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Vector mosquito image classification using novel RIFS feature selection and machine learning models for disease epidemiology



Furqan Rustam^a, Aijaz Ahmad Reshi^{b,*}, Wajdi Aljedaani^c, Abdulaziz Alhossan^{d,e}, Abid Ishaq^a, Shabana Shafi^b, Ernesto Lee^{f,g,*}, Ziyad Alrabiah^d, Hessa Alsuwailem^d, Ajaz Ahmad^d, Vaibhav Rupapara^h

^a Department of Computer Science, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan 64200, Pakistan

^b Department of Computer Science, College of Computer Science and Engineering, Taibah University, Al Madinah Al Munawwarah, Saudi Arabia

^c Department of Computer Science and Engineering, University of North Texas, Denton, TX, USA

^d Department of Clinical Pharmacy, College of Pharmacy, King Saud University, Riyadh 11451, Saudi Arabia

^e Corporate of Pharmacy Services, King Saud University Medical City, Riyadh, Saudi Arabia

^f Department of Computer Science, Broward College, Broward County, FL, USA

^g Baker College, Department of Business Administration, USA

^h School of Computing and Information Sciences, Florida International University, USA

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ABSTRACT

Every year about one million people die due to diseases transmitted by mosquitoes. The infection is transmitted to a person when an infected mosquito stings, injecting the saliva into the human body. The best possible way to prevent a mosquito-borne infection till date is to save the humans from exposure to mosquito bites. This study proposes a Machine Learning (ML) and Deep Learning based system to detect the presence of two critical disease spreading classes of mosquitoes such as the Aedes and Culex. The proposed system will effectively aid in epidemiology to design evidence-based policies and decisions by analyzing the risks and transmission. The study proposes an effective methodology for the classification of mosquitoes using ML and CNN models. The novel RIFS has been introduced which integrates two types of feature selection techniques – the ROI-based image filtering and the wrappers-based FFS technique. Comparative analysis of various ML and deep learning models has been performed to determine the most appropriate model applicable based on their performance metrics as well as computational needs. Results prove that ETC outperformed among the all applied ML model by providing 0.992 accuracy while VVG16 has outperformed other CNN models by giving 0.986 of accuracy.

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1. Introduction

Every year mosquitoes cause notable damage to human populations as they spread deadly infectious diseases like yellow fever, malaria, encephalitis (Thomas et al., 2016). It is supposed that half of the world's population is at risk of dengue fever, which also spreads by mosquitoes (W.H. Organization et al., 2020). There is also solid evidence of an outbreak of combined infection of dengue and chikungunya pathogens in humans (Furuya-Kanamori

et al., 2016). For the age group of nine years and above a renowned vaccine Sanofi PasteurCYD-TDV for dengue shows its efficiency around 65.5% and for the age group under nine-year, its efficiency decreases to 46.6% (Hadinegoro et al., 2015). The major means of transmission of dengue, chikungunya, zika, and yellow fever include mosquitoes such as Aedes, Anopheles, and Culex (Roth et al., 2014; Jasinskiene et al., 1998).

Mosquitoes are very small flying insects that have the ability to hide anywhere. Use of the pesticides and fogs has difficulty permeating into these hideouts. Mosquito nets show some ability to prevent them but this is not the perfect solution for decreasing the mosquitoes' proliferation. Entomological characterizations the basic tool for obtaining information about mosquitoes. Aedes and Culex are the two notorious types of mosquitoes. They are famous for spreading deadly diseases (W.H. Organization, 2021). Aedes and Culex are common types of mosquitoes, which are present commonly in almost every part of the world under all suitable

* Corresponding author.

E-mail addresses: aijazonnet@gmail.com (A.A. Reshi), elee@broward.edu (E. Lee).

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weather conditions. Dengue fever is being spread by the *Aedes albopictus* and *Aedes Aegypti* (T. center for disease control, 2021). On the other hand, *Culex tritaeniorhynchus* and *Culex annulus* are infamous for the spread of Japanese Encephalitis (D. control center Taiwan, 2021). While studying the works related to the diseases transmitted by the mosquitoes demands an efficient automatic system for the detection, and classification of the mosquitoes.

To contribute to this important and critical disease spread domain, it demands an efficient automatic information system for the detection and classification of the special types of mosquitoes. The system will aid the health authorities and other stakeholders to check the presence of any disease spreading mosquito in the area of their interest. The proposed system will effectively aid in epidemiology to design evidence-based policies and decisions by analyzing the risks and transmission. It will prepare the authorities to take preventive measures in the targeted areas to control its spread at the right time. This study proposes an effective methodology for the classification of mosquitoes using the deep learning approach.

The dataset used in this study has been obtained from IEEE dataset contain to the type of mosquito images (Reshma Pise, 2020). The proposed system uses different techniques in data preprocessing to ensure the maximum classification performance as well as to explore the methods to classify the images using the lowest possible computational efforts. These preprocessing techniques include data augmentation and the proposed feature selection approach RIFS, a hybrid approach based on Image processing filters to focus on specific parts of an image which is significant in classification, and forward features selection (FFS) to select the best features from the ROI based RGB feature sets.

As a first step towards preprocessing the data augmentation has been performed to increase the size of training data (Reshi, 2021). After data augmentation, the feature selection has been done using the RIFS approach to select the specific features for the learning of models. The proposed machine learning (ML) and convolutional neural networks (CNN) have been used to learn on RIFS generated features. The performance of the models has been evaluated in terms of accuracy, precision, recall, and F1-score.

The key points of the study are:

- This study performs the classification of mosquitoes (*Aedes* and *Culex*) using ML and deep learning approaches.
- Data pre-processing has been done using data augmentation and the proposed novel feature selection technique RIFS which improves the performance and reduces the computational cost of the models
- A strong comparison has been done with the baseline pre-trained and well-tuned models that have been done in this study
- Results show that ML models can also perform well in image classification if the datasets are preprocessed properly models are tuned well.

The rest of the paper is divided into four sections. Section 2 contains the related work of the study, Section 3 contains the detailed description of the dataset, proposed methodology, and techniques. Section 4, contains the results of the experiments, Section 5 presents the discussion and Section 6 contains the conclusion of the study.

2. Related work

Mosquito classification has gained much interest by researchers to work. Recent studies proposed different classification

approaches, but efficiency and computational complexity are still a tradeoff in most of the research studies conducted so far. Several researchers have performed studies in this domain such as Garcia et al (Garcia et al., 2018) worked on the classification of mosquito larva. They used machine learning classifiers support vector machine (SVM) and K-means with low features like local binary pattern (LBP), co-occurrence matrix (CM), and Gabor filtering features (FG2). In their study, they used 308 images of “*Aedes*” and “others”. Feature extraction was used for classification. The obtained results show that K-mean accuracy on low features and local binary pattern (LBP), co-occurrence matrix (CM), and Gabor filtered features (FG2) the Achieved accuracy was 59% for CM, 55% LBP, and 60% for the FG2. On the other hand, the accuracy achieved by the SVM was 67% for CM, 72% on LBP, and 79% for FG2.

