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An Improved Transfer Learning Based Larvae Detection and Classification Using Densenet121

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***Abstract*—Bangladesh is currently experiencing a surge in dengue fatalities due to increased Aedes mosquito activity during rainy seasons. To address this issue, this paper proposes a solution for detecting Aedes larvae in water bodies near and inside homes using deep learning models. A pre-processed image dataset is utilized to train transfer learning models, including DenseNet-121, Inceptionv3, Xception, ResNet50, VGG16, VGG19, and Ensemble boosting. The results demonstrate the exceptional performance of the DenseNet121 model, achieving 100% accuracy, precision, and recall scores. Therefore, a system has been developed to assist social workers in classifying collected images and detecting Aedes and non-Aedes larvae. This study highlights the potential of using deep learning models to classify mosquito larvae, offering significant implications for controlling diseases transmitted by mosquitoes such as dengue and Zika. By leveraging technological advancements and community engagement, the prevention and management of mosquito-borne illnesses can be greatly improved.**

***Index Terms*—Aedes larva, transfer learning, binary classification, AI support system, densenet121, vgg16, vgg19, resnet50, inceptionv3, xception.**

I. Introduction

Dengue, a viral infection transmitted by Aedes mosquitoes, is prevalent in tropical and sub-tropical urban areas. With four serotypes, sequential infections increase the risk of severe dengue [1]. While many cases are mild or asymptomatic, early detection and appropriate care are crucial in preventing deaths, as there is no specific treatment for dengue. Bangladesh, where dengue was first recorded as "Dacca fever" in the 1960s [2], faces increasing dengue cases due to factors like regional rainfall patterns, rising temperatures, and shifting climate conditions, making it conducive for the transmission of dengue and other vector-borne diseases.

Since the first dengue cases were discovered in Bangladesh in 2000, around 49,000 people have been affected by the disease, with at least 316 documented fatalities. Most patients received care in hospitals and clinics in the capital city of Dhaka or its neighboring regions. While the number of cases exceeded 6,000 only three times in the previous 18 years (in 2002 and 2016), it had already reached 6,479 as of the most recent report [3]. Dengue fever is caused by all three strains of the dengue virus, which are carried by the Aedes aegypti mosquito. This same mosquito species also transmit other diseases such as chikungunya, Zika fever, and yellow fever [4].

In 2019, a significant outbreak of dengue occurred in Bangladesh, extending to non-endemic areas. A total of 123 children with dengue were treated at a general hospital in Tangail between June and September. The majority of patients were male, with an average age of over seven years. More than a quarter of patients developed bleeding symptoms, and two children experienced dengue shock syndrome. Common clinical symptoms included fever, body aches, headaches, and rash. About 40% of cases had thrombocytopenia [5].

Dengue fever has emerged as a significant public health concern globally, with Dhaka reporting the highest number of cases each year. The underlying factors contributing to this trend need to be comprehensively investigated to devise effective mitigation strategies [6]. Interdisciplinary efforts involving epidemiological, entomological, and environmental studies are essential in this regard. The main challenges faced were the unavailability of public datasets for Aedes larvae detection compelled us to rely on data acquired from other researchers, obtained through specific requests due to our current limitations in tools and infrastructure for data collection. These research gaps were found during research for relevant papers for this research:

- The enhanced model and enlarged photos showed high accuracy in findings, while other models like grayscale, inverted grayscale, cut-to-fit, and square models had lower accuracy.
- Darker pictures help with detection, but they have trouble with spherical shadows and items hidden by other things. These problems could be fixed by enhancing darker photographs and conducting color space research.
- Water mapping errors are primarily caused by flooded vegetation, water body depth, agricultural facilities, floating algae, and surface salt crusts in rice fields and wetland systems.
- It's crucial to be aware that adding the Esri model definition file to the geoprocessing tools can lead to an error while installing the deep learning framework Python packages into a real-time iOS app platform.

One approach to curbing the spread of dengue fever is through the detection and prevention of Aedes larvae growth [7]. Therefore, our contribution can lead to,

- Developing a compact pipeline for Aedes larvae detection and destruction can potentially aid in this effort.

