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Segmentation Automation for Identification of Aedes Larvae Using Deep Learning Methods

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Abstract**—**To enhance the accuracy of Aedes larvae identification and classification stands as a crucial initial measure in combating mosquito-borne diseases such as Dengue and the Zika virus. This project proposes an innovative approach by harnessing the power of deep learning, specifically employing convolutional neural networks (CNNs), to automate the segmentation of Aedes larvae from images captured in diverse watery settings. The primary objective is to develop a robust deep learning model adept at precisely detecting and delineating Aedes larvae amidst complex backgrounds. This, in turn, aims to alleviate the reliance on manual labor and bolster the scalability of larval surveillance efforts. The methodology adopted for this project is comprehensive and begins with the meticulous collection of a diverse dataset featuring images of Aedes larvae captured in various watery environments. Advanced image segmentation techniques are then applied to precisely outline the distinct larval regions within these images. This segmentation process is a crucial step, enabling the model to discern the boundaries and characteristics of Aedes larvae accurately.

Index Terms**—**Aedes larvae, Identification, Classification, Convolutional Neural Networks(CNN), Segmentation.

I. INTRODUCTION

Dengue fever is a viral ailment spread by mosquitoes that has grown prevalent in over 100 countries worldwide. The dengue virus, which has four serotypes that are genetically related, is the cause of the illness. Not only is the Aedes mosquito the main vector of the virus, but it also spreads the Zika and Chikungunya infections. With millions of cases recorded each year, dengue fever has become a serious public health concern in many nations. The number of cases keeps rising even while the sickness is being controlled. Since there are no effective drugs or vaccinations to treat dengue at this time, it is essential to keep an eye on and manage viral carriers. This has prompted the creation of automated systems, like the one that is suggested here that makes use of ensemble learning, to effectively cull the spreading of dengue and other mosquito-borne diseases.

Addressing Aedes mosquitoes during their larva stage plays a pivotal role in curbing the transmission of diseases like dengue fever. These mosquitoes serve as primary vectors for the dengue virus, and interrupting the hatching and maturation of Aedes larvae significantly diminishes the threat of dengue outbreaks. Targeting Aedes mosquitoes at the larva stage proves highly effective since they are most susceptible at this phase and lack the ability to transmit diseases without a proboscis. Moreover, distinctive morphological features enable the specific identification of Aedes larvae, facilitating precise targeting. Conventional methods, involving manual examination by expert entomologists using microscopes, are cumbersome and impractical. Yet, recent strides in information technology and artificial intelligence have yielded automated systems capable of accurately identifying Aedes larvae from low-resolution images. This technological advancement expedites identification and prevention, presenting a more pragmatic and efficient approach to mosquito-borne disease control. The proposed system, incorporating ensemble learning, computer vision, and deep learning, showcases both practical utility and high accuracy in Aedes larvae identification, emerging as a valuable tool in the battle against the dengue endemic and associated mosquito-borne illnesses.

II. LITERATURE SURVEY

A. Aedes Larva Detection Using Ensemble Learning to Prevent Dengue Endemic[1]

The research presents a novel method that employs computer vision and deep learning to recognize Aedes mosquito larvae in order to stop the spread of diseases like dengue fever, which is carried by Aedes mosquitoes. Recognizing that traditional methods are time-consuming and subjective, the proposed system leverages collaborative learning and U-net segmentation to achieve superior performance compared to previous approaches.

Method:

Traditional methods of identifying Aedes larvae are laborious, arbitrary, and unfeasible. The proposed method addresses these problems by combining ensemble learning with U-net segmentation, which works well to differentiate Aedes larvae with over 99 percent accuracy from lowmagnification pictures. This goes beyond what is currently being monitored.

About 85 percent of the U-net segmentation was accurate. This kind of architecture can be used for a variety of tasks, particularly when it's necessary to recognize many items from an image. It does this by using segmentation as a preprocessing method before classifying data. Following segmentation, an ensemble model was used to classify each larval body. To make use of everyone's strengths, this ensemble model brought together a number of weak learners.

Drawbacks:

Issues with computational resources and expertise are introduced by the proposed system's reliance on deep learning and ensemble learning approaches. To effectively deploy and maintain the system's ability to combat Aedesborne infections, it is imperative to have a proficient team and adequate infrastructure. This emphasizes the significance of taking these variables into account during both the implementation and ongoing maintenance phases of the system's operation.