Ortiz et al (Ortiz et al., 2018). Proposed a system for mosquito larva classification by using a VGG16 pre-trained convolutional neural network. The dataset used in their work was consisting of two types of mosquitoes: *Aedes* and other genera. For training purposes, they used different values of epochs. Due to the pre-trained bottleneck features, they achieve the highest accuracy of 97%. Therefore, the localization of vectors could be accurate and the process of fumigation could be more efficient.

In continuation of their work Ortiz et al (Sanchez-Ortiz et al., 2017) used AlexNet CNN for the classification of mosquitoes. They used images of eight segments of the larva. The images they have used in the study were obtained from the smart phone. They used nearly 300 images in their study. The number of iterations performed to increase the accuracy. On the 200 epochs, the proposed network achieved an accuracy of 96.8%.

Okayasci et al (Okayasu et al., 2019) used (Sanchez-Ortiz et al., 2017) types of features in their work. They used handcrafted feature extraction and SVM for the classification. They built their dataset consisted of 14,460 images of mosquitoes with the three different types of mosquito species. This study compared the conventional and deep learning methods. Conventional methods provided the highest accuracy of 82.4% while the accuracy given by the deep learning model was 95.5% in the residual network using data augmentation. Data augmentation has been proved helpful for the classification of mosquito species.

Motta et al (Motta et al., 2019) used a convolutional neural network to perform automatic morphological classification of mosquitoes. They used LeNet, GoogleNet, and AlexNet in their study. By using GoogleNet, they achieved an accuracy of 76.2%. The dataset used in their studies consisted of 4056 images of mosquitoes. Li-Pang et al (Huang et al., 2018) worked on the automatic classification of mosquitoes which can identify *Aedes* and *Culex* (species of mosquitoes). They used edge computing and deep learning in their work. They implemented their system with the help of IoT-based devices. The highest accuracy they have achieved was 90.5% on test data.

Fuchida et al (Fuchida et al., 2017) worked on vision-based perception and classification of mosquitoes. Their proposed system has the capacity to identify mosquitoes from the other bugs (bees, flies) by extracting morphological features. They used the machine learning algorithm SVM variants in their work. SVM-II achieved an accuracy of 85.2% for mosquitoes and 97.6% for the bugs, and SVM-III achieved an accuracy of 98.9% for the mosquitoes and 92.5% for bugs.

Fuad et al. (Fuad et al., 2018) classified *Aedes Aegypti* larvae and float value with three different learning rates. They have used 534 images in their study. They achieved the highest accuracy of 99%. They have compared the values of their accuracy and cross-entropy errors of the training set with the different learning rates. Minakshi et al. (Minakshi et al., 2017) proposed a learning algorithm that was designed to process the image of a mosquito taken by the mobile phone camera to identify the species of the

mosquitos. The sample size was 60 images and seven species were used in their study. Random forest achieved the highest accuracy was 83.3% with good precision and recall value. As the dataset was of only 60 images so, it was not very suitable for classification.

Fahioudakis et al. (Fanioudakis et al., 2018) worked on a large-scale classification experiment based on optical recordings of six different species of mosquitoes. They study the signal and attributes of a mosquito's wing beat. They have used 279,566 flight sound beats of mosquitoes and used top-tier deep learning approaches for the implementation of classification. They reached an accuracy of 96%.

Akter et al. (Akter et al., 2020) used CNN with data augmentation for mosquito classification. Their dataset contains was 442 images. They used random forest, SVM, XGBoost, and CNN (VGG16). CNN outperforms the other classifiers in terms of accuracy where it gives the accuracy of 93%. After augmentation of images, the number of images was 36000. Junyony Park et al. (Park et al., 2020) worked on the morphological analysis of vector and classification of mosquitoes. They have collected 3600 images of eight different species of mosquitoes. They used CNN and achieved an accuracy of 96.6%. The summary of related work is present in Table 1.

The proposed system uses data pre-processing technologies to achieve maximum classification performance and explore the methods to classify the images using minimum computational complexity. These pre-processing techniques include data augmentation, Region of interest (ROI) based image slicing to focus on specific body parts of the mosquito image, forward features selection (FFS) to select the best features from RGB feature sets. The image classification has been done using different ML and Deep learning models to analyze each approach and model for its best performance and computational complexity. The proposed study uses Aedes and Culex dataset obtain from IEEE data port.

3. Materials and methods

3.1. Dataset description

This study uses an open-access image dataset of Aedes and Culex mosquitoes species (Reshma Pise, 2020) obtained from the IEEE data port. The dataset contains images of two species of mosquitoes named Culex and Aedes. There are a total of 1404 images of the mosquitoes. Out of 1,404 images, there are 810 images of Aedes and 594 images of Culex class. In the Culex class, out of 594 images, 432 images have been used for training purposes, and 162 images are used for the testing. Similarly, out of 810 images of the Aedes class, 591 images have been used for the training, and 219 images

used for the testing purpose. Thus, the total images for the training are 1023 and 381 images for testing as shown in Table 2 and the sample of the dataset is shown in Fig. 1.

3.2. Data augmentation

The data processing technique is used to increase the amount of data by adding slightly modified copies of already existing data or develops new synthetic data from the existing data. It works as a regularizer and assists to overcome over-fitting while training a model (Shorten and Khoshgoftaar, 2019). Data augmentation techniques are closely related to the oversampling in data analysis. It increases the diversity of data that is available for training models without actually collecting new data. In this study, a sharp filter for data augmentation has been used to generate one more image from an original image. Data augmentation has only being applied on the training set. Training images count after augmentation shown in Table 3 and applied sharp kernel shown in Fig. 2.

Sharpening an image is a feature enhancement methodology whose purpose is to highlight the fine details in an image. Typically, this technique uses linear filters for implementing the high pass filters, which may produce unlikely results. The reason being, the linear filters are incapable of sharpening correctly if the image is being corrupted with noise. Therefore, before image sharpening, image soothing and filtering need to be carried out, which involve low pass filters and replacement of pixels. Sharpening enhances the structure and the other details of an image. These line structures and edges of an image can be obtained through the application of a high pass filter over an image. The high pass filter is a spatial operation that takes the difference between the current and averaging weights of the nearby pixels by using matrices. The high pass filter is then used to design a sharpening filter that produces the desired, appropriately scaled, high-pass sharpened image, and the result after applying a sharp filter is shown in Fig. 3.