- Additionally, automating the detecting system could optimize it for government use, making it more efficient and effective.
- To fully understand the overall scenario, a demo web implementation of the system needs to be created.
  Outcomes: This will lead to the detection and destruction process contributing to minimizing the risk of mosquito-borne diseases efficiently. Also, the automation enhances the utilization of resources and a proactive response to potential outbreaks, thereby improving overall public health outcomes. Lastly, the demo web implementation serves as a valuable tool for garnering support, feedback, and potential collaborations, thereby fostering community engagement in disease control efforts.

This research pipeline can present valuable insights into how the system works and how it can be improved. In conclusion, the main motivation for taking these steps will help address the ongoing public health emergency of dengue fever and contribute to a healthier, safer population.

II. Literature Review

In 2020, Michelle et al. explored the use of high-resolution drone mapping to identify larval habitats in mosquito-borne disease control, focusing on rural areas facing LSM challenges. They utilized drone mapping and larval surveys in the Kasungu district, employing manual methods and GeoOBIA analysis to identify water bodies and aquatic vegetation in drone imagery. The study achieved a high median accuracy of 98% in identifying larval habitat characteristics through GeoOBIA analysis of images from a standard camera. These findings demonstrate the potential of drone mapping as a feasible approach for identifying larval habitats in mosquito-borne disease control, especially in rural areas where traditional methods have limitations [8].

Similar to the previous study Gabriel et al. investigated the use of unnamed aerial vehicles to identify breeding sites of Nyssorhynchus darlingi, a malaria vector conducted in Amazonian Peru, Using high-resolution imagery and examining the multispectral profile, the study achieved an overall accuracy ranging from 86.73% to 96.98 in discriminating water bodies conducive to Ny. darlingi breeding. This proof-of-concept study showcases the potential of high-resolution multispectral imagery in detecting malaria vector breeding sites in the Amazonian region of Peru, contributing to larval source management (LSM) for malaria control. Further research is needed to refine the methodology and assess its applicability in other malaria-endemic areas [9].

On the other hand, Kenia et al. conducted a groundbreaking study in Mexico, evaluating the field effectiveness of drones in identifying and managing mosquito breeding sites, specifically Aedes aegypti breeding sites on building rooftops and backyards. Their study compared drone surveillance with the existing government Aedes vector surveillance program in Tapachula City. The results revealed that drone surveillance successfully identified 983 containers across 10 different types, whereas ground surveillance inspected only one-third of these containers distributed in 26 types. Integrating drones into mosquito control efforts can enhance monitoring and intervention strategies, providing more targeted and effective control measures in dengue-endemic regions with numerous potential breeding sites. This innovative technology represents a valuable tool for improving mosquito-borne disease management in endemic areas [10].

Some researchers give importance to the other side of the study like Zaria et al. focused their research on the classification of mosquito larvae images using deep neural networks (DNNs) and visualization techniques. Their approach aimed to distinguish between Aedes and Non-Aedes mosquitoes based on the comb-like figure in the larvae's abdomen segments. The study employed a DNN architecture and visualization technique, achieving an identification performance of 97% in classifying input images. This research showcases the potential of advanced techniques such as DNNs and visualization methods for automatically identifying and classifying mosquito larvae, contributing to improved mosquito surveillance and control efforts. Further data collection is necessary to enhance the training process and achieve even higher classification accuracy [11].

On a different aspect, Fuad et al. [[12] focused their attention on water storage and artificial containers as non-accessible breeding sources, which are significant concerns according to the World Health Organization. In their initial study, the authors selected prominent sources of Malaysian epidemiology and collected 534 images. These images were used to train and classify Aedes aegypti larvae. Their primary objective was to compare the accuracies and cross-entropy errors of the training set using different learning rates. Remarkably, with three different learning rates, they achieved the highest accuracy of 99.98% in larval classification. This research showcases the effectiveness of their approach in accurately identifying Aedes aegypti larvae in non-accessible breeding sites, making a valuable contribution to mosquito control efforts.

Continuing their investigations, Fuad et al. [13] conducted another study on this topic in the subsequent year. This time, they employed a single-shot multi-box detector with transfer learning. The detection task utilized SSD with Inception V2 architecture, resulting in an impressive 80% accuracy without any false alarms. The adoption of advanced detection methods with transfer learning demonstrates the promising potential for effectively identifying Aedes aegypti larvae. These findings provide valuable insights for enhancing mosquito surveillance and control strategies.