B. Dengue Mosquito Larvae Identification Using Digital Images[2]

This paper explores the development of a deep learning computational model for the real time identification of Aedes mosquito larvae from digital photographs. The increasing incidence of dengue, a mosquito-borne illness, especially in tropical areas like Sri Lanka, is the impetus for this study. The suggested model seeks to overcome these difficulties by quickly and precisely recognizing Aedes larvae from digital images taken with cameras or cellphones.

Method:

The study divides larvae into Aedes and Non-Aedes groups using Convolutional Neural Networks (CNN) and the ResNet50 architecture. Enlarged photos captured with a microscope are compared to digitally zoomed images obtained without a microscope. With an overall accuracy of 86.65 percent, the results show that the model can successfully distinguish between the two types of larvae. By using pre-processing methods, its accuracy can be increased even more to 98.76 percent for enlarged photos. Drawbacks:

The accuracy of detecting Aedes mosquito larvae may be limited by the reliance on digital magnification for image acquisition. The investigation of potentially better models for the identification of mosquito larvae may be limited by the study's concentration on the ResNet50 CNN model. Variations in external factors, such illumination, climate, or the existence of water-related debris, could potentially affect the model's functionality. It is crucial for the model's practical usefulness to ensure that it is resilient to these fluctuations.

C. Aedes Larvae Classification and Detection (ALCD) System Using Deep Learning[3]

The Aedes Larvae Classification and Detection (ALCD) System, which uses deep learning technology to identify and categorize Aedes mosquito larvae, is covered in this paper.

Method:

The suggested ALCD system design combines software and hardware elements, such as TensorFlow, Keras, and PyCharm, with elements like the Blips micro lens, smartphone, and other accessories. The six processes that make up the architecture of the system include image capture, prediction, and result output. The process is broken down into five research phases: background study, literature evaluation, pattern recognition and categorization, portable ALCD system creation, and testing. The system uses deep learning methods, most especially the Convolutional Neural Network (CNN), to process photos of larvae and categorize them according to their kind.

The results of the ALCD model training are presented in the document, which shows a 64.58 percent ultimate accuracy rate.

Drawbacks:

The Aedes Larvae Classification and Detection (ALCD) System has limitations in terms of predicted output accuracy and lesser accuracy when compared to laboratory testing. Furthermore, the system can have trouble reaching high accuracy rates and might not be as accurate as the conventional approach. Additionally, the ALCD system necessitates the usage of particular hardware and software components, which can restrict its applicability and accessibility.

D. Mosquito Larvae Detection using Deep Learning[4]

The use of deep learning models for mosquito larvae identification is examined in this paper, with an emphasis on the Aedes species. This work explores the effective detection of Aedes mosquitoes through the use of sophisticated neural network architectures. Aedes mosquitoes are known to spread diseases such as dengue fever. This study evaluates four convolutional neural network (CNN) models: VGG16, VGG19, ResNet50, and InceptionV3. The models are used to classify photos of mosquito larvae based on the species to which they belong.

Method:

Metrics like as accuracy, log-loss, and AUC-ROC are used to evaluate the models' performance, and file size and training time are compared. According to the results, ResNet50 is the best option for incorporation into online or mobile applications because it obtains the highest accuracy and AUC-ROC. Additionally, the publication offers thorough insights into the procedures for gathering data, pre-processing, and training CNN models.

Drawbacks:

High-quality and representative training data sets are critical to the effectiveness of deep learning models. The model may not be as generalizable to real-world events if the training dataset is not sufficiently diverse or covers a range of environmental circumstances. For training and inference, deep learning models—especially those with bigger architectures like ResNet50—demand a substantial amount of processing power. For academics and practitioners with restricted access to high-performance computing resources, this can be a limitation.

E. Real-Time Mosquito Species Identification using Deep Learning Techniques[5]

This research explores the use of deep learning approaches for real-time identification of mosquito species, involving those that carry diseases like malaria and dengue. The authors highlight the significance of identifying carrier mosquitos as a critical stage in disease prevention strategies. They present the WINGBEATS dataset, which contains recordings of several species of mosquito wingbeats, and describe the usage of various deep learning models for mosquito species identification, such as ResNet, DenseNet, and XGBoost.

Method:

The authors include the WINGBEATS dataset preprocessing, the conversion of audio recordings into spectrograms for input data, and the training and testing of various deep learning models. They also address the use of Extreme Gradient Boosting (XGBoost) for audio classification and emphasize the Multi-Layer CNN model's promising results in detecting mosquito species.