3.3. CNN variants used in this study

3.3.1. VGG-16

VGG-16 is a renowned convolutional network. It was developed by the visual geometry group which is also known as VGG-16. Instead of having many hyper parameters, VGG16 only focuses on having convolutional layers of 3×3 filters with stride 1 and uses the same max pool and padding layer of 2×2 filters of stride 2. In the end, it has 2 fully connected layers followed by the softmax for the output. This 16 in VGG-16 represents the 16 layers that have weights. VGG-16 has approximately 138 million parameters so, it is a large network. VGG is a pre-trained version of the net-

Table 1
Summary of the systematic analysis studies in related work.

Study	Year	Dataset	Accuracy	Classes
Garcia et al. (Garcia et al.)	2017	Self-made 306 images	SVM, k mean 67%, 72%, 79%	Aedes and others
Sanchez-Ortiz et al. (Sanchez-Ortiz et al., 2017)	2017	Self-made 300 images	96.8 alex net cnn	N/A
Fuchida et al. (Fuchida et al., 2017)	2017	400 images	SVM I and SVMII 98.9%	Mosquitoes and flies
Minakshi et al. (Minakshi et al., 2017)	2017	60 images	83.3%	–
Fuad et al. (Fuad et al., 2018)	2018	Self made 534 images	99% cross entropy	Aedes larvae
Fanioudakis et al. (Fanioudakis et al., 2018)	2018	N/A	96%	Classification of the mosquitoes based on the wingbeats
Huang et al. (Huang et al., 2018)	2018	Self-made	90.5% CNN	Aedes and culex
Ortiz et al. (Ortiz et al., 2018)	2018	Self-made with mobile camera	97%	Aedes and others
Okayasu et al. (Okayasu et al., 2019)	2019	Self-made, 14,460 images	95.5% residual network using data augmentation	N/A
Motta et al. (Motta et al., 2019)	2019	4056 images	76.2% CNN with googlenet	N/A
Akter et al. (Akter et al., 2020)	2019	36,000 images self made	93% CNN(VGG-16)	N/A
Park et al. (Park et al., 2020)	2020	3600 self-collected	96.6% CNN	N/A

Table 2
Random splitting of training and testing.

Type	Total	Training	Testing
Culex	594	432	162
Aedes	810	591	219
Total	1404	1023	381

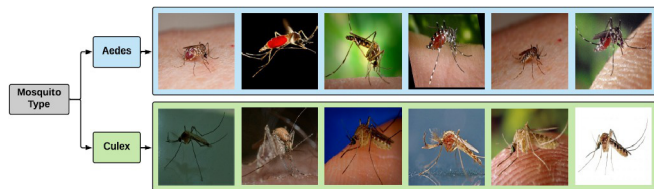


Fig. 1. Sample of dataset.

Table 3
Data augmentation.

Type	Training Set	Sharp Kernel	Total
Culex	432	432	854
Aedes	591	591	1182
Total	1023	1023	2046



Fig. 2. Sharp filter.

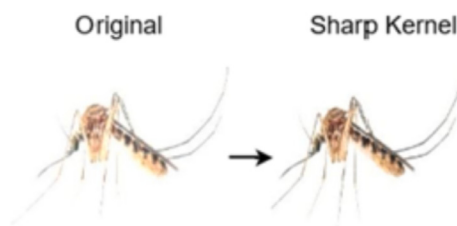


Fig. 3. Sample image before and after applying sharp filter.

work trained on more than a billion images from the ImageNet database (Simonyan and Zisserman). It can classify images into thousands of object categories, which results in the learning of networks on rich features representation for various images. The image input size in VGG-16 is 224×224 (Theckedath and Sedamkar, 2020).

3.3.2. Inception V3

By modifying the previous inception architecture inception, V3 has a quality that it uses less computation power. Comparing other inception networks like GoogLeNet/ inception V1, inception V3 is

more efficient in terms of memory and resources. In the inception V3 network, some techniques for optimizing the network have been put suggested to loosen the constraint for easier model adoption. Their techniques are factorized convolutions, dimension reduction, regularization, and parallelized competitions. Due to factorized convolution, inception V3 uses less number of parameters involved in the network. Bigger convolution replaced with smaller convolution might increase the training speed of the inception V3. In inception V3, auxiliary classifier acts as a regularizer, and grid size reduction is usually done by pooling operation.

3.3.3. ResNet-50

ResNet-50 is a variant of a convolutional neural network that is 50 layers deep. It is frequently used as a starting point for transfer learning. The concept of skip connection was firstly introduced by residual network 50. The ResNet model consists of five stages where each with the convolutional and identity block. Every convolutional block comprises 3 convolutional layers. ResNet-50 has over 23 million trainable parameters. Skip connections are used to add the output from a previous layer to the next coming layer. This helps to mitigate the vanishing gradient problem. Resnet-50 is comparable to the VGG-16 accept that ResNet-50 has the capability of additional identity mapping (Theckedath and Sedamkar, 2020) as shown in Fig. 4.

ResNet-50 predicts The Delta which is necessary to reach the final prediction from one layer to another(He et al., 2016).

3.3.4. EfficientNetBo

EfficientNet is a group of convolutional neural networks. It is more effective than most of its contemporaries. EfficientNet model consists of eight models from the B0 model to the B7 model (Tan and Le, 2019). With every subsequent model number referred to variants with more parameters and higher accuracy. Similar to any other model, EfficientNet saves time and computational power. In doing so, it gives better results than many known models. This is all because of intelligent scaling at depth, width, and resolution. EfficientNet enables the use of deep learning on mobile and other edge devices. There is a compound scaling method in EfficientNet that uses compound coefficient ϕ to uniformly scale network width, depth, and resolution in a principle way:

$$\text{depth} : d = \alpha^{\phi} \quad (1)$$

$$\text{width} : w = \beta^{\phi} \quad (2)$$

$$\text{resolution} : r = \gamma^{\phi} \quad (3)$$

$$\text{s.t} : r = \alpha \beta^2 \gamma^2 \approx 2 \quad (4)$$

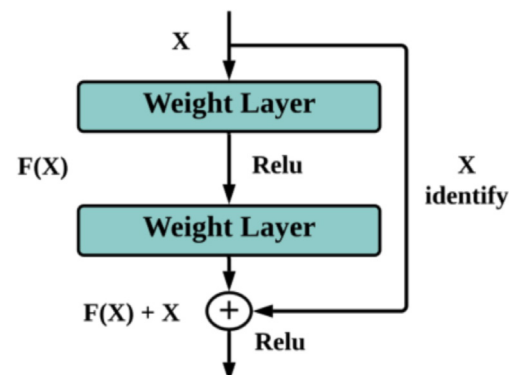


Fig. 4. Identity mapping function in ResNet-50.

