Retina Pathology Diagnosis

INTRODUCTION TO NEURAL NETWORKS

https://github.com/slilly4/OCT-Retina-Classification

Problem Statement

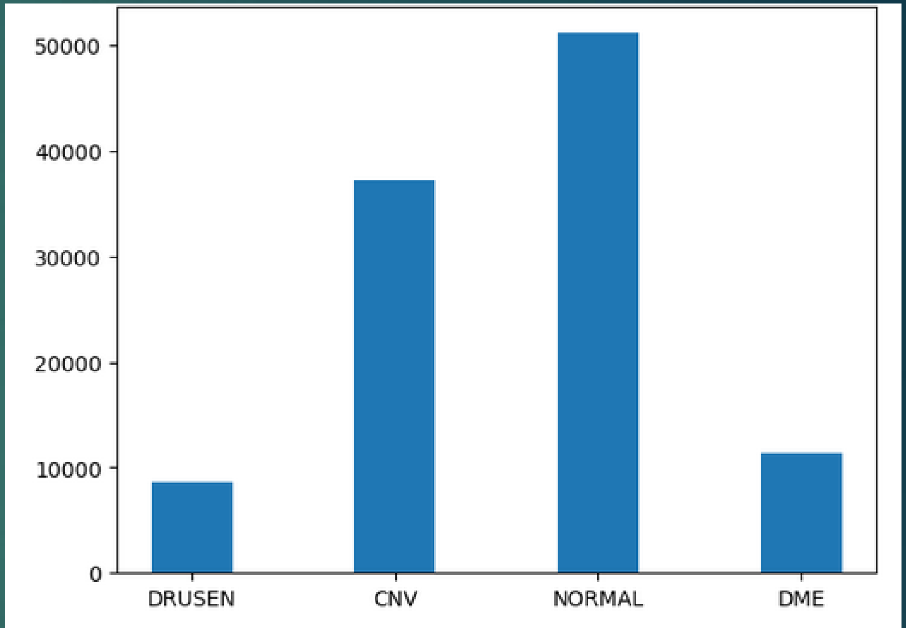
- This project attempts to classify optical coherence tomography (OCT) images of the retina. OCT is a non-invasive imaging technique that uses light to generate cross-sectional scans. When applied to the retina, a number of pathologies can be identified. Traditionally, diagnoses have been made by a qualified medical professional. However, with the power of neural networks, it should be possible to automatically detect the health of the retina.
- In addition to attempting to achieve a high classification accuracy on this task, I would also like to explore the use of transfer learning to speed up training on CNNs.

Data

- The OCT images used in this project were initially employed for research conducted by Daniel S. Kermany and other researchers at the University of California San Diego and the Guangzhou Women and Children's Medical Center. Their results were published in the 2018 article, "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning."
- Citation:
  - *Kermany, Daniel; Zhang, Kang; Goldbaum, Michael (2018), "Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images", Mendeley Data, V3, doi: 10.17632/rscbjbr9sj.3*

Data Attributes

- 108,309 images in 4 classes
  - Choroidal Neovascularization (CNV)
  - Diabetic Macular Edema (DME)
  - Drusen
  - Normal
- Imbalanced
- 3 channels, but inconsistent dimensions
- Data will be normalized; flip, zoom, and shear to be added for diversity
- Dimensions standardized to 496x496 pixels

