
3/3 [==============================] - 10s 3s/step - loss: 0.6490 - accuracy: 0.7083 - val_loss: 0.8138 - val_accuracy: 0.597
2
Epoch 96/100
3/3 [==============================] - 10s 3s/step - loss: 0.6735 - accuracy: 0.6632 - val_loss: 0.7264 - val_accuracy: 0.611
1
Epoch 97/100
3/3 [==============================] - 10s 3s/step - loss: 0.6677 - accuracy: 0.7188 - val_loss: 0.7161 - val_accuracy: 0.611
roll output; double click to hide
Epoch 98/100
3/3 [==============================] - 10s 3s/step - loss: 0.6271 - accuracy: 0.7083 - val_loss: 0.7661 - val_accuracy: 0.625
0
Epoch 99/100
3/3 [==============================] - 10s 3s/step - loss: 0.6705 - accuracy: 0.7118 - val_loss: 0.8086 - val_accuracy: 0.611
1
Epoch 100/100
3/3 [==============================] - 10s 3s/step - loss: 0.6872 - accuracy: 0.6667 - val_loss: 0.7187 - val_accuracy: 0.625
0
```

Fig 6. Classification report after augmentation

```
8
Epoch 95/100
8/8 [==============================] - 48s 7s/step - loss: 0.3666 - accuracy: 0.8424 - val_loss: 1.2156 - val_accuracy: 0.658
3
Epoch 96/100
8/8 [==============================] - 48s 6s/step - loss: 0.3976 - accuracy: 0.8319 - val_loss: 0.8353 - val_accuracy: 0.688
9
Epoch 97/100
8/8 [==============================] - 48s 6s/step - loss: 0.3663 - accuracy: 0.8424 - val_loss: 0.8529 - val_accuracy: 0.694
4
Epoch 98/100
8/8 [==============================] - 48s 6s/step - loss: 0.3400 - accuracy: 0.8590 - val_loss: 1.0450 - val_accuracy: 0.658
3
Epoch 99/100
8/8 [==============================] - 48s 6s/step - loss: 0.3437 - accuracy: 0.8576 - val_loss: 1.0901 - val_accuracy: 0.638
9
Epoch 100/100
8/8 [==============================] - 48s 6s/step - loss: 0.3893 - accuracy: 0.8451 - val_loss: 1.0138 - val_accuracy: 0.652
8
```

Results: For the classification of Ades, Anopheles, and Culex mosquitoes, we employed CNNs both before and after augmentation.After augmentation, our accuracy improved.The accuracy and loss of both CNNs are depicted in a graph before and after.The plot of accuracy and loss versus the number of epochs is shown in Figs. 7 and 8.The accuracy plot demonstrates that accuracy rises as the number of epochs rises, reaching its maximum accuracy of 85.76% after about the 94th epoch.The loss is also observed to be decreasing as the number of iterations rises, going from 1.5 to less than 0.6.

Fig 7 Graph Accuracy and Loss before augmentation

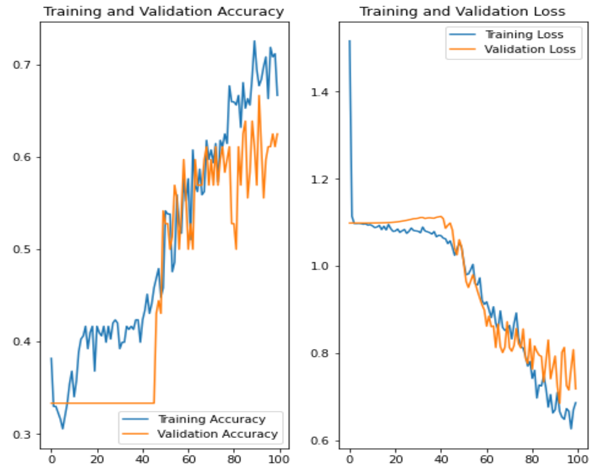
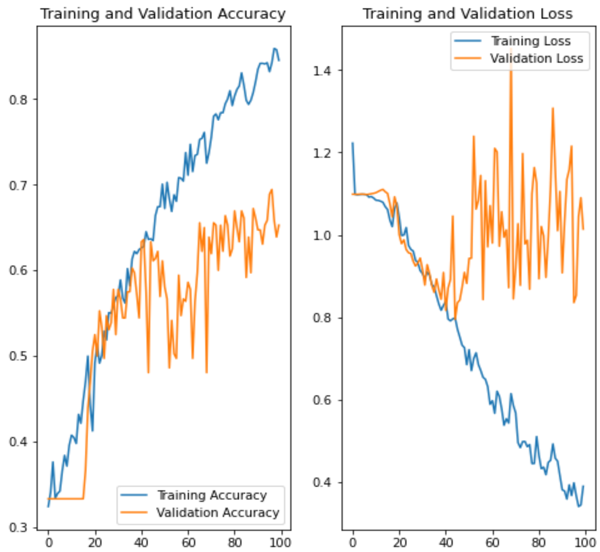


Fig 8 Graph Accuracy and Loss after augmentation



By making predictions, comparing them to the test values, and computing the accuracy based on the mean, the accuracy achieved from this convolutional neural network is calculated. The number of epochs that can be used in an experiment is set to 100 in order to enhance the number of execution iterations and increase the amount of features extracted from the data for increased image accuracy at each epoch. Table 5 compares accuracy and loss data from CNN before and after augmentation.

Table 5 Accuracy and Loss

Classifier	Accuracy	Loss
Before Augmentation	66.67	0.6872
After Augmentation	84.51	0.3493

Conclusion

In this study, a deep learning model based on CNN is proposed to classify visuals of three different mosquito species using a multi-classifier network. Images of Aedes, Anopheles, and Culex mosquitoes are included in the dataset. To identify the images of different mosquito species, we employed a convolution neural network. Since the deep learning model does not require any human labelling to extract the features, the gross incompetence in data prediction is decreased. The classification results are evaluated with those obtained both before and after augmentation. According to the data, CNN's multiclass classifier achieves an accuracy rate of 84.51 percent with a loss of less than 0.3 percent. By adding different architectures into deep learning models, this research can be expanded. Just after datset's augmentation, the model's accuracy improved.

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