Where, the constants α , β , and γ can be found by using small grid search. ϕ represents a user-specified coefficient which determines the number of resources ready for model scaling. And To determine the assignment of extra resources to network width, depth, and resolution is represented by α , β , γ respectively.

3.4. Machine learning models

3.4.1. Extra tree classifier (ETC)

ETC develops a group of unpruned decision trees following the top-down method. While splitting a node of a tree, involves randomizing both attribute and cut point selection strongly. In extreme conditions, it develops fully randomized trees with structures independent of the training sample's output value. The main difference between the other famous ML model random forest, ETC is:

- ETC uses the whole dataset for the training of a model, while random forest uses bootstrap replica for training.
- ETC randomly picks the best features along with the corresponding values to split the node.

Due to these qualities, an extra tree classifier is less likely to over-fit a dataset and gives better performance (Geurts et al., 2006).

Extra tree classifier has pros for calculation of the essential features. For calculating the importance feature X_m for predicting Y in a tree structure T by summing up the decrease in the weighted impurity $(p_t)\Delta i(S_t, t)$ for all nodes t , where feature X_m is used, then averaging over all N_t trees in the forest.

$$Imp(X_m) = \frac{1}{N_t} \sum_T \sum_{t \in T: v(S_t)=X_m} (p_t \Delta i(S_t, t)) \quad (5)$$

where $p(t)$ is the proportion of N_t^{NT} samples reaching node t and $v(S_t)$ is the feature used in split S_t (Bhati and Rai, 2020). The decrease in some impurity measures $i(t)$ at node t is represented by the following formula:

$$\Delta i(s, t) = i(t) - p_L i(t_L) - p_R i(t_R), \quad (6)$$

Where, $p_L = N_L/N$, $p_R = N_R/N$ and split $st = s^*$ for which the partition of the N node samples into two subsets t_L and t_R uplift the decrease in the impurity is identified. The construction of trees stops if the nodes are pure in terms of Y . Gini index is used as an impurity function and this is known as Gini importance or means decrease Gini.

Table 4 shows the hyper-parameters for the used machine learning models. The models tuning has been performed to get this parameters setting.

Table 4
Hyper-parameters of machine learning algorithms used in our study.

ML Algorithms	Hyper-parameters
Random Forest (RF)	n estimators = 300 max depth = 300 random state = 2
Logistic Regression (LR)	multi class = 'ovr' C = 3.0 Solver = 'liblinear'
Support Vector Machine (SVM)	C = 3.0 kernel = 'linear'
Extra Trees Classifier (ETC)	no. of estimators = 300 max tree depth = 300 random states = 2
K-Nearest Neighbor (KNN)	n neighbors = 6 wt = 'uniform'

3.5. Feature selection

Training a model on a high-dimensional dataset is generally very challenging. Many ML models can easily over-fit and usually need wary hyper-parameter tuning when trained on a high-dimensional dataset. The feature reduction techniques help reduce the dimensions of a given dataset (Singh et al., 2009). The feature reduction process has to be performed very carefully to eliminate the redundant or irrelevant features from the data set. This elimination is done based on their predictive power, rather than eliminating features randomly. The feature reduction presents the following advantages:

- Training time is decreased due to decreased number of features.
- Fewer chances of overfitting due to reduced dimensionality.
- Increases interpret-ability in models and makes them simple.
- Decreases the effect of the curse of dimensionality.

Feature selection is the process of finding the most appropriate features of a given dataset (Reshi, 2021). It is beneficial for the improvement of classification accuracy as well as computational speed. In most of the classification problem domains, the number of features is in hundreds and thousands, so selecting useful features out of such a large number of features is a challenging task. In this study, a hybrid feature selection method named RIFS has been introduced, which combines two feature selection methods – the ROI-based image filtering and the wrappers-based FFS technique. The refined images with selected ROI have been first obtained from the primary feature set using image filters. These features have further been refined by applying wrapper feature selection methods like FFS. This hybrid mechanism takes advantage of both the image filters and the wrappers. The mechanism has been examined by using different ML and CNN models. The results prove that a smaller refined feature set produces better classification accuracy with decreased computational complexity than feature sets with a large number of features.

{ROI} ROI extraction deals with the extraction of the intended shape signatures by applying edge detection techniques. Edge detection is a digital image processing technique in which an image is segmented into different regions with discontinuities. Edge detection techniques are most commonly used in image morphology, pattern recognition, and feature extraction. In feature extraction edge detection-based ROI extraction technique enables us to select an intended region of the total image. It minimizes the computational complexity by reducing data processing to recognize the required features for any classification task. Thus, the edge detection technique has been applied to the whole images to crop the needed region of the images necessary in mosquito classification.

3.5.1. FFS

FFS is a technique that notably reduces the number of models that need to be learned (Whitney, 1971). The technique starts with a null model, and the features are added one at a time, choose the best model among the bests in each iteration. That is, the next feature is selected, and its metric value is calculated. The feature which gives the best metric value is added to the feature list. The process is repeated for two features, one from the selected feature set and one selected from the set of all remaining features. Again the metric value is evaluated, and compared to every featured pair, the feature with the best metric value is added to the selected feature set. The process is reiterated till a desired n number of features are obtained. This feature set of n features can be referred to as hyper-parameter FFS is thus a feasible technique to tune the hyper-parameter to obtain the optimal performance.