Drawbacks:

Due to its high processing requirements, the Multi-Layer CNN model, while effective, may not be suited for deployment on devices with very low hardware capabilities, according to the research. Furthermore, the authors point out even tiny changes in the time and frequency dimensions of spectrograms might cause classification mistakes, thereby lowering the model's performance.

F. Implementation of a deep learning model for automated classification of Aedes aegypti (Linnaeus) and Aedes albopictus (Skuse) in real time[6]

The creation and application of a deep learning model for the real-time automatic categorization of Aedes albopictus and Aedes aegypti mosquitoes is the main topic of this paper. The study tackles the difficulties associated with imprecise mosquito samples and the requirement for precise categorization because of the potential for dengue disease. By utilizing computer vision and deep learning techniques, the research seeks to offer a workable solution for automated mosquito classification.

Method:

The study developed its models using a web-based platform that combined hyperparameter analysis and transfer learning. The model's hardware implementation—the Aedes Detector—enabled real-time deployment and produced accuracy on par with that of a human expert. The study also underlined how crucial feature presentation and picture capture are to accurately classifying mosquitoes, especially when the insects' physical characteristics have vanished. To improve the model's performance, the study carried out hyperparameter analysis with an emphasis on the learning rate and epochs.

Drawbacks:

The main flaw in the model is that, when used in a real-time trap or surveillance system, it requires frequent calibration and monitoring. This is brought on by possible problems such model drift, in which case training data may not accurately reflect production data, and the requirement for model management and upkeep. The study also brought attention to issues with mosquito sample condition, including the loss of morphological characteristics like the head and thorax that might affect classification accuracy. In addition, there were difficulties with the model's mobility and compatibility with the hardware throughout its hardware rollout. These flaws show that continued monitoring is necessary to guarantee the accuracy of the model's predictions.

G. Detecting Aedes aegypti mosquitoes through audio classification with convolutional neural networks[7]

The paper presents a comprehensive analysis of machine learning techniques for identifying Aedes aegypti mosquitoes through their wingbeat sounds. The study emphasizes the importance of community engagement and the potential of ubiquitous devices like smartphones in addressing mosquito-borne diseases. The authors highlight the vision that an effective solution for tackling mosquito-borne diseases requires broader engagement from local communities and propose the use of smartphones as an appropriate option to aid in this endeavor. The paper also discusses the challenges in accurately identifying mosquito species based solely on wingbeat sound analysis, particularly in the context of class imbalance and the complexity of multiclass classification.

Method:

During the investigation, three different classifiers were trained: an ensemble of binary classifiers, a multiclass classifier, and a binary classifier. The evaluation findings demonstrated significant achievements for both the binary and ensemble models, with the binary classifier exhibiting a high accuracy of 97.65 percent and the ensemble classifier displaying a sensitivity of 98.82 percent. By comparison, the accuracy of the multiclass classifier was 78.12 percent. A comparison of several Fast Fourier Transform (FFT) parameter combinations was also part of the inquiry, and the results showed that the models worked best with 60 bands and 40 frames. Interestingly, the ensemble classifier did not show a statistically significant gain in performance over the base classifiers, however the multiclass classifier performed robustly, especially in detecting Aedes aegypti and Culiseta incidens.

Drawbacks:

The study found that the base classifiers had low precision and that there was a significant increase in false positives when categorizing new instances that belonged to a different class than the positive and negative classes that were utilized in the model training. Furthermore, the ensemble classifier showed a noteworthy impact on precision; yet, difficulties continued to arise in achieving high recall and precision for every species of mosquito.

H. U-Net: Convolutional Networks for Biomedical Image Segmentation[8]

In the document, the U-Net—a convolutional network intended for biological picture segmentation—is discussed. By using data augmentation, it overcomes the difficulty of training deep networks with a small number of annotated samples. A contracting path is used in the design to collect context, while an expanding path is used for exact localization.

Method:

The network performs better than earlier techniques on the ISBI challenge for cell tracking in light microscopy pictures and neural structure segmentation. The network architecture, training procedure, and data augmentation methods are all covered in the study. It highlights the value of data augmentation with elastic deformations, weighted loss functions for distinguishing touching objects, and the U-Net's seamless segmentation for huge images. On a variety of segmentation tasks, including cell segmentation in light microscopy images and neural structure segmentation in electron microscopy recordings, the UNet performs exceptionally well.

Drawbacks:

The paper's presentation of the U-Net architecture's shortcomings includes the difficulty of separating contacting objects of the same class in cell segmentation tasks and the requirement for significant data augmentation as a result of the restricted availability of training data. Because unpadded convolutions are used in the U-Net design, the output image is always smaller than the input, which can result in overhead and a smaller batch size. UNet++ overcomes these drawbacks and provides better segmentation performance, which increases its efficacy and benefits under specific conditions.