III. Proposed Methodology

This study presented a four-step approach to guarantee the reliability of the results. The approach encompasses essential aspects like describing the dataset, pre-processing the data, constructing and validating the models, and evaluating the models. The overall pipeline, illustrated in Figure 2, reflects this methodology. Apart from the methodology, the study also introduced significant technical contributions that offer

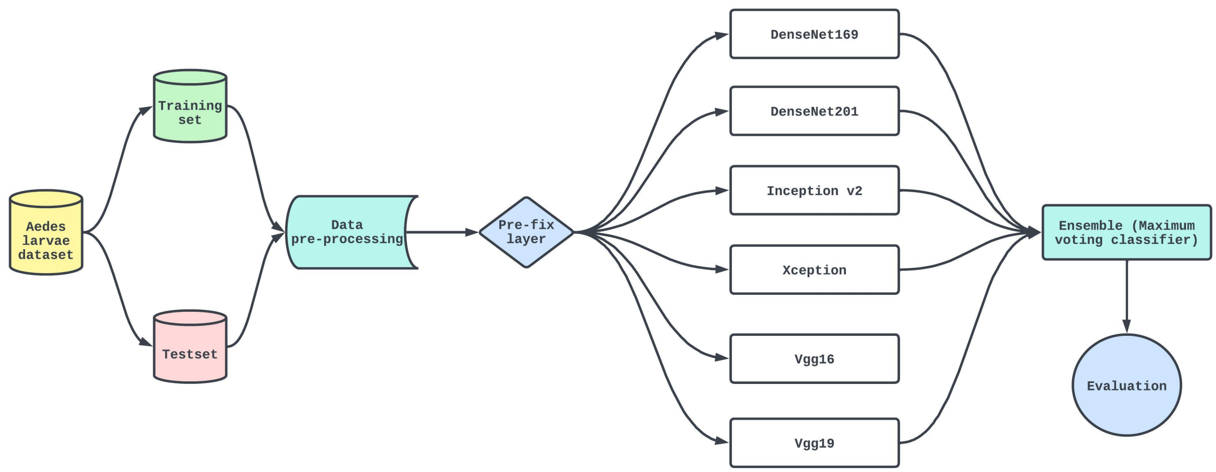

Fig. 1: Aedes larvae detection using transfer learning approach

valuable insights into the research domain. These contributions are expected to enhance the research's credibility and establish it as a reliable source of information.

A. Dataset

The data utilized in this study was originally extracted from De Silva et al. [14] specifically, where their zoom 374 zoomed images set was used in this study. Out of these, 355 images they selected for training purposes, while the remaining 19 images were reserved for testing.

B. Data pre-processing

During the training and testing phases of the research, the dataset comprised of two distinct classes, namely Aedes and Non-Aedes. A total of 355 images were selected for training purposes, with 255 images belonging to the Aedes class and 100 images representing the Non-Aedes class. To evaluate the performance of the model, 19 images were reserved exclusively for testing, consisting of 9 Aedes images and 10 Non-Aedes images.

To ensure uniformity and consistent input sizes for the deep learning model, a pre-processing step was implemented. This involved scaling all the images to a standardized width and height of 224 pixels.

Given that the dataset was sourced from a different research paper, the authors of the current study extracted the best-performing split of the data based on their expertise. Considering the nature of the data, which was collected from wild sources, it was deemed impractical to augment the dataset. Therefore, the researchers explored various data splits and identified the one that yielded the highest performance. Consequently, this specific data split was adopted in our research to maintain consistency with the original study.

C. Pre-fix layer

The utilization of a pre-fix function in this pipeline offers flexibility when working with multiple pre-trained models. It enables convenient modification of layer names to prevent conflicts. This function takes a pre-trained model and a prefix string as inputs. Subsequently, it returns a new model that retains the same weights as the input model, but with each layer name prefixed by the provided string. This approach can be applied to any pre-defined model in TensorFlow, offering a straightforward and efficient solution to a frequently encountered challenge in deep learning research.

D. Model preparation and evaluation

In this study, an ensemble model was constructed by combining the outputs of six pre-trained deep neural network models: DenseNet121, InceptionV3, Xception, ResNet50, VGG16, and VGG19. Instead of averaging the individual models' predictions, the ensemble model employed a maximum voting technique, where the class determined the final projection with the highest number of votes among the individual models. This approach aimed to minimize errors and improve the overall performance of the ensemble model.

