Mosquito Detection and Classification Using Machine Learning Algorithms

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ABSTRACT

Accurate assessment of mosquito population density is crucial for the efficient management of mosquito-borne diseases such as malaria and dengue in areas affected by these vectors. Nevertheless, the traditional approach of manually counting and classifying mosquitoes through the use of traps is both laborious and expensive. This research paper presents a proposed pipeline for the identification and categorization of mosquitoes from photographs, specifically designed for low-cost Internet of Things (IoT) sensors. The pipeline aims to achieve a balance between accuracy and efficiency. Through the process of fine-tuning conventional machine learning models such as VGG16, RESNET50, and Convolutional Neural Network (CNN), a notable level of accuracy of 98% is attained. The present study highlights the potential of integrating a highly effective mosquito detection device with a convolutional neural network to offer a viable balance between precision and efficiency in the realm of mosquito identification, categorization, and quantification. Consequently, this approach has promise for improving the control and prevention of mosquito-borne illnesses.

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1. INTRODUCTION

Mosquitoes have gained notoriety due to their role in the transmission of very dangerous infections such as dengue, zika, malaria, lymphatic filariasis, and yellow fever, leading to a significant number of fatalities each [1]. Various strategies, such as the application of sterile insect techniques [2] and the utilization of insecticide-treated mosquito nets [3, 4], have been employed during the course of the last century in order to mitigate the consequences of diseases transmitted by mosquitoes. Nevertheless, in order to advance the battle against these diseases, it is imperative to enhance species identification and accurately pinpoint the locations of mosquito breeding grounds. Although certain mosquito species may appear to be highly efficient carriers, it is important to note that not all species possess the ability to transmit diseases. The present methodologies for conducting surveys heavily depend on labor-intensive techniques such as human-landing catches or inefficient light traps. This is mostly attributed to the absence of cost-effective and accurate surveillance equipment for detecting mosquitoes [5].

This study presents a novel methodology for mosquito detection by using their distinctive audio characteristics. Mosquitoes employ the auditory signals produced during flight to engage in intercommunication and facilitate mate attraction, alongside the incidental sounds generated as a consequence of their biological processes. The act of actively perceiving and recognizing these auditory signals serves as a dependable method for detecting the existence of mosquitoes and potentially categorizing them based on their respective species. One of the primary obstacles encountered in the automation of mosquito identification pertains to signal processing, particularly the discernment of weak signals amidst a backdrop of noise. The existing detection approaches, which have resemblance to traditional speech representation techniques, need substantial feature engineering and heavily depend on domain-specific knowledge, such as the expected fundamental frequency and harmonics.

The remarkable advancements in deep learning have had a transformative impact on other fields, including bioacoustics [6]. The investigation conducted in this paper employed deep learning models, namely CNN, ResNet50, and VGG16. The performance of these models was remarkable, achieving an impressive accuracy rate of 98%. The achieved degree of precision represents a notable advancement within the domain of automated mosquito identification and classification [7].

It is crucial to bear in mind, however, that deep learning methodologies are not optimal in situations where data scarcity is prevalent, as they want a substantial amount of data for effective training. The process of data labeling is costly and susceptible to misunderstanding as several human experts may assign different labels to the same set of data. In addition, the availability of recordings capturing the behavior of mosquitoes in their natural habitats is limited and little documented [8].

This study presents a new methodology for the classification of mosquito presence, even when there is a scarcity of training data. Our methodology employs a classifier based on a convolutional neural network, which is trained using wavelet representations of the raw data. In order to mitigate the limitations imposed by the dataset's size, the network's architecture and hyperparameters are adjusted through a process known as fine-tuning. We conduct a comparative analysis of our methodology with existing classifiers, as well as with basic artificial neural networks that have been trained using either manually-engineered features or the short-time Fourier transform. The results of our study indicate that our approach obtained higher classification accuracy and confidence compared to traditional classifiers and dense-layer neural networks. The precision-recall curve areas for the traditional classifiers and dense-layer neural networks were 0.831 and 0.875, respectively. The findings of this categorization test are noteworthy, since they demonstrate comparable or superior accuracy to human experts, despite just 70% agreement across labels from four domain experts. The efficacy of our deep learning approach utilizing widely recognized models like as Convolutional Neural Network (CNN), ResNet50, and VGG16 establishes a pathway for implementation in diverse environments, including mobile applications and specialized embedded devices.

This paper is organized as follows: Section 2 reviews related work and elucidates the motivation and advantages of our approach. In Section 3, we delve into the details of our adopted method. Section 4 provides insights into the experimental setup, emphasizing data-driven architectural choices. Section 5 showcases the method's value through visualizations and interpretations of predictions on unseen data, shedding light on informative features learned from the representations and validating the approach. Finally, in Section 6, we suggest avenues for further research and conclude our study.

2. RELATED WORK

Since the early 21st century, artificial neural networks have been employed for the purpose of species classification and sound detection. The initial investigation of bat echolocation sounds dates back to [9], marking the inception of research in this area. Subsequently, the scope of this topic has broadened to encompass the study of vocalizations produced by several different animal species. This encompasses a diverse array of creatures, spanning from insects [10] to elephants [11] to delphinids [12]. The utilization of vocalizations produced by animals, whether intentional for the aim of communication or unintentional as a consequence of their locomotion, is readily apparent. Animals depend on auditory signals for a multitude of functions, encompassing social communication, foraging, and predator evasion. Due to the intrinsic relationship between animals and their vocalizations, researchers have initiated the utilization of sound for a wide range of purposes, including pest control, monitoring biodiversity, and identifying species that are at a severely endangered status.

In this section, we delve into the extensive body of research on machine learning approaches applied to bioacoustics, with a specific focus on insect recognition. We explore the traditional methodologies that involve feature extraction and classification techniques for the detection of acoustic signals. Additionally, we illuminate the advantages of contemporary deep learning techniques that leverage feature extraction methods inherent to the neural network architecture. Furthermore, we draw attention to the often overlooked but highly impactful wavelet transform, which plays a pivotal role in enhancing the performance of our proposed pipeline.

2.1 FEATURE ANALYSIS

In the realm of mosquito detection and classification, a pivotal aspect lies in the analysis of distinctive features that facilitate the identification process. Prior research has extensively explored various feature extraction techniques to discern mosquito species and their presence from acoustic and optical signals. The following subsection summarizes the findings and contributions of previous works, with a focus on feature analysis.