The linear model has been mainly used with FFS to find the features subset. To reduce the time complexity because it takes less time to train than non-linear models. Consider that if there are r rows in a dataset, the time taken to run the above algorithm will be:

$$T = mr + m \log(m) + (m-1)r + (m-1) \log(m-1) + (m-2)r + (m-2) \log(m-2) + \dots + (m-n+1)r + (m-n+1) \log(m-n+1) \quad (7)$$

which can be simplify as:

$$nmr + m \log \frac{m!}{(m-n)!} - r \frac{(n-1)n}{2} \quad (8)$$

The proposed RIFS technique shown in Fig. 5 and can be defined mathematically as follows:

The proposed RIFS technique shown in Fig. 5 can be defined mathematically as follows:

$$\text{Image} = \begin{bmatrix} P_{1 \times 1} & \cdots & P_{1 \times m} \\ \vdots & \ddots & \vdots \\ P_{n \times 1} & \cdots & P_{n \times m} \end{bmatrix} \quad (9)$$

The matrix in equation (9) shows the image features and equation (10) shows the RoIs from image.

$$\text{RoIs} = \begin{bmatrix} \begin{bmatrix} P_{1 \times 1} & \cdots & P_{1 \times m} \\ \vdots & \ddots & \vdots \\ P_{n \times 1} & \cdots & P_{n \times m} \end{bmatrix} & \begin{bmatrix} P_{1 \times 1} & \cdots & P_{1 \times m} \\ \vdots & \ddots & \vdots \\ P_{n \times 1} & \cdots & P_{n \times m} \end{bmatrix} \\ \begin{bmatrix} P_{1 \times 1} & \cdots & P_{1 \times m} \\ \vdots & \ddots & \vdots \\ P_{n \times 1} & \cdots & P_{n \times m} \end{bmatrix} & \begin{bmatrix} P_{1 \times 1} & \cdots & P_{1 \times m} \\ \vdots & \ddots & \vdots \\ P_{n \times 1} & \cdots & P_{n \times m} \end{bmatrix} \end{bmatrix} \quad (10)$$

$$\text{RoIs}_{RGB} = \begin{bmatrix} RoI_{1 \times 1} & \cdots & RoI_{1 \times m} \\ \vdots & \ddots & \vdots \\ RoI_{n \times 1} & \cdots & RoI_{n \times m} \end{bmatrix} \quad (11)$$

Now, the final features set for learning models from the RIFS approach can be defined as:

$$\text{RIFS features} = \begin{bmatrix} RoI_{1 \times 1} & \cdots & RoI_{1 \times y} \\ \vdots & \ddots & \vdots \\ RoI_{x \times 1} & \cdots & RoI_{x \times y} \end{bmatrix} \quad (12)$$

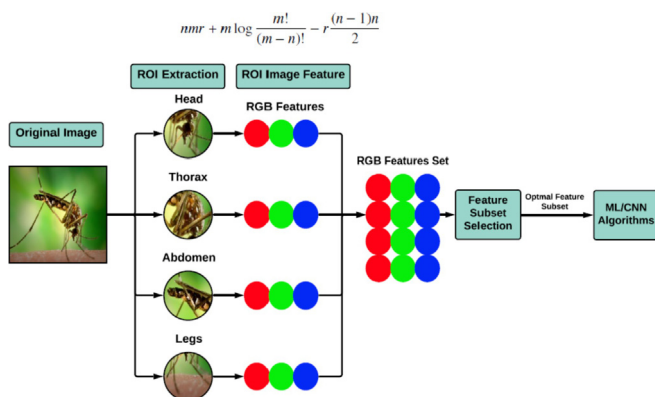


Fig. 5. RIFS Workflow diagram.

3.6. Proposed methodology workflow

This study performs all experiments on the Core i7 7th generation machine with Windows 10 operating system with 8 GB RAM and 500 GB HDD. Jupyter notebook has been used for the implementation of python code.

The proposed methodology uses different techniques and methods to classify the Aedes and Culex. As a first step in the workflow, the dataset has been obtained from an IEEE data port. The obtained dataset has then been preprocessed to improve learning models' performance and compensate for computational complexity. Thus, in preprocessing step, data augmentation and RIFS feature selection have been performed. The data augmentation technique is used to increase the number of images for models' learning because the original dataset is not large enough, so the numbers of features are not enough for a good fit. For data augmentation, a sharp filter method has been used, generating one more image corresponding to each image from the training set. The data augmentation technique has been applied only on the training set to double the training set's size, as shown in Table 5 and training, testing images count shown in Table 6.

After data augmentation, the RIFS has been applied to extract the specific parts of mosquito bodies such as the abdomen, legs, head, and thorax because these parts are important for visual recognition of both mosquito types. The effect of the ROI step of RIFS of the images is shown in Fig. 6.

The ROI phase of RIFS generates more specific features to learn as compared to learn whole images. After the ROI extraction, the RGB features have been extracted from selected images, and these RGB features have been passed to forward features selection (FFS). Through FFS, the important features are selected for the learning of models to improve the performance. Since all the features are not correlated to the target class, only the important features are selected. The models have been trained using the resulted training set, and then the performance evaluation of the models has been performed using the test data. The important metrics, including accuracy, precision, recall, F1-score, and ROC AUC, have been calculated to evaluate learning models. Proposed methodology diagram shown in Fig. 7.

Algorithm 1. Proposed approach algorithm

1. **Begin**
2. **Input:** Input_Mosquito_Images[N]
3. Augmented_Images[] = 2 N
4. initialization:
5. **loop** image in Augmented_Images[]:
6. **loop** RoI in images:
7. Images_Feature_Set.append(RGB(RoI))
8. **end loop**
9. Images_Feature_Set(Images_Feature_Set[])
10. **endloop**
11. Train_Model(Images_Feature_Set[])
12. **Output:** Evaluate_Model(New_Images[])
13. **End**

Table 5
Training data size after data augmentation.

	Original	Augmented Images	Total
Total	1023	1023	2046

Table 6
Training and testing images count.

Type	Training	Testing
Culex	854	162
Aedes	1182	219
Total	2046	381

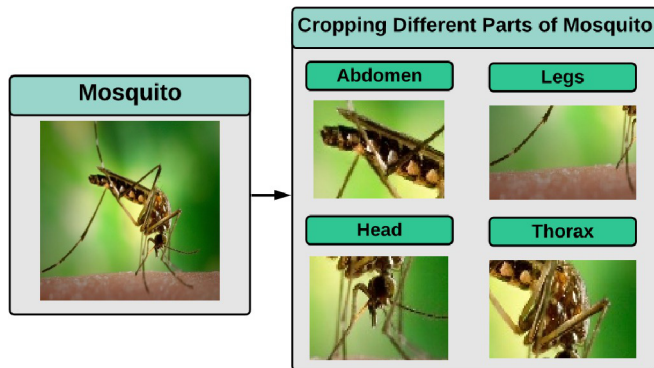


Fig. 6. Rols from an image.

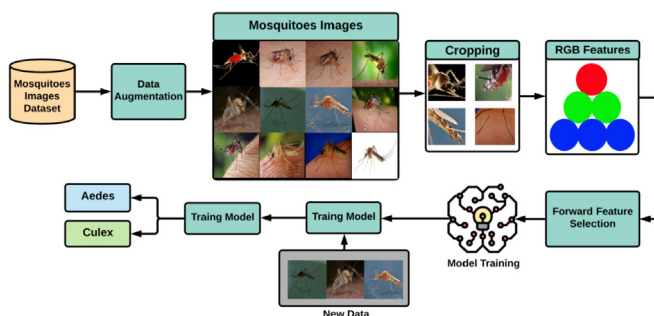


Fig. 7. Proposed methodology diagram.