During the training process, categorical cross-entropy was used as the loss function, and the Adam optimizer was employed to optimize the model's parameters. The model was trained for 20 epochs, with the number of steps per epoch corresponding to the size of the training dataset. Accuracy served as the evaluation metric during training, and the performance of the model was monitored using validation data.

Following training, the effectiveness of the ensemble model was assessed using an independent test set. Predictions were generated for the test images and compared to the actual labels to determine the model's classification accuracy. To further evaluate the classification model's efficacy, a confusion matrix was employed, and precision, recall, and F1 scores were calculated using the predicted and actual labels from the test dataset. Additionally, a precision-recall curve was plotted to evaluate the model's performance.

IV. Technical contribution

The technical contributions of this study can be categorized into two major areas. Firstly, the study introduces an ensemble model with a maximum voting approach, combining the outputs of multiple deep neural network models. This approach aims to improve accuracy and performance by leveraging the collective predictions of individual models.

Secondly, the study focuses on the deployment of the machine learning model and its integration into a web application. The Flask framework is utilized to develop a user-friendly web interface, allowing users to interact with the model by uploading data or inputting information. This seamless integration enables remote access and utilization of the machine learning model through the web interface.

A. Ensemble approach

In this study, we utilized six popular DCNN architectures: DenseNet121, InceptionV3, Xception, ResNet50, VGG16, and VGG19. Each of these models was pre-trained on the ImageNet dataset containing millions of images before fine-tuning on our specific dataset. The goal was to take advantage of the individual strengths of each model and create an ensemble that could improve the overall performance of image classification.

To create the ensemble, this proposed pipeline employed the maximum voting classifier technique, which is a popular approach in ensemble learning. In this method, each model predicted the label of a given image, and the class with the highest number of votes was selected as the final prediction. This technique allowed us to combine the outputs of each model and leverage their collective decision-making power to achieve better classification results.

Given a set of base models $\{\mathrm{M1}, \mathrm{M2}, \ldots, \mathrm{Mn}\}$ and an input instance x, the output of the ensemble maximum voting classifier can be represented as:

$$y = \mathrm{mode}(\mathrm{f}(\mathrm{M1}(\mathrm{x})), \mathrm{f}(\mathrm{M2}(\mathrm{x})), \ldots, f(\mathrm{Mn}(\mathrm{x})))$$

where $f(\mathrm{Mi}(\mathrm{x}))$ is the predicted label of the input instance x by the i-th base model Mi, and mode () returns the most frequently occurring predicted label among all the base models' predictions. In other words, the ensemble model's output is the label that receives the highest number of votes from the base models.

B. Web Interface

Deploying a machine learning (ML) model using Flask involves training the model, serializing it, and setting up the Flask framework. The web interface is developed using HTML, CSS, and JavaScript, allowing users to interact with the ML model by uploading data or inputting information. The serialized model is integrated into the Flask application, and the user interface is designed to provide a seamless experience. Finally, the application is deployed to a web server or cloud platform for remote access.

One of the major contributions of this study is the development of a user-friendly web interface Fig 3. A dedicated fully connected data server was designed, allowing users to

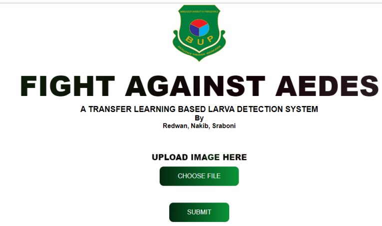

Fig. 2: Transfer learning-based web application

easily upload high-resolution larvae images for detection and classification purposes. However, it is important to note that for higher accuracy, clear and high-quality image inputs are required. Distinguishing between Aedes and non-Aedes larvae can be challenging due to the similarities in their physical structures. Nonetheless, the web interface provides a convenient platform for individuals to assess and identify larvae with the aim of improving accuracy in larval classification.

V. Result analysis and discussion

Table 1 shows a full classification report for six different pre-trained models and an average ensemble model based on precision, recall, F1 score, training accuracy, validation accuracy, training loss, and validation loss in this study.