III. PROPOSED SYSTEM

Our proposed system comprises two integral components: Classification and Image acquisition & Segmentation. In the classification phase, advanced machine learning algorithms seamlessly distinguish and categorize diverse data patterns.

Classification:

In our approach to mosquito larvae classification, we use deep learning architectures like VGG16, VGG19, ResNet50, ResNet152, and InceptionV3. These neural networks play a pivotal role in accurately discerning and categorizing various types of mosquito larvae.

1. VGG16:

A popular deep convolutional neural network for image classification applications is the VGG16 (Visual Geometry Group 16) architecture. VGG16, created by Oxford University's Visual Geometry Group, is composed of 16 weight layers, comprising 3 fully linked layers and 13 convolutional layers. It became well-known for its consistent architecture, which used 3x3 convolutional filters all over the network. This coherent framework makes implementation and comprehension simpler.

2. VGG19:

Rooted on the Visual Geometry Group's development of robust image classification systems, VGG19 is an extension of VGG16. With 19 layers—16 convolutional and 3 fully connected—VGG19 deepens the network and encourages more intricate feature learning. Like its predecessor, VGG19 keeps an architecture that is standardized and simple to understand by utilizing 3x3 convolutional filters. Its ability to represent hierarchical features is improved by the added depth, which makes it very useful for a variety of image recognition applications. By using VGG19's advantages, our mosquito larvae classification method gains from the model's capacity to recognize subtleties and complex patterns, which enhances the machine learning framework's general accuracy and dependability.

3. ResNet50:

Effective feature extraction is made possible by its depth and residual learning, which is essential for in-depth segmentation. ResNet50 uses pre-trained weights to improve its recognition of complex patterns in photos of Aedes larvae using transfer learning. The architecture is a strong alternative because to its adaptability and broad use in computer vision tasks. The deep structure and skip connections of ResNet50 help to preserve spatial information, which improves identification and segmentation accuracy 4. ResNet152:

ResNet152, an expansion of ResNet50, has 152 layers that provide even more depth, improving its ability to pick up fine details in photos of Aedes larvae. For segmentation tasks, its deep depth and residual learning capabilities are useful since they guarantee detailed feature representation. ResNet152 may be trained with pre-learned weights on huge datasets by utilizing transfer learning, which improves its capacity to identify subtle patterns unique to Aedes larvae. The skip links in the architecture help to preserve spatial information, which is necessary for precise segmentation.

5. InceptionV3:

The main advantage of InceptionV3 is that it makes use of inception modules, which effectively capture features at various scales. Aedes larvae can differ in size and shape, hence this trait is essential for precise segmentation. Because of its depth and wide range of receptive fields, InceptionV3 is able to extract complex patterns with ease, which helps with accurate recognition. By utilizing transfer learning, InceptionV3 can be trained with prelearned weights to improve its recognition of unique characteristics unique to Aedes larvae.

Image acquisition & Segmentation:

The suggested technique deviates from traditional segmentation techniques by utilizing the sophisticated Unet++ architecture for the automatic segmentation of Aedes larvae in digital photos. U-net++ is a development of the classic U-net architecture that improves feature representation and contextual information collection by incorporating deep supervision and stacked skip connections. U-net++ has the following benefits over U-net:

1. Enhanced Skip Connections:

The model is able to aggregate features from various levels of the hierarchy since U-net++ incorporates many skip connections in a dense, nested fashion. This enhances the overall accuracy of segmentation by efficiently gathering context information.

2. Improved Feature Representation: By utilizing nested skip paths, U-net++ produces a more thorough feature representation over a range of sizes. This improves the input photos' capacity to capture both fine and coarse information, which helps the model segment objects more precisely.

3. Deep Supervision:

- By placing auxiliary decoders at various network depths, U-net++ presents the idea of deep supervision. This makes it possible for the model to be trained with intermediate predictions at various resolutions.
- Deep supervision improves gradient flow during training and aids in solving the vanishing gradient issue.

4. Reduced Overfitting:

U-net++'s deep supervision technique pushes the network to pick up useful representations at many scales, strengthening the model and reducing its tendency to overfit. Additional direction is given during training by the intermediate forecasts.

5. Improved Class Imbalance Management:

- When it comes to managing class imbalance problems that frequently arise in segmentation activities, U-net++ can perform better.
- The model can focus on both foreground and background regions because of the nested skip connections and deep supervision methods, which produce more accurate and balanced segmentation results.