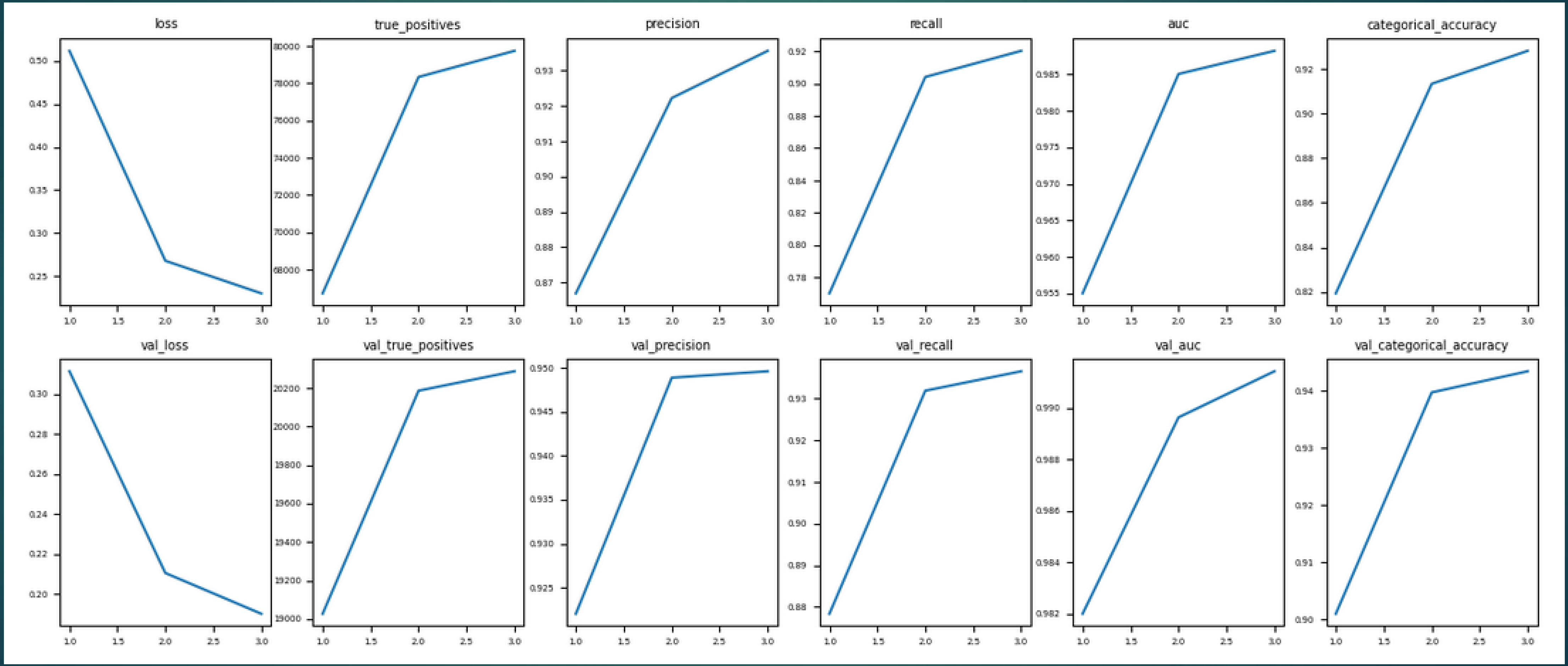


Neural Network Approach

- VGG-Style Model: 4 repeating layers of convolution and pooling with increasing filters.
  - 327,060 parameters
- ResNet-Style Model: 4 blocks of residual layers, each of which includes “skips” to allow to for deeper networks.
  - 153,076 parameters
- ResNet50V2: Pre-Trained on ImageNet dataset
  - 23,572,996 parameters

