Recognition and classification of Aedes aegypti using image processing techniques

[1] E.Ambica , [2] A.Saravanan, [3] V. Mercy Rajaselvi Beaulah
[1]PG student, [2]Dean (Academic), [3]Associate professor
[1]Department of computer science and engineering
[1]Easwari engineering college, Chennai, India
[2]Department of computer science and engineering
[2]Easwari engineering college, Chennai, India
[3]Department of computer science and engineering
[3]Easwari engineering college, Chennai, India

***Abstract :** This paper uses a classification algorithm for the recognition of Aedes mosquito using the image processing techniques. Aedes mosquitoes are the carrier of dengue virus. The dengue fever is a fatal disease which does not have vaccine or treatment. Thus eliminating the Aedes population is the only remedy available to reduce the risk of dengue fever. Image processing techniques help in recognizing the Aedes mosquitoes in the image that is taken from the mosquito-prone area. The recognition of Aedes mosquito is done through a trained classifier using the image features. The image feature is the white patch in the body and legs of Aedes mosquito which is extracted by processing the RGB channel of the image. The classifier is trained based on the extracted image features. The trained classifier categorizes the mosquito image into 'Aedes' and 'Non-Aedes' classes. In the real-world environment, the number of classes of mosquito increases dynamically, so there is a need for a classifier to adapt to the growing categories.*

To adapt to the increasing number of classes, a hybrid incremental algorithm Nearest Class Mean Forests (NCMF) method is used, which is a variant of random forest method. The system is trained and tested using the mosquito images.

IndexTerms - Aedes mosquito, threshold, nearest class mean classifier, random forest

---

I. INTRODUCTION

Image processing techniques help in retrieving the information from the image for benefits of user's requirements. It converts the input image into signal and extracts the required information. It can also be used to enhance the quality of image. It is extensively involved in signal processing techniques where the image is processed and produced the extracted feature or characteristics as output to the required user as an output. In general, image processing basically contains three major steps such as (i) importing the image via image acquisition tools; (ii) analysing and manipulating the image; and (iii) generating output which is the report that is based on image analysis. The image classification is another challenging area in image processing for making categorization of the images. Image processing and image classification are used in various domains such as agriculture, health sector, medical imaging, remote sensing, pattern recognition, object recognition. This survey focuses on the application of image processing and classification in the field of the health sector.

Many researchers are focusing on various fields to analyse information with the support of captured images. For example, the image of the crop from agriculture field is processed to recognize the presence of pest and to classify the type of pest in the field. This is used to make a decision on the amount of pesticide to be applied. Thus helps the agriculturist to limit the usage of pesticide and grow healthy crops. The ideology of pest recognition was also used in the health sector for recognizing the vectors of human diseases such as mosquitoes. The presence of mosquitoes and their type are identified from the image using the image processing techniques. This helps in preventing some vector-borne diseases such as dengue, malaria that are spread by mosquitoes. This survey focuses on the recognition of species of mosquitoes using the image processing techniques.

Each genus of mosquitoes has some physical features that are used to differentiate among one another. One such genus of mosquito called "Aedes" is the carrier of Dengue fever which can be recognized by its physical features such as (1) abdomen with prominent silvery-white lateral patches, cerci short, scarcely visible and (2) abdomen with lateral patches yellowish or white, not silvery-white; cerci long, plainly visible [12]. This survey has discussed about different features that it is originally extracted from the image of mosquito.

II. RELATED WORKS

Initially, the mosquito was classified based on DNA sequence and the wing beat sequence rather than the mosquito images. A.K. Banerjee et al. (2008) [1] have discussed on classifying mosquito based their DNA sequence. Tai-Hsien Ouyang et al. (2015) [16] have discussed on the wing beat sequence used to differentiate the mosquito species. This research was only depended on the wing beat, but further research works were handled using the image of a mosquito. Thereafter, the image classification algorithm played the key role in categorizing the mosquito based on the image. Some of the research work related to mosquito image processing are discussed separately below:

2.1Image Processing

The image acquired have to be pre-processed for increasing the quality of the image. The pre-processed image is used to extract the feature vector which serves as input to classification algorithms.

There are several processing techniques used in insect recognition so far. Below are few of them:

Natalia et al. (2008) [13] have discussed on segmenting the stonefly from background using the principal curvature based region detector. Barbedo et al. (2014) [3] have discussed on noise removal using erosion morphological operator. Noise is unwanted signal added to the image during acquisition. Da-Dong et al. (2016) [5] have discussed on the segmenting the foreground image from background using the masking technique. Fuchida et al. (2017) [10] have discussed on the image segmentation using the split and merge algorithm. The split and merge algorithm extracts the region of interest from the background region.