4. Results

This study deals with the classification of mosquito images for that different deep learning and ML models have been used. The comparative analysis of model performances and computational complexity of different approaches has been evaluated. This section presents the results of all models individually on the given datasets in different scenarios.

4.1. Model performances on primary dataset

The performance evaluation results of all the used models on the original dataset without any preprocessing have been presented in this section. The models in this scenario have been trained on the RGB features of the original images of the primary dataset, and the performance metrics of ML models such as accuracy, precision, recall, and F1 score has been presented in Table 7.

Table 7
Performance of machine learning models on the original dataset.

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.601	0.540	0.413	0.468
RF	0.703	0.696	0.537	0.606
ETC	0.713	0.708	0.555	0.622
LR	0.627	0.589	0.407	0.481
KNN	0.706	0.686	0.567	0.621

The confusion matrix obtained from the current model scenario has been shown in Table 8.

The performance of the CNN variants has also been evaluated for the same on the same original dataset images and has been reported in Table 9. As shown in the results VGG16 in this case outperforms all the other CNN Variants and the ML models whose results are presented in the previous subsection. Thus VGG16 gives 0.955 accuracy score which shows the significance of the deep learning approach in the current application domain.

4.2. Model performance after ROI extraction of images

In this scenario the models have been trained on ROI processed dataset. The highest performance in this setup has been given by ETC followed by RF. As shown in the results the ETC provided accuracy score of 0.98 and RF performs closely with the accuracy score of 0.979. As shown in Table 11, the performances of all models improve when trained on this refined version of the dataset. As shown in Table 12, ETC gives the highest number of correct predictions, i.e 376 out of 381 and lowest false predictions as compared to other ML models.

The CNN variants' performance is shown in Table 13, and results show that the performance of the CNN variants also improves after ROI extraction of images. The performance of VGG16 increased from 0.955 to 0.986, which shows the significance of ROI-based region specific feature learning for both machine learning and deep learning models. As discussed earlier, the specific region of images gives the specific features for learning which is significant to improve model performances.

4.3. Model performance on application of proposed RIFS technique

This section presents results after the application of the RIFS technique to select the important features from images. RIFS is a combination of ROI and FFS techniques that help to boost ML models' performance and gives the highest results of this study. RIFS return important features which are significantly correlated features to learn as compared to original dataset image features. All ML models improve their performance with RIFS, as shown in Table 15. ETC gives the highest accuracy score of 0.992, which shows the significance of the proposed feature extraction approach, while the other models as RF and LR, and also improve their performance with an accuracy score of 0.984 and 0.976, respectively. Table 16 shows the confusion matrix for all ML models, and results show that ETC gives 378 correct predictions out of 381, which is the highest correct prediction ratio of the study.

The CNN variants' performance also improves with RIFS, which shows the significance of the RIFS approach for mosquito image classification using both types of classification models. The results of the CNN variants are shown in Table 17, and according to the results, InceptionV3, ResNet-50, and EfficientNetB0 improve their results compared to previous results, while VGG16 results remain the same as on ROI based feature extraction. According to the confusion matrix in Table 18, the VGG16 is on top with 376 correct classifications and only five wrong classifications. CNNs' accuracy and loss graph shown in Fig. 8.

4.4. Comparison with other studies

To check the significance of this study, a comparative analysis with prior studies on mosquito image classification has also been performed. The proposed models used in these studies have been applied to the dataset used in this study. The results show that the proposed approach has more significant results than prior studies. The comparison of results with state-of-the-art models

Table 8

Confusion matrix for all machine learning models on the original dataset.

Model	TP	TN	FP	FN	CP	WP
SVM	162	67	57	95	229	152
RF	181	87	38	75	268	113
ETC	182	90	37	72	272	109
LR	173	66	46	96	239	142
KNN	177	92	42	70	269	112

Table 9

Performance of CNN variant on the original dataset.

Model	Accuracy	Precision	Recall	F1-Score
VVG16	0.955	0.981	0.942	0.961
Inception V3	0.892	0.917	0.897	0.907
ResNet50	0.910	0.931	0.914	0.923
EfficientNetB0	0.905	0.954	0.889	0.920

Table 10

Confusion matrix for all CNN variants on the original dataset.

Model	TP	TN	FP	FN	CP	WP
VVG16	215	149	4	13	364	17
Inception V3	201	139	18	23	340	41
ResNet50	204	143	15	19	347	34
EfficientNetB0	209	136	10	26	345	36

Table 11

Performance of machine learning models after applying ROI extraction technique.

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.968	0.951	0.975	0.963
RF	0.979	0.987	0.962	0.975
ETC	0.986	0.987	0.975	0.984
LR	0.965	0.951	0.969	0.960
KNN	0.955	0.909	0.993	0.949

Table 12

Confusion matrix for all machine learning models after applying ROI extraction technique.

Model	TP	TN	FP	FN	CP	WP
SVM	211	158	8	4	269	12
RF	217	156	2	6	373	8
ETC	218	158	1	4	376	5
LR	211	157	8	5	368	13
KNN	203	161	16	1	364	17

Table 13

Performance of CNN variant after applying ROI extraction technique.

Model	Accuracy	Precision	Recall	F1-Score
VVG16	0.986	0.990	0.986	0.988
Inception V3	0.910	0.992	0.796	0.883
ResNet50	0.960	0.980	0.925	0.952
EfficientNetB0	0.934	0.915	0.932	0.923

Table 14

Confusion matrix for all CNN variants after applying ROI extraction technique.

Model	TP	TN	FP	FN	CP	WP
VVG16	217	159	2	3	376	5
Inception V3	218	129	1	33	347	34
ResNet50	216	150	3	12	366	15
EfficientNetB0	205	151	14	11	356	25

Table 15
Performance of machine learning models after applying RIFS techniques.

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.960	0.956	0.950	0.953
RF	0.984	0.993	0.969	0.981
ETC	0.992	0.993	0.987	0.990
LR	0.976	0.975	0.969	0.972
KNN	0.955	0.923	0.975	0.948

Table 16
Confusion matrix for all machine learning models after applying RIFS techniques.

Model	TP	TN	FP	FN	CP	WP
SVM	212	154	7	8	366	15
RF	218	157	1	5	375	6
ETC	218	160	1	2	378	3
LR	215	157	4	5	372	9
KNN	206	158	13	4	364	17

Table 17
Performance of CNN variant after applying RIFS techniques.