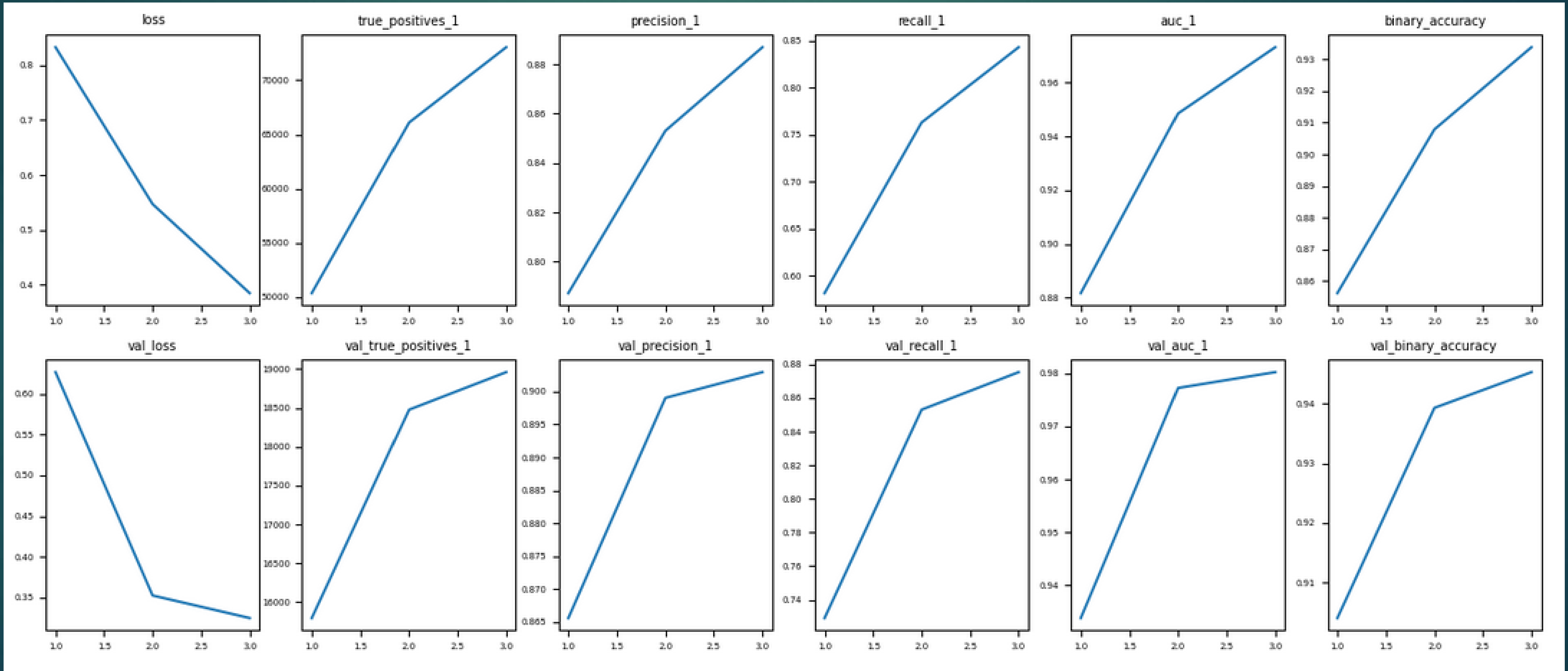
VGG-Style

- Validation Accuracy over .94, with precision and recall over .93



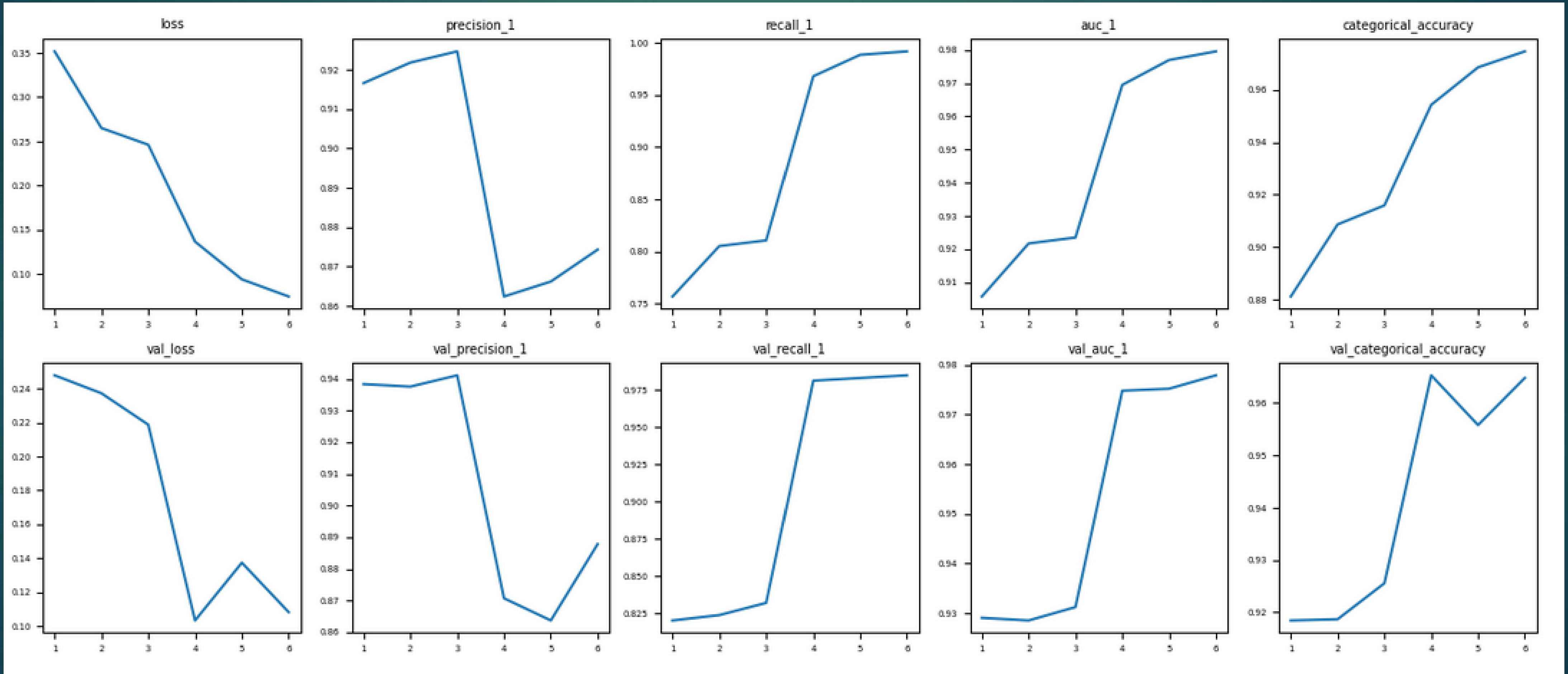
ResNet-Style