DenseNet121 demonstrates exceptional performance by achieving perfect precision, recall Fig 4, and F1 Score, indicating the flawless classification of all instances. Furthermore, the model exhibits a remarkable training accuracy and validation accuracy of 1.00, reflecting its ability to thoroughly learn from the training data. The model's training loss and validation loss are exceptionally low in Fig. 5 and 6, signifying an outstanding fit to the data.

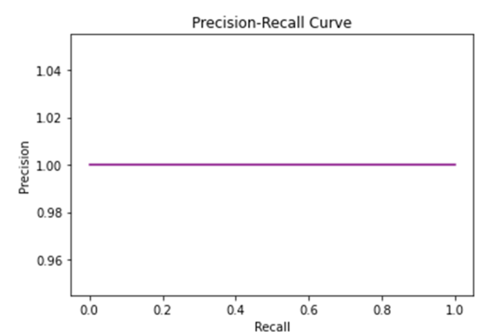

Fig. 3: Precision-recall curve of DenseNet121

In Fig 7, a confusion matrix shows how the training dataset was used to evaluate the DensNet121 model. The matrix displays the model's performance in predicting the aedes or non-aedes larvae where a total of 19 images are used. The true positive prediction rate for the aedes scan is 9 and the non-aedes scan is 10, meaning the model correctly identified each negative and positive case.

InceptionV3 exhibits commendable performance, as evidenced by its high precision, recall, and F1 Score, indicating

TABLE I: Results for different transfer learning model

Model	Precision	Recall	F1 Score	Training Accuracy	Test Accuracy	Training Loss	Test Loss
DenseNet121	1.00	1.00	1.00	1.00	1.00	2.3111e−05	4.3919e−08
InceptionV3	0.93	0.94	0.97	0.9922	0.9688	0.0561	0.1577
Xception	0.93	0.94	0.97	0.9609	1.00	0.1708	0.0021
ResNet50	0.92	0.82	0.86	0.93	0.93	0.20	0.23
VGG16	0.56	0.00	0.00	0.5703	0.5625	0.7064	0.6847
VGG19	0.93	0.94	0.97	0.9453	0.9688	0.1335	0.0932
Ensemble Boosting	0.98	0.971	0.973	0.9842	0.9871	0.0173	0.0468

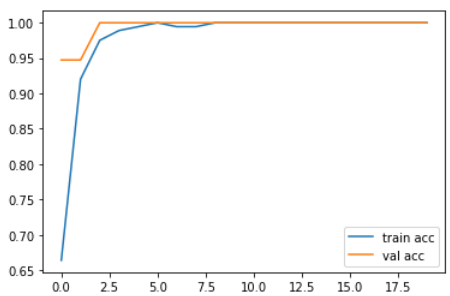

Fig. 4: Training and Validation Accuracy of DenseNet121

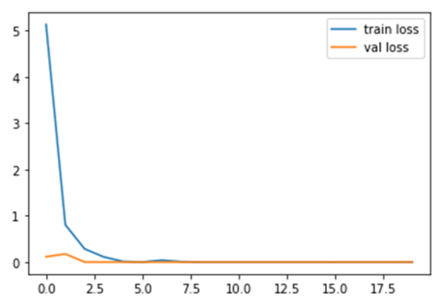

Fig. 5: Training and Validation Loss of DenseNet121

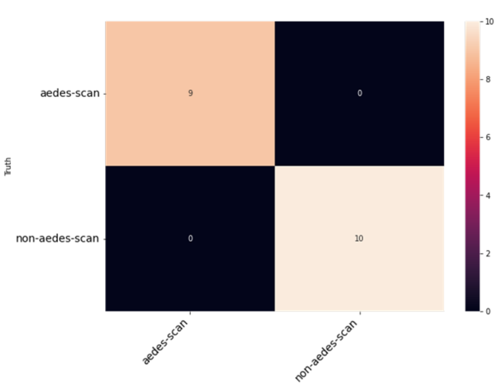

Fig. 6: Confusion matrix of DenseNet121

strong overall performance. The model demonstrates a training accuracy of 0.9922 and a validation accuracy of 0.9688, suggesting effective generalization capabilities. Moreover, the model's training loss and validation loss are relatively low, indicating a satisfactory fit to the data.

Similarly, Xception showcases comparable precision, recall, and F1 Score to InceptionV3, indicating a good level of performance. Although the training accuracy is slightly lower at 0.9609, the model achieves a perfect validation accuracy of 1.00. The training loss is slightly higher compared to InceptionV3, but the validation loss remains extremely low, further affirming the model's strong performance.

