Project 04 Background Reading Presentation:

Vision Guided Mosquito Dissection for the Production of Malaria Vaccine

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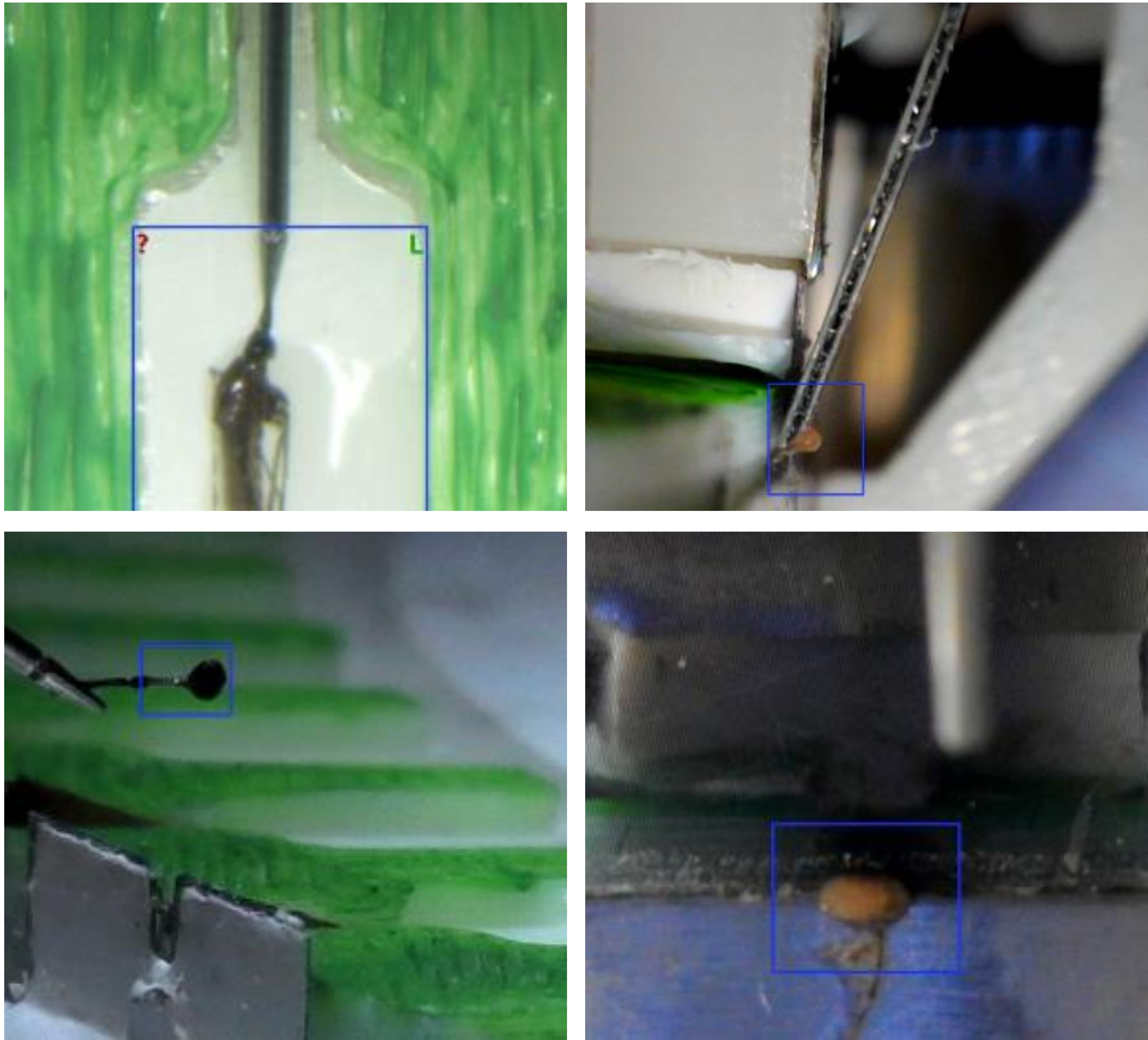
Project Summary

This project aims to create computer vision algorithms for the robot mosquito dissection system. Specific aims are to develop new DL-based CV methods and integrate existing CV methods for the mosquito dissection system, which include:

1) Mosquito Orientation Detection
2) Exudate Quality Evaluation
3) Prediction of Dissection Success
4) Exudate Volume Estimation



Paper detail

- **Title:** A comparative analysis of eleven neural networks architectures for small datasets of lung images of COVID-19 patients toward improved clinical decisions.
- **Author:** Yuan Yang, Lin Zhang, Mingyu Du, Jingyu Bo, Haolei Liu, Lei Ren, Xiaohe Li, M Jamal Deen
- **Journal:** Computers in Biology and Medicine (2021)
- **Relevance:**

✓ The paper addresses the use of deep learning in imaging classification, which is a rapidly growing field relevant to my project.