- Validation Accuracy over .94; lower precision and recall



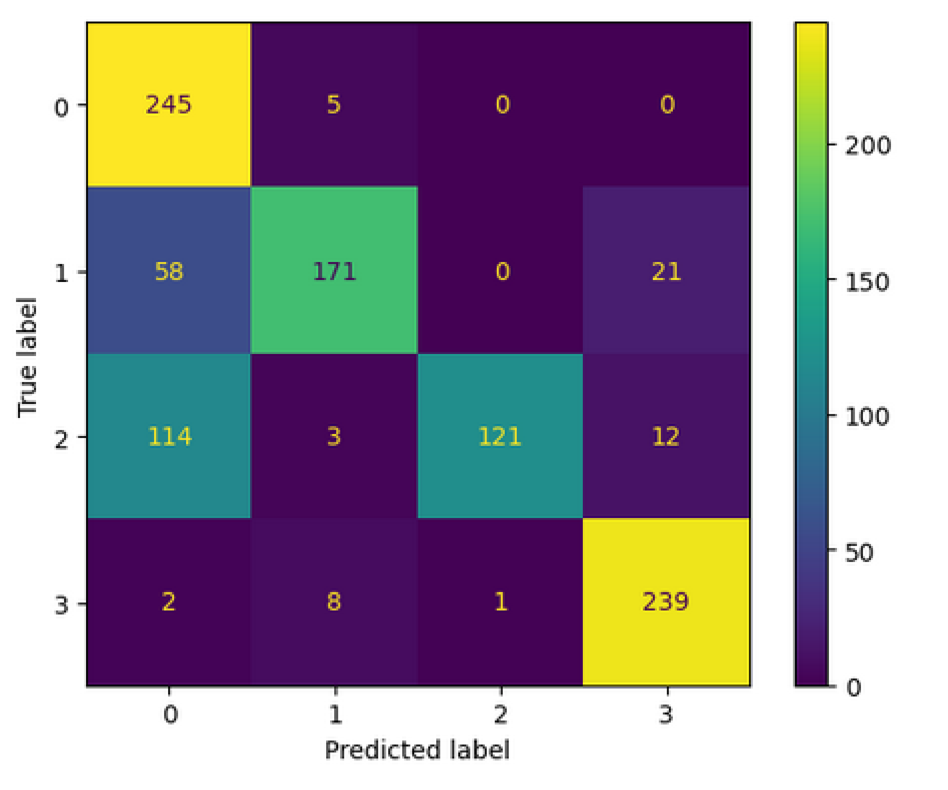
ResNet50v2

- Validation Accuracy over .96. Includes both training of lower levels and fine tuning