In contrast, ResNet50 exhibits relatively lower precision, recall, and F1 Score compared to the aforementioned models. However, the model still demonstrates decent generalization with a training accuracy and validation accuracy of 0.93. The training loss and validation loss are relatively high, indicating potential areas for improvement in the model's performance.

VGG16, unfortunately, demonstrates poor performance with low precision, F1 Score, and a recall of 0.00. Both the training accuracy and validation accuracy are also low, suggesting the model struggles to effectively learn and generalize from the data. Additionally, the model exhibits high training loss and validation loss, indicating a poor fit to the data.

On the other hand, VGG19 showcases performance similar to InceptionV3 and Xception, exhibiting high precision, recall, and F1 Score. The model achieves a relatively high training accuracy of 0.9453 and a good validation accuracy of 0.9688. The training loss and validation loss are moderate, indicating a reasonable fit to the data.

The Ensemble was generated without the VGG16 model as it performs worst in this study without the VGG16 the Boosting model demonstrates high precision, recall, and F1 Score, indicating strong overall performance. Both the training accuracy and validation accuracy are high, suggesting effective generalization capabilities. Additionally, the model showcases relatively low training loss and validation loss, indicating a flattering fit to the data.

The variation in results could be attributed to various factors, including the model's architecture, the quality and quantity of data used, and the optimization parameters used during training. However, models such as DenseNet121, InceptionV3, MobileNetV2, VGG16, and VGG19 have been shown to work well in many image-based applications. In contrast, ResNet50's lower performance could imply that the model is not the best fit for this particular task or dataset.

However, achieving 100% performance with the DenseNet121 model is not indicative of overfitting, as demonstrated by the absence of any signs of overfitting in Fig 5 and Fig 6. Instead, this achievement stands as a testament to the rigor and quality of our approach. First and foremost, the dataset we use is of exceptionally high quality, collected using drones equipped with powerful lenses. These images are not only high-resolution but also free from noisy or misleading data, which minimizes the chances of introducing errors that could lead to overfitting.

It's worth highlighting that the Densenet121 model's impeccable performance extends across multiple evaluation metrics, including accuracy, precision, recall, and F1 score, showcasing its genuine and exceptional performance. Moreover, when comparing this model against other baseline transfer learning methods and existing benchmarks, we consistently observe a significant improvement. This comparison further reinforces the idea that presented results are not mere artifacts of overfitting but rather the outcome of an innovative and effective approach.

Overall, the presented models exhibit varying levels of performance where DenseNet121 achieves perfect performance, while InceptionV3, Xception, and Ensemble Boosting also perform well. VGG16 performs poorly, likely indicating a significant issue with the model. The other models, ResNet50 and VGG19, achieve moderate performance but have room for improvement. Further analysis, such as examining the dataset and considering other factors like computational requirements, would be needed for a more comprehensive evaluation.

VI. Conclusion and Future Work

Most importantly, this research carries substantial real-world significance. Achieving perfect accuracy in mosquito larvae detection, particularly for diseases like dengue and Zika, holds immense practical relevance. This underscores the potential impact of our results in disease control efforts. It's worth noting that there is a notable lack of available dengue or Zika data collected by drones, limiting our ability to explore the full potential of the DenseNet121 model. However, as part of our ongoing efforts, we are actively collecting additional data. This future data collection will enable us to further validate the capabilities of DenseNet121 and deepen our understanding of its potential in combating mosquito-borne diseases. Though 100% performance may appear extraordinary, it reflects the meticulous attention given to data quality, preprocessing, model selection, and validation.

While this study has provided promising results, there are several avenues for future research. Firstly, expanding the dataset to include a larger variety of images and diverse environmental conditions would enhance the generalizability of the models, deploying the developed system in real-world scenarios and evaluating its performance in detecting Aedes larvae under different field conditions would be crucial for practical implementation. Lastly, we will use state-of-the-art methods for using drones equipped with high-quality AI cameras for capturing detailed site mapping that can be used as datasets for rural areas that are unmanned and unreachable swamps, as per aerial views. Overall, the integration of advanced technologies and data-driven approaches holds great promise for effective control and surveillance of mosquito-borne diseases in densely populated regions like Bangladesh.