Ebrahimia et al. (2017) [12] have discussed on the image segmentation using the gamma operator and binary conversion. The gamma operation will compensate the brightness level of the image. The processed image undergoes conversion to binary form. The binary image will have only black and white color in it. The color image will be converted to black and white image. Now, the pest has been extracted by reversing the binary image. This helps in finding the pest over the flower. Thus the image of pest is segmented from the flower.

2.2Image classification algorithms

The different classification methods used for various parameter prediction is discussed separately below:

2.2.1 Single Mosquito

Lorenz et al. (2015) [9], Favret et al. (2016) [4] and Rafael et al. (2016) [14] have discussed identifying the species of mosquito from its image based on wing morphology. Lorenz et al. (2015) [9] discussed on classifying the wing morphology using the artificial neural network (ANN). The input to ANN was the feature extracted using the principal component analysis (PCA). Wang et al. (2012) [19] have also discussed on the feature extraction using PCA. The feature considered in this research was the morphology of wing based on eighteen points named as the landmark, (specifically on the right wing). The position of the landmark helps in identifying the species of the mosquito. Rather, Favret et al. (2016) [4] and Wieland et al. (2017) [20] used support vector machine (SVM) classifier to recognize the genus of mosquito. The input to SVM was the greedy adaptive discrimination (GAD) feature vector (which consist of the common wing signature of a class of species). The trained SVM was used for pattern recognition. Though ANN and SVM were performed well, they are not suitable for increasing dataset and moreover the quality of the image acquired in these research works was dependent on the specimen of the mosquito. Some specimen developed scale over their wings as years passed. In such cases, the veins in the wings of the preserved specimen were not clear. Apart from these work where the genus of single mosquito is identified, there were research works that gather information on the population of mosquito from the image. One such research work is discussed below.

2.2.2Group of mosquitoes

Keun Young Lee et al. (2016) [8] have discussed on using the artificial neural network to predict the mosquito abundance in an area. The mosquito population is predicted according to the weather condition which serves as input variables to ANN. The number of mosquitoes is calculated using the mosquito monitoring system. The infrared sensor inside the monitoring system counted the number of mosquitoes trapped. The ANN employed in this system was a feed-forward network with five input variables, one hidden layer with 19 neurons and one output variable. The input variables are meteorological factors that include air temperature, humidity, wind speed, precipitation and mosquito population in past record. The learning rate was set as 0.7. The number of neuron and learning rate were selected based on trial and error method. Edwin et al.(2017)[6] have compared SVM,ANN and RF classifier. This research was only to get the population of mosquitoes as a whole in an area, further research work was about getting the population of male and female mosquito in an area.

Yaniv et al. (2017) [21] and W Ding et al. (2016) [18] have discussed the method of counting the number of male and female mosquito in the petri dish image using the inception deep learning architecture. The patch based convolutional neural network (CNN) is employed for making the prediction of the number of mosquito in the focus region. The petri dish consists of the immobilized mosquitoes, the image of the petri dish is divided into different patches. Each patch count is summed up to arrive at the total number of mosquito in the image. In addition, the number of male and female mosquito is also calculated in each patch. The mosquito is classified as male and female based on their body structure. The female mosquito is identified by its longer body and little or no feather on their antennae.

2.2.3Incremental algorithm

The incremental algorithm is suitable for the dataset with the dynamically increasing number of classes.

Marko Ristin et al. (2014) [11] have proposed NCM Forest which is a hybrid incremental algorithm. It combines nearest class mean classifier and random forest classifier. It helps in training the newly added classes to the classifier with the existing dataset without re-training from scratch.

Tingting et al. (2016) [17] have discussed on heterogeneous incremental nearest class mean random forests (hi-RF). The hi-RF trains the tree for the new data with the reduced computational load. The computational load is reduced by splitting the dataset based on the distance from the class centroid. New classes were integrated using rolling release NCM decision tree where only leaf nodes were modified.

Huimin et al. (2016) [7] have discussed on the hybrid incremental algorithm IKNN-SVM which integrates K-nearest neighbours (KNN) and support vector machine (SVM) algorithms. KNN was used to find the nearest neighbouring data and SVM was used to categorize the sample.

Arturo et al. (2016) [2] have discussed on the NCM forest algorithm along with Haar cascade classifier to categorize the underwater terrain deformation. First, the images were fed into Haar cascade which retrieves all possible regions of interest. Further, the region of interest was given to the NCM Forest classifier to classify the marine species which is more likely to cause deformation.

The nearest class mean forest algorithm was able to handle the dynamically increasing number of classes and it also preserved the accuracy. The new classes were added by re-using the subtrees of the random forest.