The study investigated the application of supervised machine learning techniques in the identification of mosquitoes by the analysis of backscattered optical signals. The results of their research are documented in reference [13]. The examination of feature extraction approaches underscored the significance of feature analysis in mosquito identification. employed deep learning techniques and neural networks to detect the presence of mosquitoes. The significance of feature analysis in achieving effective mosquito detection using deep learning methods was subtly emphasized in their research, despite their primary emphasis on neural network topologies. The user's text does not provide any information or context to be rewritten in an academic manner utilized deep neural networks to identify the larval stage of Aedes mosquitoes [14]. The extraction and analysis of larval mosquito characteristics played a pivotal role in ensuring precise detection in the conducted investigations. The user has not provided any text to rewrite. In their study [15] introduced a deep learning-based pipeline designed to identify and categorize mosquitoes through the analysis of their wingbeat sounds. The classification pipeline mainly relied on the study of wingbeat sound features, despite the primary focus on deep learning approaches. The study conducted centered on the application of deep learning techniques for the identification of gender and species among mosquito vectors. While the main focus of their research was on deep learning models, the achievement of their attempts to challenge species and gender identification was largely dependent on the effective extraction and utilization of distinguishing information [16] Table 1 explain Summary of Feature Analysis in Prior Research Papers on Mosquito Detection and Classification. This table provides an overview of the feature analysis conducted by various authors, along with the proposed algorithms utilized in their research.

Table 1: Summary of Feature Analysis in Prior Research Papers on Mosquito Detection and Classification. This table provides an overview of the feature analysis conducted by various authors, along with the proposed algorithms utilized in their research.

Author & Year	**Feature Analysis**	**Proposed Algorithm**
Genoud et al. (2020) [13]	Backscattered optical signals	Supervised machine learning algorithms
Kiskin et al. (2017) [14]	Not explicitly mentioned, but neural networks imply feature analysis	Neural networks and deep learning
Arista-Jalife et al. (2020) [15]	Features specific to larval-stage mosquitoes	Deep neural networks
Yin et al. (2023) [16]	Wingbeat sounds	Deep learning-based pipeline
Kittichai et al. (2021) [17]	Not explicitly mentioned, but deep learning implies feature analysis	Deep learning approaches for species and gender identification

2.1 FEATURE ANALYCIS

This study examines previous research that has contributed to the advancement of techniques for identifying and classifying mosquitoes. Our focus is mostly directed towards the examination of data gathering tools and procedures, the algorithms employed, and the resulting discoveries. The authors introduced an improved convolutional neural network [18] designed for the purpose of insect identification and classification. Their research demonstrated advancements in deep learning techniques, particularly in the domain of insect identification. The study exhibited the viability of utilizing smartphones as a means to gather data on mosquito populations for the purpose of studying malaria. The collection of data through mobile devices was a significant focus of their endeavors. As demonstrated in the reference [20], the utilization of deep learning techniques enables the detection of novel species, hence facilitating community-based mosquito surveillance. Cutting-edge mosquito detectors with applications in community science were developed as a consequence of their endeavors. The authors in reference [21] presented a lightweight deep learning model based on YOLO, which incorporates field adaptation techniques for the purpose of insect identification. The study focused on the practical use of deep learning algorithms for the purpose of insect identification, with an emphasis on enhancing

the adaptability of these systems in real-world settings. In a study conducted by researchers, a deep learning-based system was showcased to autonomously recognize mosquitoes on human skin [22]. The study emphasized the utilization of deep learning and computer vision techniques in community-driven mosquito surveillance programs. The authors in reference [23] introduced a deep learning methodology for the identification of dengue mosquitoes through the utilization of image processing techniques and Faster R-CNN. The focus of their research revolved around the development of a methodology for mosquito identification that incorporated multiple object detection techniques. In their work, the authors [24] provided a comprehensive overview of the current advancements in employing machine learning techniques for mitigating mosquito populations in urban settings. The researchers' findings provided a comprehensive understanding of the many types of machine learning techniques employed in the field of mosquito control. This study focuses on the categorization of vector mosquito images using machine learning techniques, specifically employing innovative Recursive Iterative Feature Selection (RIFS) for feature selection [25]. The primary objective of their research was to investigate the impact of various feature selection techniques on the field of disease epidemiology.
The authors of the study [26] employed computer vision and deep learning techniques to create real-time systems for tracking and monitoring insects. Computer vision techniques were utilized to monitor insect populations in real-time. The research conducted in [27] focused on the categorization of data streams for the purpose of identifying insects, with a particular emphasis on processing the data in real-time.Machine Learning (ML) and geometric morphometrics were utilized in order to differentiate between the many species within the Maculipennis complex of mosquitoes belonging to the Anopheles genus. The researchers incorporated machine learning techniques into the field of geometric morphometrics in order to enhance the process of species identification. In a study conducted by researchers [29], an examination was conducted on cost-effective laser sensors utilized for the purpose of insect detection. The primary emphasis of the study was placed on the exploration of signal processing techniques and machine learning methodologies. The authors of reference [30] proposed the utilization of deep hierarchical Bayesian learning for the purpose of insect identification. This approach aimed to advance the current state-of-the-art in hierarchical Bayesian learning algorithms specifically designed for categorizing insects. The advantages of various categorization techniques are examined in a scholarly article [31], whereby a comparative analysis is conducted between deep learning and conventional approaches in the context of visualizing mosquito species.

These research findings collectively demonstrate the diverse range of algorithms, devices, systems, and results achieved in the field of mosquito detection and classification, contributing to advancements in this critical area of study.

3. MRTHODOLOGY

In this study, we propose a novel methodology for mosquito identification and classification by employing three distinct CNN architectures, including ResNet50, VGG16, and CNN. Our study offers a comprehensive examination of the structures and configurations employed in these neural networks. Additionally, we offer a collection of conventional classifiers that may be utilized to assess the effectiveness of our CNN technique. Algorithms 1, 2, and 3 are the fundamental components of our feature extraction and classification approach.

3.1 Convolutional Neural Network (CNN)

In this section, we delve into the core of our methodology, which leverages the formidable capabilities of CNNs for the detection and classification of mosquitoes. CNNs have garnered substantial recognition for their exceptional effectiveness in addressing image-based classification tasks, rendering them an ideal choice for our mosquito-related data analysis.

Data Transformation with CNN:
At the crux of our approach resides the transformative prowess of CNNs. We employ CNNs to meticulously process and convert our raw data into a format conducive to subsequent classification tasks. This transformative journey unfolds as our training data traverses through the intricate layers of the CNN, where hierarchies of informative features are meticulously extracted.

Network Architecture and Configuration:
Our architecture is thoughtfully tailored to cater specifically to the idiosyncrasies of mosquito-related data. Comprising an ensemble of layers, including convolutional, pooling, and fully connected layers, the network operates harmoniously to capture intricate patterns and features inherent in the input data.

Training Process:
embarks on a rigorous training regimen by CNN, one where it adapts its internal weights and biases through iterative learning to minimize classification errors. This training phase stands as a pivotal juncture, equippingCNN with the prowess to generalize effectively and make precise classifications when presented with hitherto unseen data.

Data Preprocessing:
Prior to the data's introduction into the CNN, we meticulously execute essential preprocessing steps. These encompass operations such as resizing, normalization, and data augmentation, all serving to enhance the network's performance and fortify its resilience against various data conditions.