References

[1] M. E. H. Kayesh, I. Khalil, M. Kohara, and K. Tsukiyama-Kohara, "Increasing dengue burden and severe dengue risk in bangladesh: An overview," *Tropical Medicine and Infectious Disease*, vol. 8, no. 1, p. 32, 2023.

[2] M. Aziz, J. Gorham, M. Gregg *et al.*, ""dacca fever"- an outbreak of dengue." *Pakistan Journal of Medical Research*, vol. 6, no. 2, pp. 83–92, 1967.

[3] F. U. Ahmed, C. B. Mahmood, J. D. Sharma, S. M. Hoque, R. Zaman, and M. S. Hasan, "Dengue and dengue haemorrhagic fever in children during the 2000 outbreak in chittagong, bangladesh." 2001.

[4] T. Nakase, M. Giovanetti, U. Obolski, and J. Lourenço, "Global transmission suitability maps for dengue virus transmitted by aedes aegypti from 1981 to 2019." 2022.

[5] S. Yesmin, S. Sarmin, A. M. Ahammad, M. A. Rafi, M. J. Hasan *et al.*, "Epidemiological investigation of the 2019 dengue outbreak in dhaka, bangladesh," *Journal of Tropical Medicine*, vol. 2023, 2023.

[6] M. A. Nahian, "Public health impact and health system preparedness within a changing climate in bangladesh: A scoping review," *Challenges*, vol. 14, no. 1, p. 4, 2023.

[7] Y.-X. Chen, C.-Y. Pan, B.-Y. Chen, S.-W. Jeng, C.-H. Chen, J.-J. Huang, C.-D. Chen, and W.-L. Liu, "Use of unmanned ground vehicle systems in urbanized zones: A study of vector mosquito surveillance in kaohsiung," *PLOS Neglected Tropical Diseases*, vol. 17, no. 6, p. e0011346, 2023.

[8] M. C. Stanton, P. Kalonde, K. Zembere, R. Hoek Spaans, and C. M. Jones, "The application of drones for mosquito larval habitat identification in rural environments: a practical approach for malaria control?" *Malaria journal*, vol. 20, no. 1, pp. 1–17, 2021.

[9] G. Carrasco-Escobar, E. Manrique, J. Ruiz-Cabrejos, M. Saavedra, F. Alava, S. Bickersmith, C. Prussing, J. M. Vinetz, J. E. Conn, M. Moreno *et al.*, "High-accuracy detection of malaria vector larval habitats using drone-based multispectral imagery," *PLoS neglected tropical diseases*, vol. 13, no. 1, p. e0007105, 2019.

[10] K. M. Valdez-Delgado, D. A. Moo-Llanes, R. Danis-Lozano, L. A. Cisneros-Vázquez, A. E. Flores-Suarez, G. Ponce-García, C. E. Medina-De la Garza, E. E. Díaz-González, and I. Fernández-Salas, "Field effectiveness of drones to identify potential aedes aegypti breeding sites in household environments from tapachula, a dengue-endemic city in southern mexico," *Insects*, vol. 12, no. 8, p. 663, 2021.

[11] G. Zaira, K. Yanai, M. Nakano, A. Arista, L. Cleofas Sanchez, and H. Perez, "Mosquito larvae image classification based on densenet and guided grad-cam," in *Pattern Recognition and Image Analysis: 9th Iberian Conference, IbPRIA 2019, Madrid, Spain, July 1–4, 2019, Proceedings, Part II 9*. Springer, 2019, pp. 239–246.

[12] M. A. M. Fuad, M. R. Ab Ghani, R. Ghazali, T. A. Izzuddin, M. F. Sulaima, Z. Jano, and T. Sutikno, "Training of convolutional neural network using transfer learning for aedes aegypti larvae," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 16, no. 4, pp. 1894–1900, 2018.

[13] ——, "Detection of aedes aegypti larvae using single shot multibox detector with transfer learning," *Bulletin of Electrical Engineering and Informatics*, vol. 8, no. 2, pp. 514–518, 2019.

[14] W. De Silva and S. Jayalal, "Dengue mosquito larvae identification using digital images," in *2020 International Research Conference on Smart Computing and Systems Engineering (SCSE)*. IEEE, 2020, pp. 31–36.