III. EXPERIMENT

The experiment NCM forest classifier on recognition of 'Aedes' mosquito is discussed below.

3.1Training phase

The mosquito images are retrieved from the data store and preprocessed to remove the noise. For each training image the region of interest (ROI) specifically the leg of the mosquito in the image is selected. The white pixel in the selected ROI is calculated and the classifier is trained. There are two classes of mosquito namely 'Aedes' and 'Non Aedes' is used in training the classifier. In training phase of NCM forest classifier, the random forest is formed using the nearest class mean of each class as splitting criteria.

3.2Testing phase

In the testing phase, the NCM forest classifier predicts the class of the dataset by using the Euclidean distance between 'Aedes' and 'Non-Aedes' classes. The region of interest is selected in the testing image. In case of testing image containing single mosquito, single ROI is selected. But, in case of testing image with the group of mosquitoes multiple ROI is selected. The ROI is preprocessed and fed to the classifier.

The classifier predicts the class of mosquito. In case of testing image with group of mosquitoes, the population ratio of 'Aedes' and 'Non-Aedes' class is calculated from the predicted class and projected.

IV. RESULT AND DISCUSSION

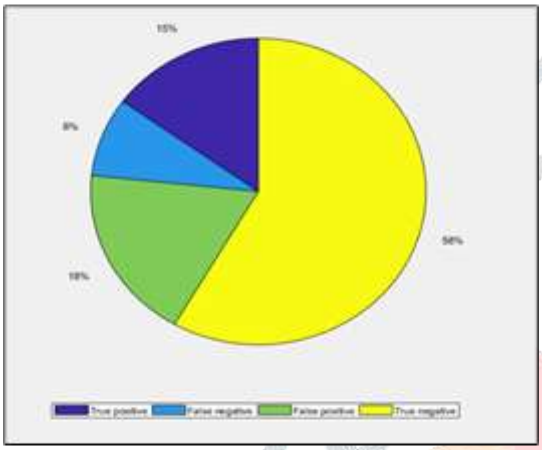
The performance of nearest class mean forest classifier is compared with nearest class mean classifier. The comparison between classifiers with respect to accuracy, specificity, precision and recall is shown in the below table.

TABLE I.

TABLE II. RESULT COMPARISON

Performance measure	Classification algorithm	
	NCM	NCM Forest
Accuracy%	73	73
Specificity%	76	73
Precision%	45	30
Recall%	64	75

NEAREST CLASS MEAN CLASSIFIER



NCM FOREST CLASSIFIER

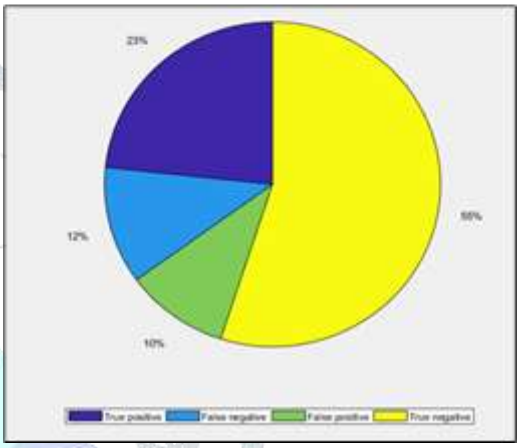


Fig.2. Result comparison

V. CONCLUSION

In this paper, the hybrid incremental learning algorithm NCM forest was used. In this algorithm, the nearest class mean and random forest classifier is integrated. The incremental algorithm is well suited for the dynamically increasing number of classes and number of species. The future work includes optimizing the algorithm by increasing the precision percentage.

REFERENCES

[1] A.K Banerjee, K. Kiran, U.S. Murty, C. Venkateswarlu,"Classification and identification of mosquito species using artificial neural networks." Computational biology and chemistry, Vol. 32, pp. 442-447, Dec 2008.

[2] Arturo Gomez Chavez, Jorge Fontes, Pedro Afonso, Max Pfingsthorn, Andreas Birk, "Automated Species Counting using a Hierarchical Classification Approach with Haar Cascades and Multi-Descriptor Random Forests", Proceedings of the IEEE Conference OCEANS 2016 Shanghai,May2016.

[3] Barbedo, J. G. A., "Automatic Method for Counting and Measuring Whiteflies in Soybean Leaves Using Digital Image Processing", Conference: IX Brazilian Congress of Agro-informatics, 2014, pp. 685-694.

[4] C. Favret, J.M. Sieracki, "Machine vision automated species identification scaled towards production levels machine vision ID", Systematic Entomology, Vol. 41, pp. 133-143, Jan 2016.