6. Increased Model Capacity:

U-net++ has a higher model capacity than the original U-net because of its layered skip connections and extra layers. The model can now learn more elaborate representations and recognize complex patterns in the data because to its expanded capabilities.

7. Flexibility and Adaptability:

U-net++ is made to be adaptive and versatile enough to handle a wide range of segmentation jobs. Many image analysis applications can benefit from the multi-scale feature learning technique offered by the stacked skip connections.

8. State-of-the-art performance:

U-net++ has shown cutting edge results on multiple segmentation benchmarks. It is a good option for segmentation jobs due to its architecture, which has been demonstrated to be successful at capturing context and intricate structures.

The architecture of U-net++ is as follows:

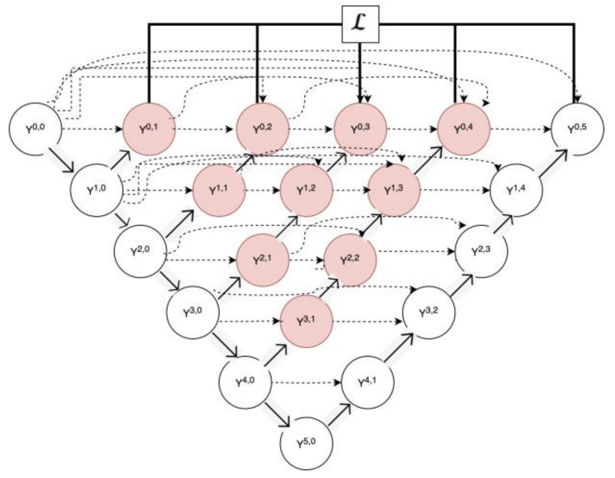

Fig. 1.U-net++ Architecture with 6 levels

The U-Net++ architecture's nested encoder and decoder architecture is depicted in the figure. It is evident that the feature map from the lower level gets entangled with the upper-level feature, rather than utilizing a conventional skip connection, and the resulting combined feature data is subsequently sent on.

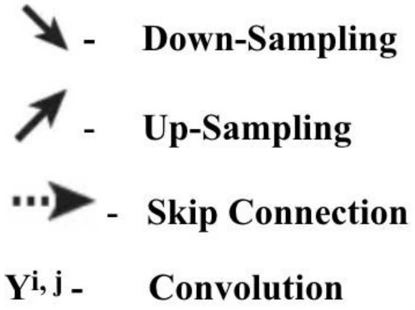

Fig. 2.Components of U-net++

In the figure the down arrow symbolizes "DownSampling". In the encoder path of U-net++, downsampling is typically performed using convolutional layers. This enables the network to capture hierarchical aspects by decreasing the spatial dimensions while increasing the number of channels.

The up arrow represents "Up-Sampling". Up-sampling is done in the decoder path in order to restore the spatial information that was lost during down-sampling. Transposed convolutional layers or other up-sampling methods are frequently used for this. During up-sampling, skip links between the encoder and the decoder aid in the combination of low-level and high-level features. The arrows with dashed lines represent "Skip Connection" which can improve the model's capacity to catch both fine and coarse details in the input data by allowing it to retain and use characteristics from various scales. The network can effectively transfer information across different levels thanks to the skip connections, which makes it easier to split objects in photos.

And finally, the

$$Y\, i,j$$

represents "Convolution" which refers to the feature map generated at a particular network level by a particular convolutional layer. In particular, "i" stands for the layer's level or depth, and "j" for the feature map's index within that level. For instance, if you have an encoder level in Unet++ and you apply multiple convolutional filters to the input, the feature map generated by the first filter may be represented by

$$Y\, i,1$$

; and the second, by

$$Y\, i,2$$

, and so forth.

IV. CONCLUSIONS

The proposed system facilitates swift identification and preemptive measures against Aedes mosquitoes by detecting them at the larval stages. Employing deep learning technology, this system relies on a digital image of the larva hatching site. Initially, it leverages U-net++ segmentation, a deep learning-based technique, to extract the region of interest—specifically, the larva's body—from the hatching site image. Subsequently, an ensemble model is deployed to classify each larva's body. The utilization of U-net++ segmentation plays a pivotal role in eliminating unnecessary background information, thereby reducing complexity for the classifier and enhancing overall system performance. This design, incorporating segmentation as a preprocessing step before classification, holds versatile applicability, particularly in tasks necessitating the identification of multiple objects within an image.

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