A Comparative Analysis of Different Convolutional Neural Network Architectures for Mosquito Genera Classification

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Abstract

Vector-borne diseases, such as Dengue virus, Zika virus, Malaria, and West Nile virus, cause an estimated 700,000 annual deaths. Aedes, Culex, and Anopheles, three common mosquito genera, carry and transmit these diseases. Their disease-carrying capacities vary due to their unique adaptations, making classification valuable in understanding the susceptibility of some viruses. Therefore, our group built a research project centered around the following question: which convolutional neural network (CNN) architecture can most effectively distinguish between Aedes, Anopheles, and Culex mosquito larvae? We trained four convolutional neural networks (CNN) and compared their ability to identify mosquito genera with image classification. The CNNs used for larvae classification were LeNet-5, AlexNet, VGG-516 Net, and ResNet-50. Understanding the accuracy of CNN architectures when identifying mosquito genera can support further research regarding computer vision techniques in biological fields and combining this research with other mosquito tracking algorithms can save lives, specifically in areas most sensitive to mosquito-vectored diseases.

Research Question

Which convolutional neural network (CNN) architecture can most effectively distinguish between Aedes, Anopheles, and Culex mosquito larvae?

Introduction

In 2020, Malaria still caused approximately 620,000 deaths across 87 countries and territories. In addition to Malaria, mosquitoes spread dozens of other deadly viruses like Dengue, which threatens about 40% of the world's population. As more people suffer from these diseases, there is increasing pressure on institutions to implement preventative measures that may start with classifying mosquito larvae using CNNs or other image classifiers. Image classifiers can inform how governments and organizations invest their resources and focus their efforts. Determining mosquito larvae type is important to help prevent vector-borne diseases and thousands of deaths yearly can focus efforts to eliminate the breeding habitats of certain mosquitoes.

Image classification can be achieved using GLOBE Observer Mosquito Habitat Mapper Images and Neural Networks, which are machine learning algorithms that consist of an input layer, some number of hidden layers, and a calculated output layer. Convolutional Neural Networks (CNNs) are Neural Networks specifically applied to Computer Vision tasks. Each Convolutional Layer in a CNN contains multiple feature detectors, which are groups of filters that detect patterns in an image based on location and a set of image matrices formed from RGB values.

Research Methods

- Collected images from the GLOBE Observer Mosquito Habitat Mappers database. (data collection dates ranged from 1995 to 2022 and from study sites across the globe)
- Python script filtered the data from a CVS file down to images that were accepted by GLOBE and labeled by genus type
- We used the requests library to download the images through the associated URLs. We implemented the naming scheme, imageID-genus.jpg to efficiently sort the images into three folders by genus
- The downloaded images were scanned to check if there were any invalid entries
- The refined dataset consisted of 2880 Aedes larvae images, 1996 Anopheles larvae images, and 1760 Culex images. However, only 100 images from each classification (300 images in total) were used in the training dataset to ensure each genus was equally represented and manage computing time

- Using the cv2 and NumPy Python libraries, we transformed the larvae dataset in a script that resized and vectorized the images based on RGB values
- The complete dataset of images was split into training and testing data using the scikit-learn library's train_test_split function
- We constructed two different data generators using the Keras Python library, one for testing and one for training data
- Used the Keras library to create a line-by-line reconstruction of each of the four Neural Networks
- Each model was retrained and tested ten times, with the runtime being restarted each trial

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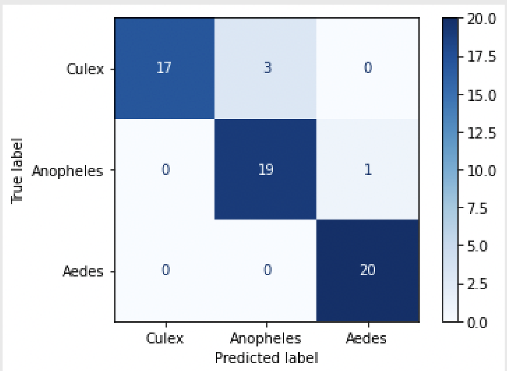
Results

To compare CNN performances, 10 trials were conducted to gather evidence of each architecture's mean performance accuracy. After the conclusion of the trials, the mean accuracy and loss were calculated. The most accurate model was AlexNet, with an average accuracy of 89%. Next was LeNet-5 with an average of 87.3% accuracy. In third place was VGG-16 Net, with an average of 87% accuracy. The CNN with the lowest accuracy was ResNet-50, which had an average of 84% accuracy. Considering the small size of the sample dataset, these averages exceeded most of our group's initial expectations. The model with the lowest error was ResNet, which had an average loss of 0.60. Next was LeNet-5, which had an average loss of 0.87. LeNet-5 was followed closely by AlexNet, which had an average loss of 0.89. The CNN architecture with the largest loss was VGG-16 Net, which had a mean loss of 1.73.