✓ The paper tackles the challenge of using deep learning with small datasets, which is a common issue in medical imaging.

✓ The paper analysis is essential in deep learning task as it helps identify the best-performing model for a given task..

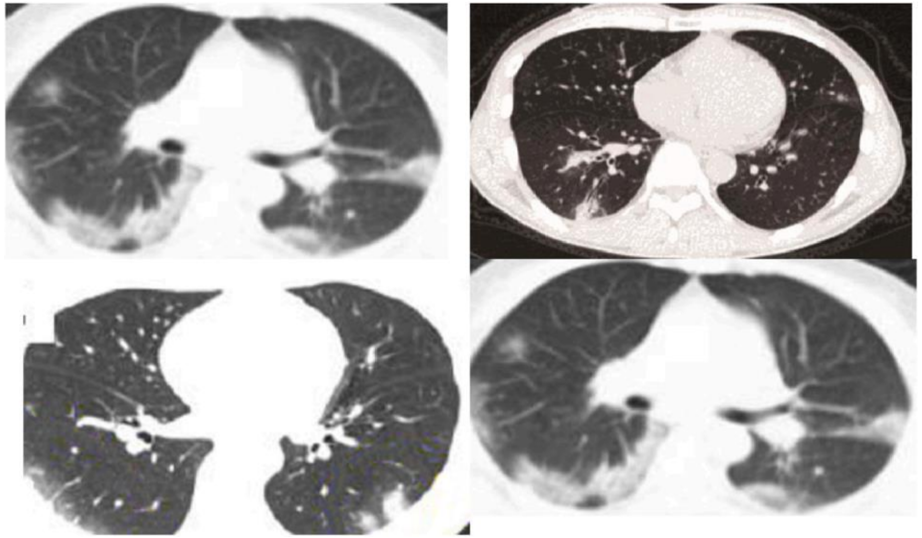


Figure1: Four CT images that are positive for COVID-19 [1]

Technical Approach

▪ Deep learning study

The authors of the paper introduce 8 deep learning methods, 3 of which are related to the deep learning method I will use, they are VGG, ResNet, and DenseNet.

▪ Image acquisition

Two datasets used in this paper:

1) UCSD-AI4H dataset (746 images)
2) Italiancase dataset (735 images)

▪ Data augmentation methods

In this paper, the authors only used the most basic data enhancement methods. The parameters of the data enhancement method used by the authors and the sample results are shown in Table and Figure on the right. The reason for these operations is that the author don't want the picture information to change significantly.

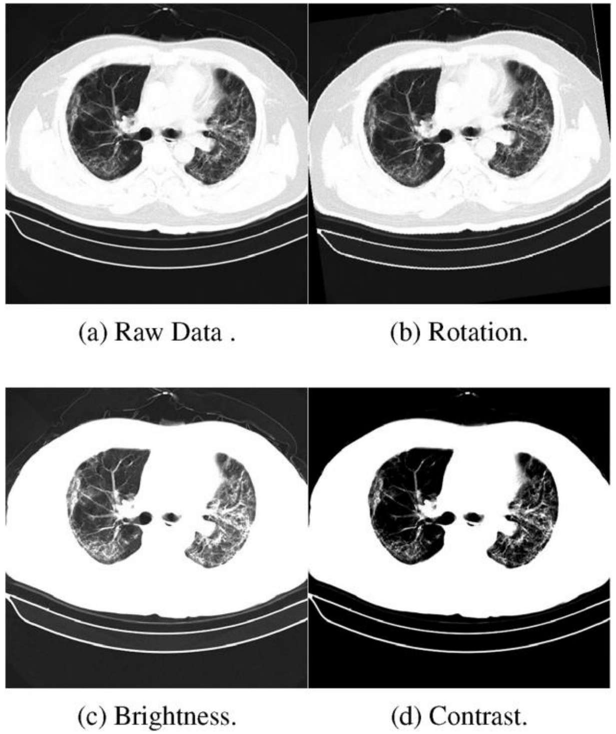


Figure2: Example transformations after data augmentation [1]

Data augmentation.