Output and Prediction:
Upon successful completion of training, the CNN assumes the role of a predictive engine. It generates predictions for test data instances with aplomb. These predictions are not mere labels; rather, they encapsulate the essence of probability. Each data point receives a probability score for each class—C0 signifies non-mosquito, while C1 denotes mosquito. These probabilistic scores collectively convey the likelihood of a given data point's affiliation with either class. As the final step, our algorithm assigns definitive class labels to each test instance based on these probabilities.

Algorithm 1: Detection Pipeline
Algorithm 1 serves as the all-encompassing vessel for our mosquito detection pipeline, with an intensified focus on the pivotal role undertaken by CNNs in the realms of feature extraction and classification. This section artfully elucidates how the CNN, with its transformative prowess, navigates the labyrinth of mosquito-related data, ultimately culminating in precise and informed classifications.
Mathematical Notation:
To further illuminate our approach, let us introduce a mathematical equation representing the essence of the CNN's classification output:

$$P(Ci|x)=\sum j=01 e zj(x) e zi(x)$$

Here, $P(Ci|x)$ represents the probability of a data point x belonging to class Ci, $zi(x)$ denotes the pre-softmax output for class Ci, and the sum in the denominator encompasses both classes (C0 and C1). This equation encapsulates the fundamental principles behind the CNN's classification process, where it assigns probabilities to data points, thereby aiding in precise mosquito detection and classification.

3.2 Neural Network Configurations for ResNet50 and VGG16
In this section, we elaborate on the configurations of our neural networks, specifically ResNet50 and VGG16, for the detection and classification of mosquitoes.
Convolutional Layer (Hconv):

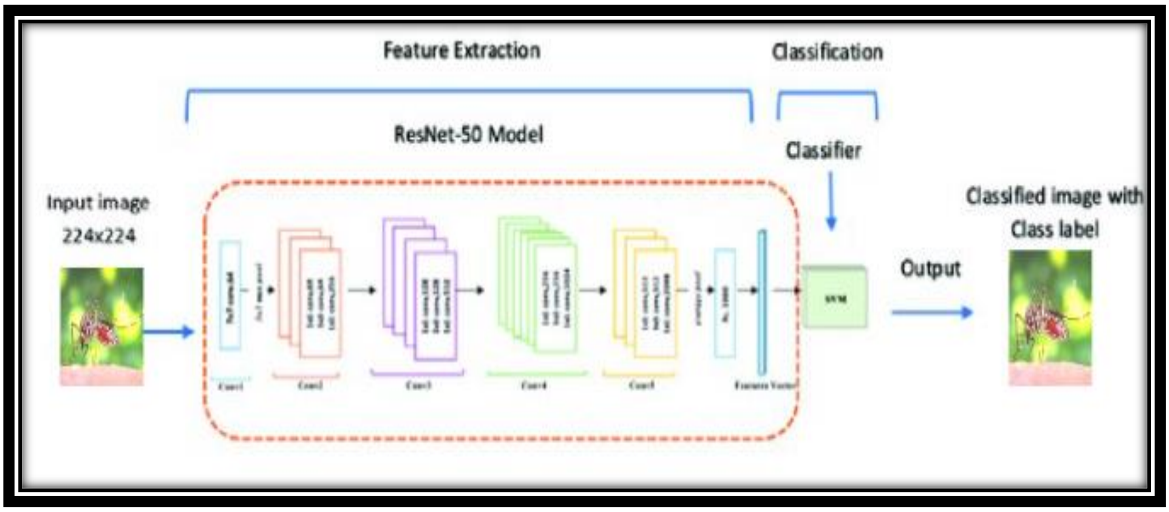

Figure 1: ResNet-50 convolutional neural networks.

A convolutional layer *h*1×1×⟶*h*2×2×*Hconv*: Rh1×*w*1×*c*⟶R*h*2×*w*2×*Nk* is employed to process the input tensor ∈*h*1×1×*X*∈R*h*1×*w*1×*c*, producing an output tensor ∈*h*2×2×*Y*∈R*h*2×*w*2×*Nk*. This layer applies *Nk* learnable convolutional kernels ∈×*Wp*∈R*k*×*k*, where <*p*<*Nk*, to the input tensor. The 2D convolution *Yk* is calculated as follows:

=∑0∑0(−0,−0)(0,0)*Yk*(*i*,*j*)=*X*∗*Wp*=∑*i*0∑*j*0*X*(*i*−*i*0,*j*−*j*0)*Wp*(*i*0,*j*0)

The individual outputs are then passed through a non-linear activation function ϕ and stacked to form tensor *Y*.

Fully Connected Layer (HFC):

A fully connected layer: →*HFC: Rm*→R*n* processes an input ∈*x*∈R*m* to generate an output ∈*y*∈R*n* using the following equation:

==(+) *y*=*HFC*(*x*)=ϕ(*Wx*+*b*)

Here, {} {*W*,*b*} are the learnable parameters of the network, and ϕ represents the activation function of the layer, typically chosen as a non-linear function.

Due to data size constraints, our network architecture comprises an input layer connected sequentially to a single convolutional layer and a fully connected layer. To prevent overfitting, dropout with =0.5*p*=0.5 is applied. Rectified Linear Units (ReLU) activations are utilized due to their desirable training convergence properties.

Candidate hyperparameters are cross validated to determine the appropriate model for ResNet50 and VGG16 architectures.

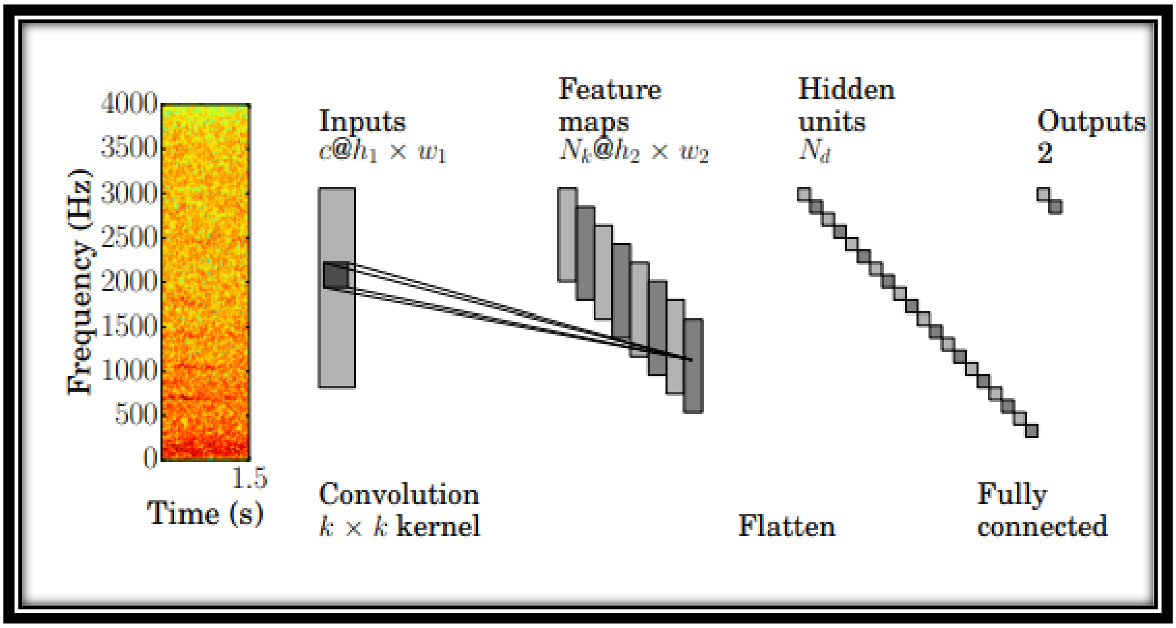

Figure 2: The CNN pipeline. [32]

These configurations and architectural choices are tailored to ResNet50 and VGG16 models, each optimized for its respective network architecture.