Model	Accuracy	Precision	Recall	F1-Score
VVG16	0.986	0.995	0.981	0.932
Inception V3	0.979	0.975	0.975	0.932
ResNet50	0.981	0.975	0.981	0.978
EfficientNetB0	0.947	0.943	0.932	0.937

Table 18
Confusion matrix for all CNN variants after applying RIFS techniques.

Model	TP	TN	FP	FN	CP	WP
VVG16	218	158	1	4	376	5
Inception V3	215	158	4	4	373	8
ResNet50	215	159	4	3	374	7
EfficientNetB0	210	151	9	11	361	20

are shown in [Tables 19 & 20](#). [Figs. 10 & 11](#) show the accuracy and loss for compared study models.

4.5. Time complexity comparison between proposed approach model ETC and other CNN variants

To prove the computational complexity improvement given by ETC, the selected best performing ML model. The comparative analysis has been performed between ETC and the CNN models. The results reveal that ETC takes 46 times less training time as compared to fastest trained CNN model, InceptionV3. Thus the results presented in [Table 21](#) show the computational requirements of ETC in terms of time is significantly low in terms of accuracy as compared to CNN variants and other ML models. These results prove that machine learning models can also perform very well as neural network models on image dataset in terms of both accuracy and computational time.

5. Discussion

This study deals with the development of methodology for the classification of disease spreading mosquitoes. Various state-of-the-art ML, CNN models and studies have been investigated, analyzed and applied to propose an effective method in terms of accuracy and computational time.

5.1. ML and CNN models without data preprocessing

As shown in the results, the ensemble model ETC outperforms all other ML models with a 0.713 accuracy score. RF and KNN have also performed comparatively well with accuracy scores of 0.703 and 0.706 respectively. However SVM and LR couldn't perform well, because in the current scenario these models required an extensive feature set for learning, compared to RF, ETC, and KNN. The highest correct predictions in this scenario are given by the ETC, which is 272 out of 381, as shown in confusion matrix of [Table 8](#). In addition, all CNN variants give higher performance results as compared to all the ML models. These pre-trained models used the neural networks in their architecture which are more appropriate to extract important features for learning and help to boost their accuracy. ML models have no such mechanisms to find important features for learning automatically. That is the reason ML models are not performing well as compared to CNN models. Results reveal that the VVG16 gives 364 correct predictions out of 381 and only 17 wrong predictions, as shown in [Table 10](#), which is the lowest wrong prediction ratio as compared to all other models on the original image dataset.

5.2. ML and CNN models with ROI based data preprocessing

The image dataset has been preprocessed to extract the specific regions of images using ROI extraction. Thus after getting the images consisting of only the specific parts which are relevant in mosquito image classification in a refined version of the dataset.

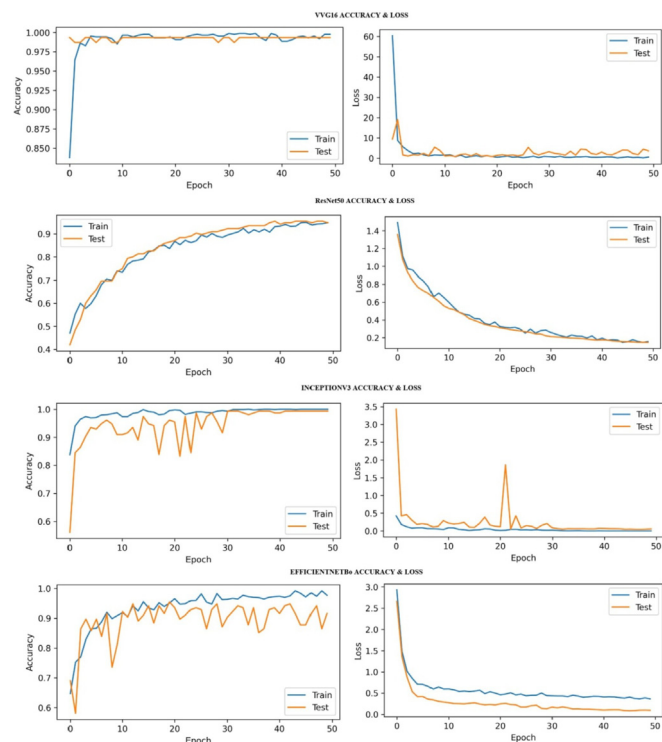


Fig. 8. Training and testing accuracy loss for CNNs with RIFS approach.

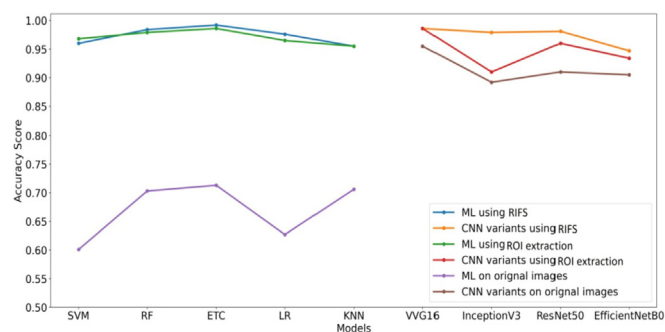


Fig. 9. Accuracy comparison between all approaches.

Table 19

Comparison results with prior studies.

Study	Model	Accuracy	Precision	Recall	F1-Score
Akter et al. (Akter et al., 2020)	CNN	0.973	0.958	0.995	0.975
Park et al. (Park et al., 2020)	CNN	0.968	0.990	0.955	0.973
This work	ETC	0.992	0.993	0.987	0.990

Table 20

Comparison results in confusion matrix with prior studies.

Study	Year	TP	TN	FP	FN	CP	WP
Akter et al. (Akter et al., 2020)	2020	210	161	9	1	371	10
Park et al. (Park et al., 2020)	2020	217	152	2	10	369	12
This work	2021	218	160	1	2	378	3

All the ML models have been then trained using the dataset containing the images with specific regions of interest. On testing the models after application of ROI based feature extraction, the model performances were significantly improved. Since the model

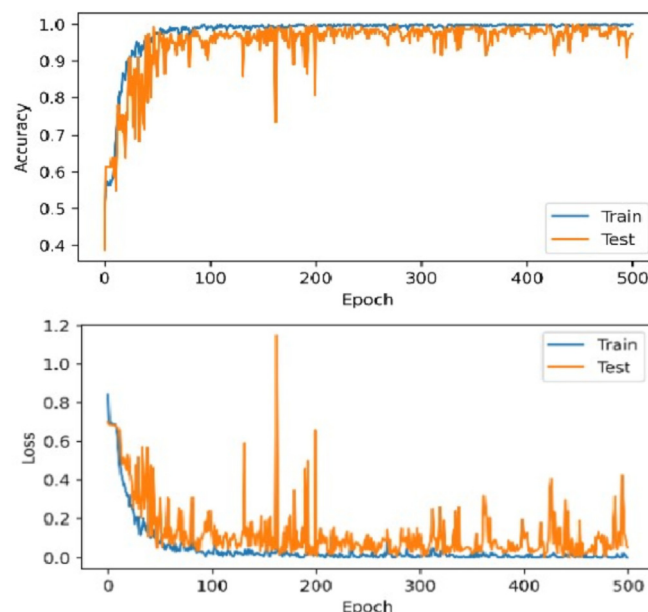


Fig. 10. Study (Akter et al., 2020) accuracy and loss.

learning in this scenario was based on more relevant features needed for image classification. While as all the other irrelevant image regions were cropped out to eliminate the features not required for the classification.