Operation Name	Range
Contrast	[0.9,1.1]
Brightness	[0.9,1.1]
Rotate	[-10,10]

Table1: Data augmentation parameters [1]

Technical Approach

- **Define evaluation metrics**

Define a confusion matrix as shown in Table 2, which contains 4 values, namely true positive (TP), true negative (TN), false positive (FP), and false negative (FN):

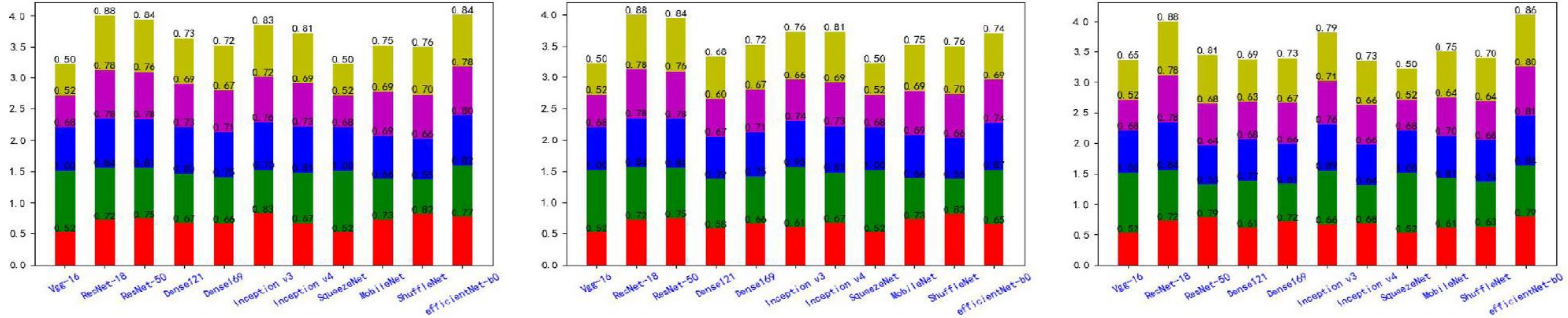
Confusion matrix.

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Table2: Confusion matrix [1]

- **Precision:** $$Precision = \frac{TP}{TP + FP}$$
- **F1-score:** $$F1 - score = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right)$$
- **Recall:** $$Recall = \frac{TP}{TP + FN}$$
- **Accuracy:** $$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$
- **AUC(Area Under the Curve):** The metric is calculated by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold values and calculating the area under the resulting curve.

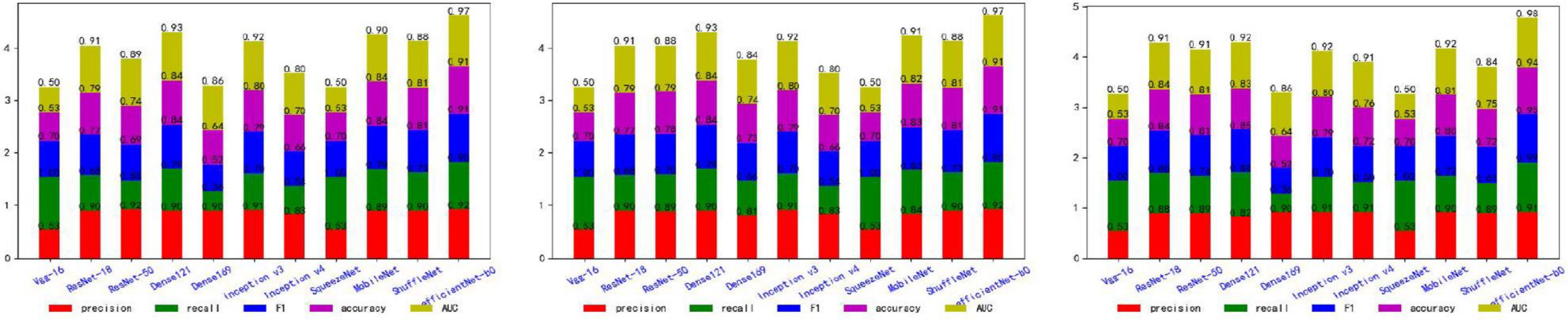
Experiment



(a) Best-acc (b) Best-F1 (c) Best-AUC

Figure3: The performance of 11 neural networks on the UCSD-AI4H dataset, with epoch = 1500,batch-size = 25. [1]