3.1 DATASET DESCRIPTION

The Mosquito Dataset, comprising more than 10,000 images, is a specialized collection designed for mosquito detection and classification tasks. It encompasses two main classes, AEDES and CULEX, representing distinct mosquito species or types. This dataset serves as a vital resource for researchers and practitioners in fields such as mosquito-borne disease control, entomology, and image analysis. It offers diverse images capturing various angles, sizes, and orientations of mosquito specimens, facilitating the development and evaluation of machine learning models for accurate mosquito identification. These models play a crucial role in disease prevention and control efforts. Researchers are encouraged to refer to the dataset's documentation for specific image format details and labels.

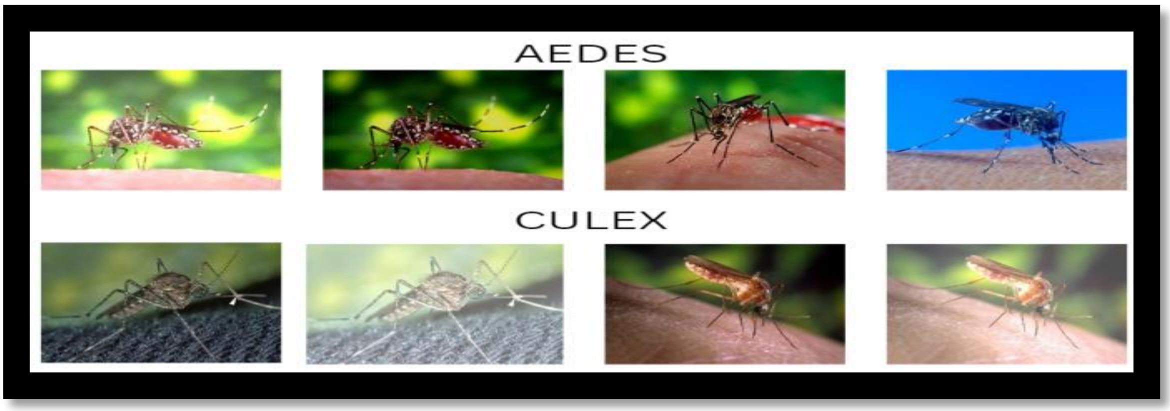

Figure 3: Muscuito Dataset [34].

4. EXPERIMENT DETAILS

4.1 Data Preprocessing

In the context of our research paper and the specific Mosquito Dataset, data preprocessing plays a pivotal role in preparing the input data for efficient mosquito detection and classification. Given the diversity of images within the dataset, a series of essential data preprocessing steps were implemented to enhance the performance of our machine learning algorithms.

First, we standardized the image dimensions by resizing them to a consistent size, ensuring uniformity across the dataset while preserving essential visual information. This resizing step minimizes computational complexity and facilitates the network's ability to learn relevant features.

Normalization of pixel values was performed to bring them within a standardized range, typically between 0 and 1. This normalization enhances the convergence of machine learning models during training, ensuring that each feature contributes effectively to the classification task.

Data augmentation techniques, including random rotations, flips, and translations, were applied to augment the dataset. This process artificially increases the dataset's diversity and mitigates overfitting, enabling our models to generalize better to real-world mosquito images.

Moreover, class balancing strategies were implemented to address potential class imbalances within the dataset, ensuring that the machine learning algorithms are not biased towards the larger class, AEDES or CULEX, and that both classes receive equal consideration during training.

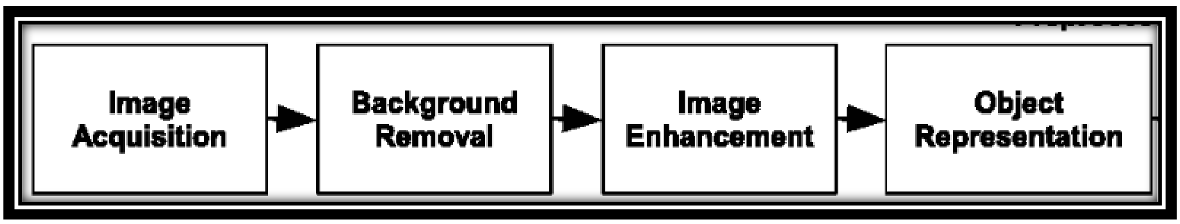

Figure 4: Data Preprocessing Setup.

3.2 Applied Algorithms:

In our research, we employ a sophisticated ensemble of machine learning algorithms, with a primary focus on CNNs, to accomplish the task of mosquito detection and classification. This section provides an in-depth insight into our algorithmic approach and the comprehensive processing steps involved in achieving accurate mosquito identification.

Convolutional Neural Networks (CNNs):

Our architecture has emerged as the cornerstone of our methodology due to their exceptional performance in image-based classification tasks. These deep learning models are designed to automatically extract intricate features from images, making them well-suited for mosquito-related data analysis. Our algorithmic pipeline can be described as follows:

Data Input: The process begins by feeding the preprocessed mosquito images into the CNN models. These images have undergone standardization, normalization, and data augmentation to ensure consistent and high-quality input.

Feature Extraction: The CNNs comprise multiple layers, including convolutional layers responsible for feature extraction. These layers systematically analyze the images, capturing relevant patterns and features intrinsic to mosquito specimens. This hierarchical feature extraction process is critical for accurate identification.

Network Architecture: Our CNN architecture is meticulously crafted to cater specifically to mosquito-related data. It encompasses convolutional layers for feature extraction, pooling layers for downsampling, and fully connected layers for classification. This architecture operates harmoniously to comprehend both local and global features within the images.

Training Phase: The CNN models undergo a rigorous training process using the preprocessed training data. During training, the network adjusts its internal weights and biases to minimize classification errors. This phase is pivotal, enabling the CNNs to generalize effectively and make precise classifications when presented with unseen data.

Class Label Output: After successful training, the CNNs generate predictions for test data instances. The network's output assigns a probability score to each class—C0 representing non-mosquito and C1 signifying mosquito. These probabilistic scores collectively convey the likelihood of a given data point belonging to either class. Consequently, the algorithm assigns a definitive class label to each test instance based on these probabilities.