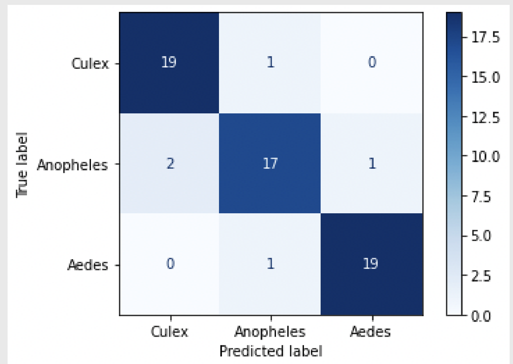
Accuracy for Each Trial:

	AlexNet		LeNet-5		VGG16 Net		ResNet50	
	Accuracy	Loss	Accuracy	Loss	Accrruacy	Loss	Accuracy	Loss
Trial 1	93.30%	0.38	85.00%	1.22	86.70%	0.38	83.30%	0.58
Trial 2	80.00%	1.84	86.70%	2.05	90.00%	0.27	86.70%	0.36
Trial 3	83.30%	1.10	81.67%	1.95	85.00%	0.52	85.00%	0.52
Trial 4	93.40%	0.03	88.33%	1.33	81.67%	0.42	85.00%	0.51
Trial 5	91.70%	0.42	95.00%	3.23	86.67%	0.65	83.33%	0.42
Trial 6	88.30%	0.37	88.33%	0.77	90.00%	0.99	81.67%	0.53
Trial 7	86.70%	1.51	88.33%	1.53	91.67%	0.56	85.00%	0.51
Trial 8	90.00%	0.53	86.70%	2.22	86.67%	0.71	83.33%	0.64
Trial 9	86.67%	1.04	88.33%	0.82	88.33%	0.91	76.67%	0.74
Trial 10	91.67%	0.39	85.00%	2.18	83.33%	0.62	86.67%	0.27
Averages	89.00%	0.89	87.33%	1.73	87.00%	0.60	83.67%	0.51
Std. Deviation	4.42%	0.58	3.44%	0.75	3.12%	0.23	2.92%	0.14

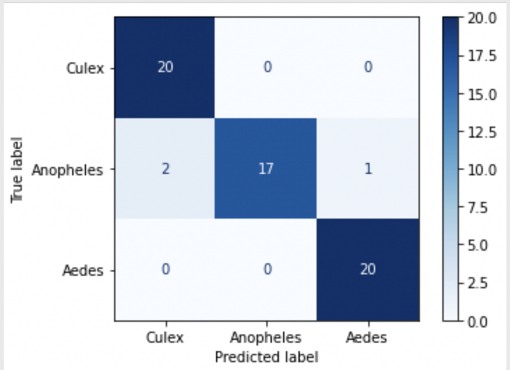
Confusion Matrices for each Model's Most Accurate Trial:



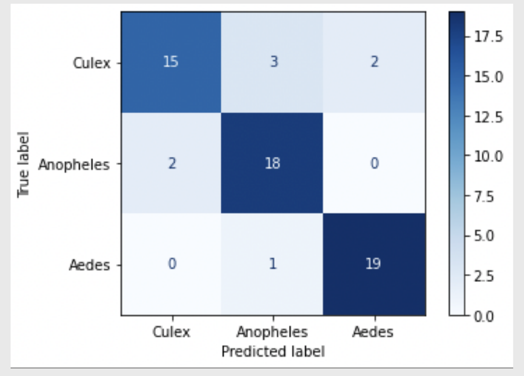
AlexNet



VGG-16 Net



LeNet-5



ResNet-50

Discussion

When looking at these accuracy, it becomes clear that there are very small differences between the models, with the highest and lowest accuracies separated by only 6%. So, instead of accuracy, our team decided to turn to average loss to determine the most effective model overall. Between the models, ResNet50 had a much lower average loss than every other model. As mentioned earlier, ResNet50 has the unique ability to eliminate attenuation using shortcut connections, which may have been the reason for its low loss. So, despite ResNet-50 having the lowest accuracy, it actually is the most effective model, due to its outstandingly low loss.

One shortcoming of using Citizen Science data is that there was little way for us to check that all user inputted labels for larvae genus were 100% accurate, leading to possible errors in our prediction models. Another important thing to note is that throughout this whole process is that we only used approximately 1/17 of the available GLOBE dataset. The reason for this is that we don't currently have the computation power to work with every image value collected.

Conclusion

After the testing process, ResNet-50 was determined to be the most successful CNN model for larvae classification based on genus due to its outstandingly low loss and the lack of deviation between model accuracies. In the future, an accurate mosquito larvae classification can be used in tropical and subtropical areas to prevent the spread of life-threatening vector-borne diseases. It is an essential step in understanding the viruses which are a threat to a considerable part of humanity as well as steps that need to be taken to further prevent their spread. It provides a guide for professionals to determine what actions need to be taken and will help them allocate their resources more effectively. Additionally, the insight into the accuracy of different CNNs can be implemented in different biological fields when using and in the further development of computer vision techniques.

If possible, our group intends to integrate our model into an IOS application, which could be added as a tool in the GLOBE observer app. Also, our group will search for a Jupyter environment with higher computing capabilities, so that we can run each model with the entire dataset.

References