VGG16 is equal in performance with machine learning model ETC because the ROI based machine learning model gets same important features. ML models provided a high score as compared to InceptionV3, ResNet-50, and EfficientNetB0 because these models perform better given a large feature set while after selected feature set size to reduce which is not suitable for CNN variant but machine learning models. VGG16 gives 376 correct predictions out of 381, equal in number with ETC shown in Table 14.

5.3. ML and CNN models with RIFS data preprocessing

The ETC model performs well in this scenario because of its ensemble architecture. It combines several decision trees in the classification procedure using majority voting criteria which

makes it a more suitable model compared to individual classification models.

The comparison between all model performances shows that ROI and RIFS based feature extraction techniques improve model

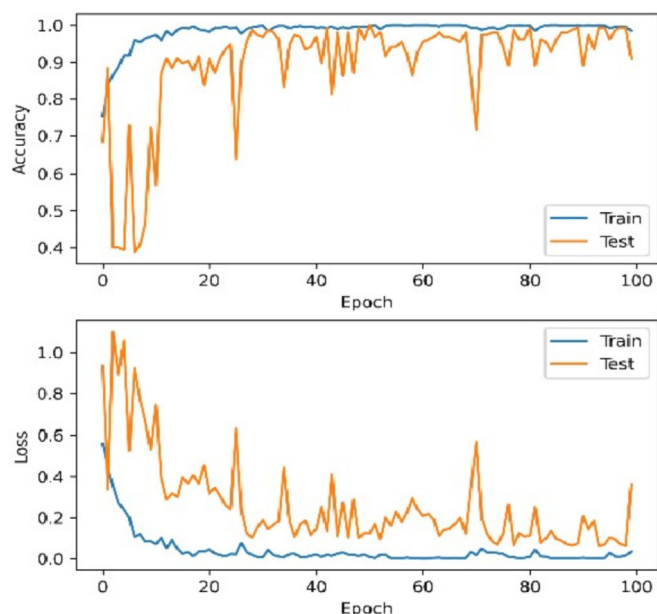


Fig. 11. Study (Park et al., 2020) accuracy and loss.

Table 21

Training and testing time between our proposed approach and CNN variants.

Model	Training Time (Sec)	Testing Time (Sec)
VVG16	4204.2	45.7
InceptionV3	1481.4	9.3
ResNet-50	3942.4	17.6
EfficientNetBo	3259.8	8.1
Proposed Approach (ETC)	32.2	0.10

performances very significantly as compared to training on features of the original dataset. This is because these techniques help extract very specific and more meaningful features for learning, which helps boost models' performance. Fig. 9 shows that ML models are not performing well on the original dataset. However, the CNNs' performance is better on original dataset images because these models automatically learn on good features. ML models' performance boosts right after the ROI extraction of specific parts of mosquito's from images. This technique enables the models to use the most appropriate features for classification and improves the results while the RIFS technique helps more to improve model performances.

Why this study is significant?

- The study experiments are based on a dataset which has never been used previously in any of the studies according to best of our knowledge.
- This study proposes a novel approach in which the ML model outperforms the strong CNN Variant.
- This study introduces the RIFS approach which shows that the focus on the important features can improve ML model performance and also can save computation time and cost.
- The study performs a strong comparison between well-tuned baseline models to show the significance of the proposed approach

6. Conclusion

Many Mosquito-borne diseases are deadly as the antiviral and antibiotic drugs are not effective in treating the infected patients. This becomes a primary reason for almost one million human

deaths per year in the world. The current best-known approach to prevent the spread of mosquito-borne diseases is to eliminate the possible presence of mosquitoes and their breeding areas using different chemical and insecticide sprays. However, the complete elimination of these flying insects becomes challenging because these sprays or chemical applications' abundant use creates resistance in the mosquitoes.

Identifying disease-transmitting mosquitoes in any potential area demands an efficient automatic system to detect and classify the particular types of mosquitoes. The system will aid the health authorities and other stakeholders to check the presence of any disease-spreading mosquito in the area of their interest. In this study, an ML and CNN-based methodology has been proposed to develop an effective system that will effectively aid in epidemiology to design evidence-based policies and decisions by analyzing the risks and transmission. It will prepare the authorities to take preventive measures in the targeted areas to control its spread at the right time. This study proposes a methodology for classifying the most important classes of disease-spreading mosquitoes such as Aedes and Culex using ML and CNN-based approaches. The study uses a primary image dataset of Aedes and Culex mosquitoes species obtained from the IEEE data port, a well-known source for the datasets. The dataset contains the images of two species of mosquitoes named Culex and Aedes. A novel feature selection approach, RIFS, has been proposed and evaluated in this study. The objective was to benefit from image filtering techniques' efficiency and the accuracy of wrapper-based feature selection techniques. So the RIFS was designed as a hybrid feature selection preprocessing technique. The first phase of the feature selection eliminates the irrelevant portions of images to increase efficiency and reduce the computational cost. In the second phase, the most appropriate features are being selected to improve the model accuracies. In the experimental setup, all the applied ML models such as SVM, RF, ETC, LR, and KNN and CNN model variants such as VG16, InceptionV3, ResNet 50, and EfficientNetB0 have been trained to evaluate the performance and computational cost of each model.

The results show that the proposed methodology based on the novel feature selection approach RIFS is very effective on both model efficiencies and computational complexity. It is also believed that the methodology can also apply to other different problem areas involving effective feature selection. The main findings in the results show that the ETC outperformed among all the ML models giving 0.992 accuracy, which was performing as low as 0.71 before the application of RIFS. VVG16 attained 0.986 accuracy when the proposed RIFS was applied. These observations prove that the low-performing ML models can also achieve a significant performance while also reducing the computational efforts when using appropriate feature selection. As can be seen in the results, the ETC model takes very less training time and testing time compared to all other models.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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