[5] Da-Dong Wang, Da-Xing Zhang, Xun Wang, Hui-Yan Wang, Le-Qing Zhu, Meng-Yuan Ma, Zhen Zhang, Pei-Yi Zhang, and Wei Wu,"Hybrid deep learning for automated lepidopteran insect image classification", Oriental Insects, Vol. 51, pp. 79–91, Nov 2016.

[6] Edwin Raczko & Bogdan Zagajewski, "Comparison of support vector machine, random forest and neural network classifiers for tree species classification on airborne hyperspectral APEX images", European Journal of Remote Sensing, Vol. 50, pp. 144-154, Mar 2017.

[7] Huimin Che1, Bo Ding, Huaimin Wang, Ben Hu and Huifang Che "IKNN-SVM: A Hybrid Incremental Algorithm for Image Classification", Proceeding of the 2nd International Conference on Artificial Intelligence and Industrial Engineering, Vol. 133, 2016.

[8] Keun Young Lee, Namil Chung, Suntae Hwang, "Application of an artificial neural network (ANN) model for predicting mosquito abundances in urban areas", Ecological Informatics, Vol. 36, pp. 172-180, Nov 2016.

[9] Lorenz, C., Ferraudo, A.S., Suesdek, L,"Artificial Neural Network applied as a methodology of mosquito species identification.", Acta Tropica, Vol.152, pp. 165–169, Dec 2015.

[10] M. Fuchida, T. Pathmakumar, R. Mohan, N. Tan, and A. Nakamura,"Vision-based perception and classification of mosquitoes using support vector machine", Applied Sciences, Vol. 7, pp. 1-12, Jan 2017.

[11] M. Ristin, M. Guillaumin, J. Gall, and L. Van Gool, "Incremental learning of ncm forests for large-scale image classification," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 3654–3661.

[12] M.A. Ebrahimia, M.H. Khoshtaghazaa, S. Minaeia, B. Jamshidiba,"Vision-based pest detection based on SVM classification method", Computers and Electronics in Agriculture, Vol.137, pp. 52-58, May 2017.

[13] Natalia L, Hongli D, Wei Z, Matt S, Jenny Y, Robert P, Andrew M, David AL, Salvador RC, Eric NM, Linda GS, Thomas GD, "Automated insect identification through concatenated histograms of local appearance features: feature vector generation and region detection for deformable objects.", Machine Vision and Application,Vol.19, pp. 105–23, Mar 2008.

[14] Rafael de Oliveira Christe, André Barretto Bruno Wilke, Paloma Oliveira Vidal, Mauro Toledo Marrelli. "Wing sexual dimorphism in Aedes fluviatilis (Diptera: Culicidae)", Infection, Genetics and Evolution, Vol. 45, pp. 434-436, Nov 2016.

[15] Richard e darsie, Jr.Inno Anna Samanidou-voyadjoglou,"Keys for the identification of the mosquitoes of Greece", Journal of the American mosquito control association, Vol. 13, pp. 247-254, Sep 1997.

[16] Tai-Hsien Ouyang, En-Cheng Yang, Joe-Air Jiang, Ta-Te Lin. "Mosquito vector monitoring system based on optical wingbeat classification", Computers and Electronics in Agriculture, Vol. 118, pp. 47-55, Oct 2015.

[17] Tingting Xie, Changjian Wang and Yuxing Peng, "hi-RF: Incremental Learning Random Forest for Large-Scale Multi-class Data Classification", Proceeding of the 2nd International Conference on Artificial Intelligence and Industrial Engineering, Vol. 133, 2016.

[18] W Ding, G Taylor, "Automatic moth detection from trap images for pest management", Computers and Electronics in Agriculture, Vol. 123, pp. 17-28, Apr 2016.

[19] Wang J, Lin C, Ji L, Liang A,"A new automatic identification system of insect images at the order level", Knowledge-Based Systems, Vol.33, pp.102-110, Sep 2012.

[20] Wieland, R., A. Kerkow, L. Früh, H. Kampen, and D. Walther , "Automated feature selection for a machine learning approach toward modelling a mosquito distribution", Ecological Modelling, Vol. 352, pp. 108-112, May 2017.

[21] Yaniv Ovadia, Yoni Halpern, Dilip Krishnan, Josh Livni, Daniel Newburger, Ryan Poplin, Tiantian Zha, D Sculley , "Learning to Count Mosquitoes for the Sterile Insect Technique", Proceedings of the 23nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1943 -1949, 2017.

[22] Zhou Wang and David Zhang ,"Progressive Switching Median Filter for the Removal of Impulse Noise from Highly Corrupted Images", IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS, VOL. 46, 1999.