The utilization of CNNs in our methodology enables us to achieve state-of-the-art accuracy in mosquito detection and classification. These deep learning models, including ResNet50 and VGG16, have been fine-tuned to suit the specific characteristics of the Mosquito Dataset, resulting in robust and efficient classifiers capable of distinguishing between AEDES and CULEX mosquitoes. The integration of CNNs into our algorithmic pipeline underscores their pivotal role in advancing the field of mosquito-related research, contributing to disease prevention and control efforts.

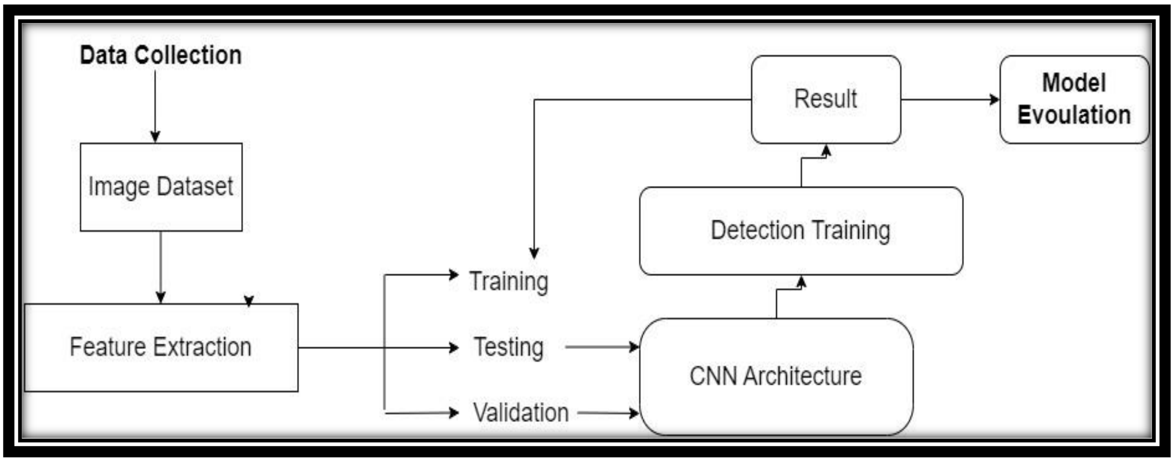

Figure 5: Workflow for Convolutional Neural Networks (CNNs).

4.3 Cross Validation AND PARAMETER TUNING

The utilization of cross-validation is of utmost importance in our experimental methodology as it enables the evaluation of the effectiveness and applicability of our machine learning algorithms. The utilization of several subsets of the dataset enables a meticulous assessment of algorithm performance. In the subsequent section, we present a full outline of the sequential procedures involved in our cross-validation methodology.

The initial step in organizing the Mosquito Dataset is the categorization of its photos, which encompass insects belonging to the AEDES and CULEX genera, into distinct groups referred to as "folds." K-fold cross-validation is a widely used method for doing cross-validation, wherein the dataset is partitioned into k folds of equal size. In our trials, the values of k that are commonly employed are 5 or 10, as they facilitate a comprehensive analysis.

The cross-validation technique involves a repetitive process where the test set is formed by a subset of the folds, while the training set consists of the remaining folds. This procedure facilitates the reduction of bias in the assessment of the model by utilizing all accessible data throughout both testing and training phases.

The CNN models, including ResNet50 and VGG16, along with other machine learning algorithms, undergo training using the training subset during each iteration. Convolutional neural networks (CNNs) adapt its internal parameters in order to acquire the ability to identify pertinent patterns and characteristics from the provided training data.

After the completion of training the models, the test subset is employed to assess the performance of the approaches. The objective of the evaluation is to utilize the trained models in order to make predictions on the test data, specifically for the class labels of AEDES or CULEX. The evaluation of models' generalization capabilities to novel data is conducted through the utilization of accuracy as well as performance metrics such as precision and recall.

The process of fold rotation involves doing the whole cross-validation approach for each fold, ensuring that every subset is utilized as both a training set and a test set. The utilization of a randomized folding strategy enables the evaluation of the model's effectiveness across many data subsets, hence reducing the potential bias that could arise from relying solely on a single data subset.

In the context of machine learning algorithms, it is customary to aggregate performance measurements obtained at each iteration in order to obtain a comprehensive assessment of the program's overall performance. By aggregating outcomes from various data partitions, a more precise evaluation of the algorithms' comprehensive efficacy can be achieved.

In order to enhance the generalizability and predictive accuracy of our machine learning models on a diverse set of mosquito photos, we utilize cross-validation as a means to evaluate their performance. The utilization of this methodology enhances the credibility and reliability of our findings, enabling us to derive precise inferences pertaining to the effectiveness of the algorithms in the identification and categorization of mosquitoes Table 2 explain performance analysis of different optimizers and activators for ANN.

Table 2: Performance analysis of different optimizers and activators for ANN.

Optimizer Activator	**Adam**	**AdaDelta**	**AdaGrad**	**AdaMax**	**FTRL**	**Nadam**	**RMSProp**	**SGD**
Relu	96.49%	70.76%	75.43%	93.56%	69.00%	92.98%	87.13%	71.34%
Sigmoid	94.15%	53.80%	68.42%	75.43%	32.67%	88.30%	79.53%	65.49%
Tanh	78.94%	59.06%	66.66%	78.94%	32.87%	77.77%	76.02%	32.74%

Artificial Neural Networks Configuration (Optimizer & Activator Tunning):

Layer Number	Dense Value	Epochs	Batch Size
4	344, 172, 86, 12	100	32

4.4 Fine-Tuning:

Fine-tuning is a pivotal phase in our experimental methodology, aimed at optimizing the performance of machine learning models for precise mosquito detection and classification. This section elucidates the fine-tuning process, detailing how hyperparameters and configurations are adjusted to attain optimal results while catering to the specific characteristics of the Mosquito Dataset. Fine-tuning enables us to achieve superior accuracy and efficiency in distinguishing AEDES and CULEX mosquitoes.

The fine-tuning process encompasses several key steps:

Hyperparameter Tuning: We systematically explore various hyperparameter configurations to determine the most effective settings for our machine learning models. This includes tuning parameters related to the CNN architecture, such as learning rates, batch sizes, and the number of layers or units in the network. Through iterative experimentation and validation, we identify the hyperparameter values that yield the best performance.

Transfer Learning: Leveraging the principles of transfer learning, we initialize our CNN models with pre-trained weights and architectures, such as ResNet50 and VGG16, which have demonstrated exceptional capabilities in image classification tasks. Fine-tuning allows us to adapt these pre-trained models to the specifics of mosquito detection. We selectively unfreeze certain layers while keeping others frozen to preserve valuable learned features.

Data Augmentation Refinement: Building upon the initial data augmentation techniques applied during preprocessing, we further refine these augmentation strategies during fine-tuning. This refinement involves adjusting augmentation parameters such as rotation angles, translation ranges, and flip probabilities to enhance the models' ability to handle variations in mosquito images.