Experiment



(a) Best-Acc (b) Best-F1 (c) Best-AUC

Figure4: The performance of 11 neural networks on the Italiancase dataset, with epoch = 1500, batch-size = 25. [1]

Experiment

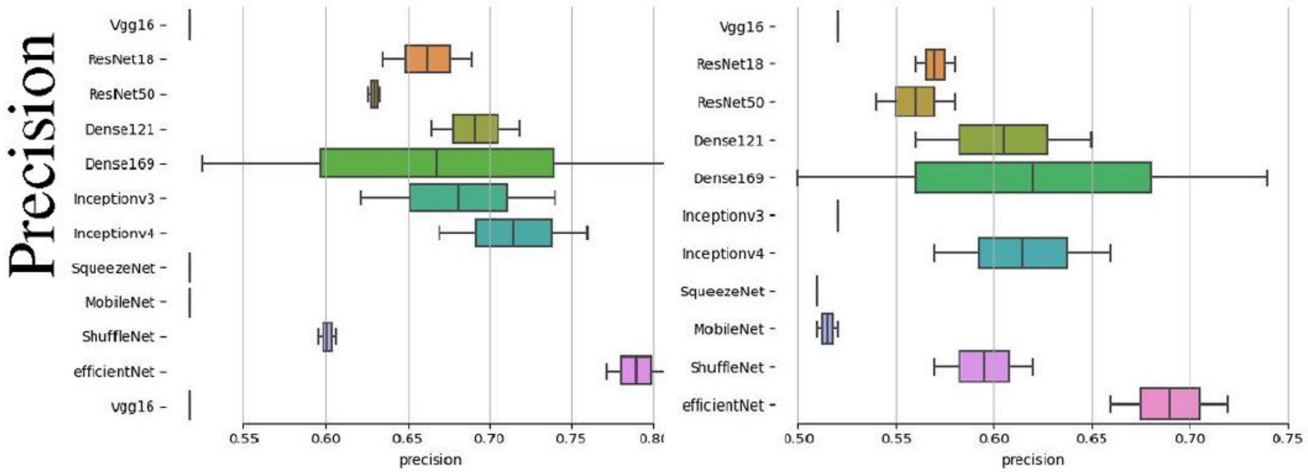


Figure5: Boxplots of precision for the UCSD-AI4H dataset in 2 experiments with data augmentation and without data augmentation [1]

Experiment

- **Results summary**

1) From Figure 3 and Figure 4 above, we can see that in the UCSD-AI4H dataset, after 1500 epochs and a batch size of 25, ResNet performs the best, with a maximum precision of 0.79; DenseNet performs well, with a maximum precision of 0.72; and VGG performs the worst with a maximum precision of 0.53. Similarly, in the Italian case dataset, ResNet performs best with a maximum precision of 0.92, DenseNet performs well with a maximum precision of 0.9, and VGG performs the worst with a maximum precision of 0.52.
2) From Figure 5, the median of the evaluation results of each deep learning network's precision is not very good before data augmentation is performed. After the data augmentation, the median of the evaluation results of each deep learning network has improved significantly, and the gap between the worst case and the best case of many networks is significantly reduced.

Critical Review

- **Pros**

1) The paper compares the performance of eleven different neural network architectures on small datasets of lung images of COVID-19 patients. This type of comparative analysis can help researchers identify the best-performing models for specific applications.

2) The paper uses a comprehensive and robust experimental design, including data preprocessing, model training, validation, and testing.

- **Cons**

The paper does not provide a detailed analysis of the interpretability of the models or how their decisions can be explained to clinicians. This is an important consideration in medical applications of deep learning.

- **Key takeaways**

1) This paper gives me an idea of who is the best fit for the project among VGG, ResNet, and DenseNet by comparing the results obtained from training different deep learning networks.

2) When the amount of data is far from enough, or when the classification model is not effective, I can use similar or even more data augmentation methods to make the model more robust.

References

[1] Yang Y, Zhang L, Du M, Bo J, Liu H, Ren L, Li X, Deen MJ. A comparative analysis of eleven neural networks architectures for small datasets of lung images of COVID-19 patients toward improved clinical decisions. Comput Biol Med. 2021 Dec;139:104887. doi: 10.1016/j.compbiomed.2021.104887. Epub 2021 Sep 24. PMID: 34688974; PMCID: PMC8461289.