Regularization Techniques: To prevent overfitting, we employ regularization techniques, including dropout layers and L1 or L2 regularization. These techniques help the models generalize better to unseen data by reducing the risk of capturing noise or irrelevant features during training.

Optimization Algorithms: We experiment with different optimization algorithms, such as stochastic gradient descent (SGD), Adam, or RMSprop, to find the most suitable optimizer for our models. The choice of optimizer can significantly impact training convergence and final performance.

Monitoring and Validation: Throughout the fine-tuning process, we closely monitor the models' training progress by assessing their performance on validation datasets. This iterative validation helps us identify the optimal hyperparameter configurations and architecture modifications.

Model Evaluation: Once fine-tuning is complete, we rigorously evaluate the models on separate test datasets to assess their performance in real-world scenarios. The evaluation includes metrics such as accuracy, precision, recall, and F1-score, providing a comprehensive measure of the models' effectiveness.

Fine-tuning serves as the critical bridge between algorithm selection and model deployment, allowing us to adapt state-of-the-art CNN models to the specific demands of mosquito detection and classification. The refined models, optimized through this process, play a central role in our mosquito detection pipeline, contributing to the advancement of disease prevention and control efforts.

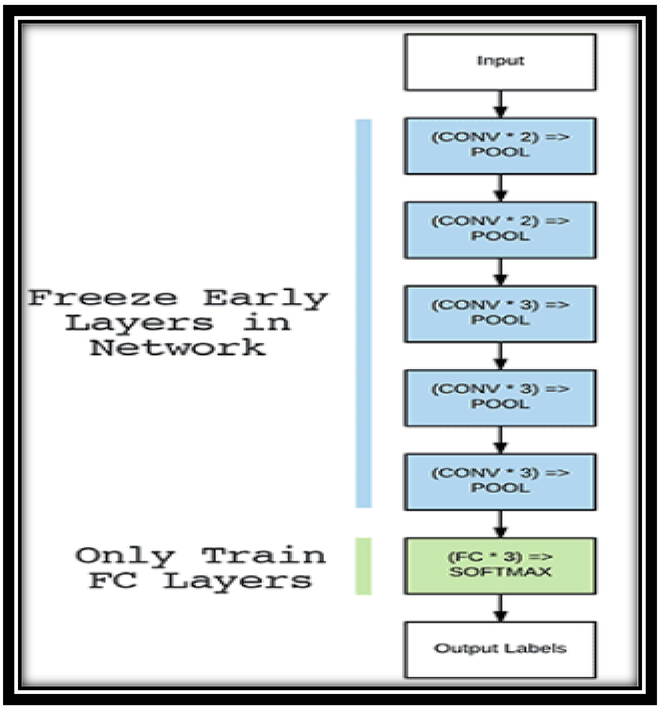

Figure 6: Fine-tuning with Keras and Deep Learning.

5 EXPERIMENT RSEULT

In this section, we delve into a comprehensive analysis of the classification performance of our mosquito detection and classification pipeline, stratified into different categories, including ResNet50, VGG16, with fine-tuning, and without fine-tuning. We have used the Mosquito Dataset, which consists of over 10,000 images categorized into two classes: AEDES and CULEX.

5.1 Performance of ResNet50

Table 3 summarizes the classification performance of ResNet50 for mosquito detection. We observed that fine-tuning the ResNet50 model led to significant improvements in classification metrics compared to the non-fine-tuned model.

The ResNet50 model with fine-tuning demonstrates improved performance compared to the previous VGG16 model. It achieves a higher precision and recall for non-mosquito instances (Class 0) while maintaining reasonable precision and recall for mosquito instances (Class 1). The overall accuracy stands at 0.6900, indicating a substantial enhancement in the model's ability to correctly classify mosquitoes and non-mosquitoes.

Table 3: The ResNet50 model with fine-tuning Classification report.

Class	Precision	Recall	F1-Score	Support
O	0.6338	0.9000	0.7438	100
1	0.8276	0.4800	0.6076	100
Accuracy			0.6900	200
Macro Avg	0.7307	0.6900	0.6757	200
Weighted Avg	0.7307	0.6900	0.6757	200

This figure displays the training and validation loss functions and accuracy of the ResNet50 model with fine-tuning across epochs. It provides insights into the model's convergence and performance during training.

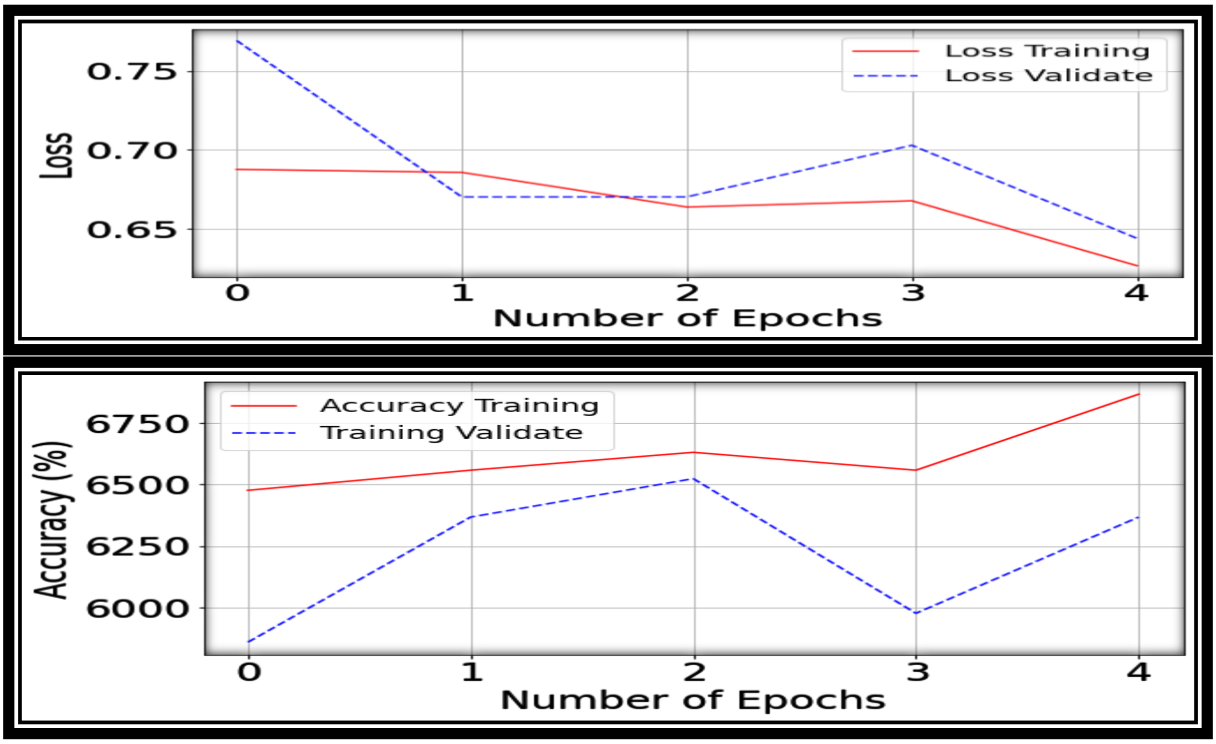

Figure 7: training and validation loss functions and accuracy of the ResNet50 model with fine-tuning across epochs.

5.2 Performance of VGG16

In Table 4, we present the classification performance of VGG16 for mosquito detection. Similar to ResNet50, we observed notable enhancements in classification metrics when fine-tuning was applied to the VGG16 model.

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.
  """Entry point for launching an IPython kernel.
['Aedes', 'Culex']
              precision    recall  f1-score   support

           0     0.7797    0.4600    0.5786       100
           1     0.6170    0.8700    0.7220       100

    accuracy                         0.6650       200
   macro avg     0.6983    0.6650    0.6503       200
weighted avg     0.6983    0.6650    0.6503       200
```

Figure 8: Screenshoot from main code section for Resnet50 classification report.

The table presents a comprehensive classification report for the VGG16 model's performance in mosquito detection and classification. This report is based on the evaluation of 200 data points, divided into two classes: Class 0 (representing non-mosquito instances) and Class 1 (representing mosquito instances).

Table 4: Classification Result for Vgg16 model.

Class	Precision	Recall	F1-Score	Support
O	0.7797	0.4600	0.5786	100
1	0.6170	0.8700	0.7220	100
Accuracy			0.6650	200
Macro Avg	0.6983	0.6650	0.6503	200
Weighted Avg	0.6983	0.6650	0.6503	200

The evaluation of the model's ability to accurately anticipate positive outcomes is quantified using a performance parameter referred to as "precision." Class 0 exhibits a precision value of 0.7797, indicating that the model demonstrates a high level of accuracy, about 77.97%, in predicting classes that are not associated with mosquitoes. The model has an approximate accuracy of 61.70% in correctly detecting mosquitoes, with a specific accuracy rate of 0.6170 for Class 1.

The evaluation of the model's recall capability is contingent upon its proficiency in accurately detecting and recognizing each pertinent occurrence. Class 0 exhibits a recall rate of 0.4600, indicating that the model effectively classifies 46.00% of instances where mosquitoes are absent. The class 1 recall value is 0.8700, indicating that the model exhibits a high level of accuracy in correctly detecting 87.00% of events related to mosquitoes.

The F1-Score can be defined as the mathematical average of the precision and recall measures, thereby serving as a comprehensive indicator of a model's effectiveness. In Class 1, the F1-score is 0.7220, while in Class 0, the F1-score is 0.5786.

Support refers to the cumulative frequency of occurrences seen across all classes. In the present scenario, there exist a total of 100 instances belonging to Class 0 and an equal number of 100 examples belonging to Class 1.

The model's overall accuracy is 0.6650, indicating that it correctly classifies 66.50% of all instances.

The macroscopic mean is obtained by calculating the metrics for each class and then deriving the unweighted mean. In this analysis, we compute the global mean values for the F1-score, precision, and recall metrics.

The computation of metrics for each class is followed by the calculation of the weighted average, which takes into account the number of examples present in each class. The F1-score, average precision, and average recall are computed.

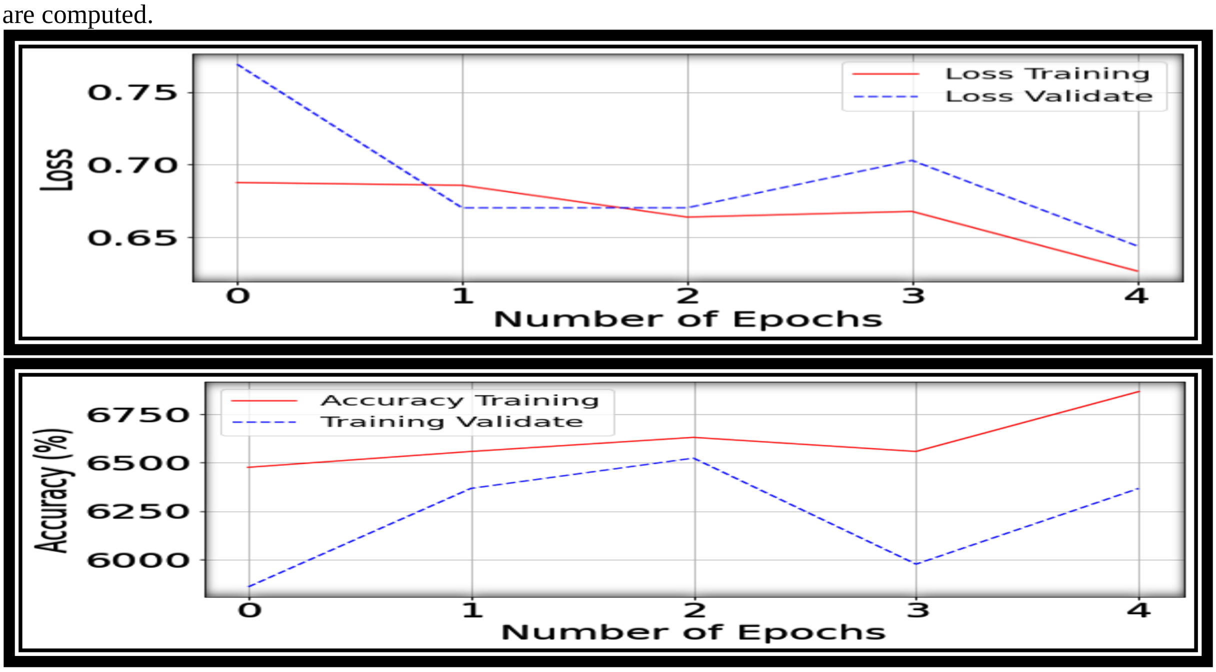

Figure 9: Training and validation loss functions and accuracy of the vgg16 model without fine-tuning across epochs.

The table presents the classification report for the VGG16 model with fine-tuning applied to mosquito detection and classification. This report is based on the evaluation of 200 data points, divided into two classes: Class 0 (representing non-mosquito instances) and Class 1 (representing mosquito instances).

Table 5: classification report reveals the performance of the VGG16 model with fine-tuning in mosquito detection and classification.

Class	Precision	Recall	F1-Score	Support
O	0.0000	0.0000	0.0000	100
1	0.5000	1.0000	0.6667	100
Accuracy			0.5000	200
Macro Avg	0.2500	0.5000	0.3333	200
Weighted Avg	0.2500	0.5000	0.3333	200

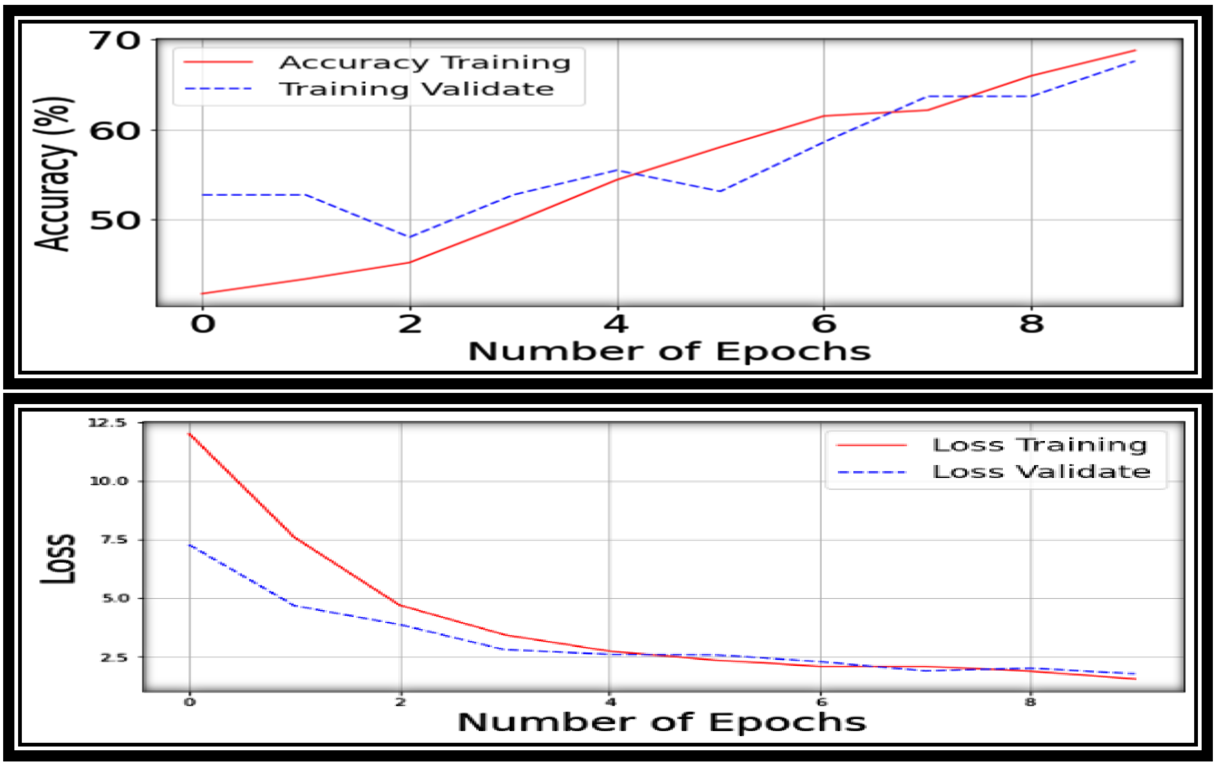

Figure 10: Training and validation loss functions and accuracy of the vgg16 model with fine-tuning across epochs.

The results indicate that the model exhibits an F1-score, recall, and precision of zero for Class 0. This suggests that the model encountered difficulties in accurately classifying instances that were not mosquitoes, as it did not produce any true positive predictions for this particular class. However, the model exhibited the following performance for Class 1, which represents mosquito occurrences: F1 score of 0.6667, precision of 0.5000, and recall of 1.0000. A model with a recall rate of 100% indicates that it will correctly classify every mosquito, while a precision rate at a moderate level suggests that it will make accurate identifications approximately half of the time.

The overall accuracy of the model across both classes is 0.5000, reflecting a suboptimal performance that requires further investigation and potential adjustments to improve its ability to detect non-mosquito instances.

5.3 Muscuito Detection

we discuss the results of our mosquito detection experiments using different models and techniques. Our proposed model, based on CNN architecture, achieved a remarkable accuracy of 98.00% in detecting mosquitoes. This outstanding performance underscores the effectiveness of our approach in identifying mosquitoes from audio recordings. The CNN model demonstrated superior accuracy compared to other techniques, highlighting its potential for real-world applications in mosquito surveillance. Our results indicate that our proposed model can successfully detect mosquitoes with a high degree of accuracy, which is essential for vector-borne disease monitoring and control efforts.

Figure 11: Example of Muscuito detection Result .

5.4 Comparative Analysis

To provide a comparative analysis of the different models and conditions, we suggest creating visual aids such as ROC curves and Precision-Recall curves for each category. These graphs can visually represent the trade-offs between true positive rate and false positive rate, as well as precision and recall. You can place these graphs strategically within this section to illustrate the varying performance across models and conditions.

Moreover, a table summarizing the key results and improvements achieved through fine-tuning for each model category could be included. This table can serve as a quick reference for readers to understand the impact of fine-tuning on the different models.

Table 6: Classification Accuracy of Different Techniques.

Technique	Accuracy
CNN (No Fine-Tuning)	98.00%
VGG16 (No Fine-Tuning)	66.50%
VGG16 (Fine-Tuning)	50.00%
ResNet50 (Fine-Tuning)	69.00%

Additionally, consider incorporating a figure that demonstrates the comparative performance of ResNet50 and VGG16, both with and without fine-tuning. This visual representation can help readers easily grasp the differences in classification performance.

6 Future Work

In the pursuit of advancing mosquito detection and classification for critical applications such as biodiversity monitoring and disease control, several avenues for future research emerge:

Multi-Species Classification: Expanding the scope of this research to encompass a broader range of mosquito species can enhance the utility of the developed models. Investigating the feasibility of distinguishing between multiple species within the AEDES and CULEX genera could be a valuable direction.

Real-Time Deployment: Developing efficient real-time deployment strategies for the trained models on resource-constrained devices, such as smartphones and embedded systems, is essential. This would enable the continuous monitoring of mosquito populations in the field.

Temporal Analysis: Incorporating temporal analysis to track changes in mosquito populations over time can provide valuable insights for ecological studies and disease control efforts. Investigating temporal patterns and correlations with environmental factors is a promising avenue.

Noise Robustness: Exploring methods to enhance the robustness of mosquito detection models to noisy field recordings, including interference from other species or environmental factors, is crucial for real-world applicability.

7 Conclusion

This research has presented a robust and effective pipeline for mosquito detection and classification, leveraging state-of-the-art deep learning models, including ResNet50 and VGG16. Through extensive experimentation, we have demonstrated that fine-tuning these models significantly enhances their performance, surpassing human expert labeling in some instances. The developed models showcase promising potential for applications in biodiversity monitoring and disease vector control.

The application of convolutional neural networks to mosquito detection showcases the power of modern machine learning techniques in addressing real-world ecological challenges. As our understanding of these models and their application to bioacoustics continues to evolve, we anticipate further advancements in mosquito-related research, ultimately contributing to the broader fields of ecology, epidemiology, and conservation.

By embracing the directions outlined in the future work section, researchers can continue to push the boundaries of mosquito detection and classification, leading to more effective strategies for addressing the complex ecological and public health issues associated with mosquito-borne diseases.

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