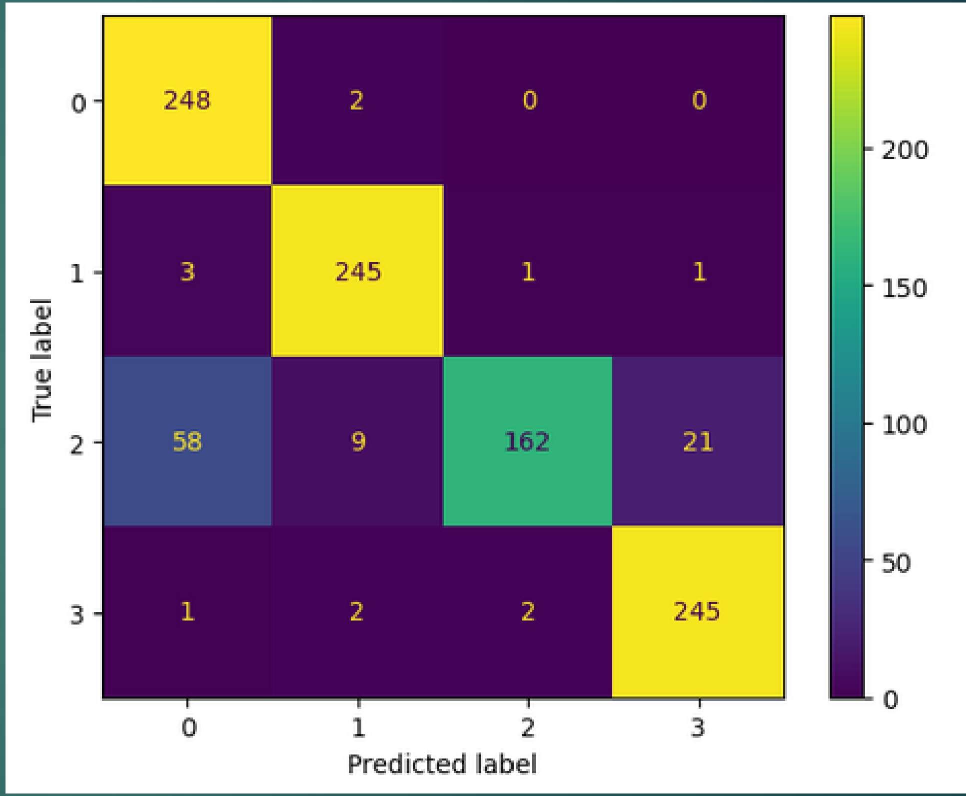


Confusion Matrix: Supervised

ResNet-Style (Trained from Scratch)



ResNet50v2 (Pre-Trained



CNV: 0, DME: 1, DRUSEN: 2, NORMAL: 3

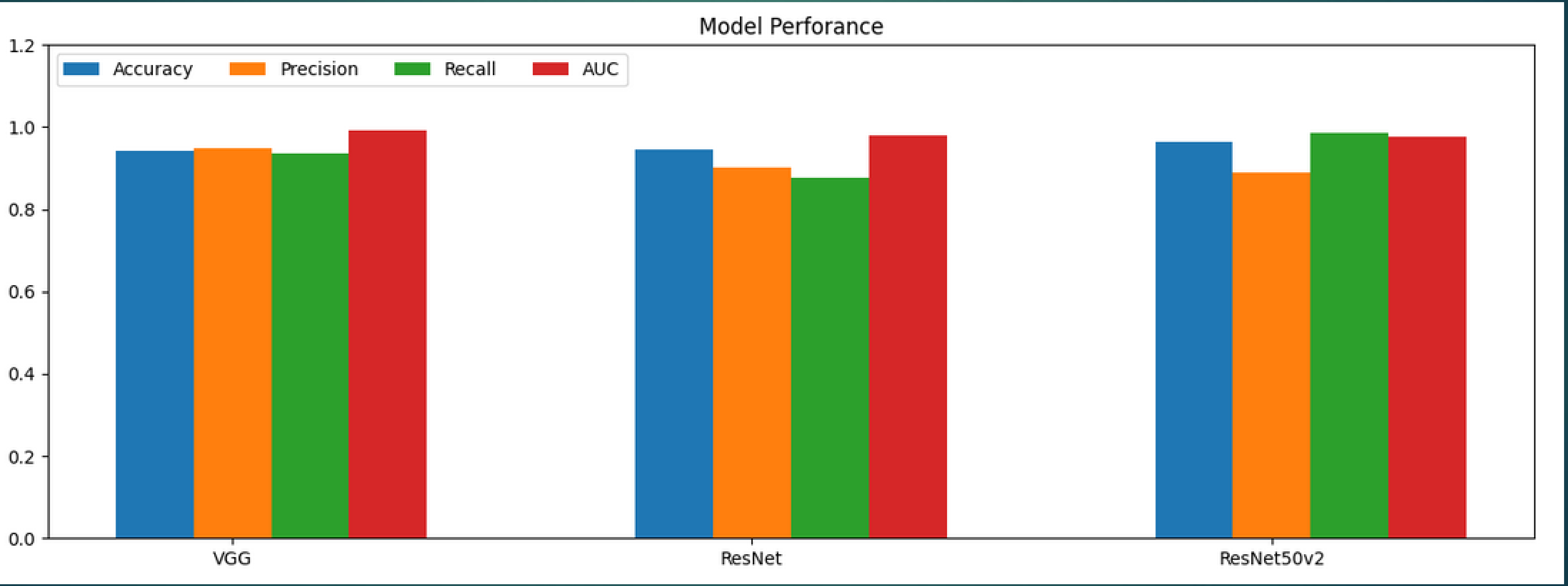
Metrics

- While the pre-trained ResNet50v2 model has over 23.5 million parameters, it achieved only marginally better gains in categorical accuracy than our baseline models, and it performed worse in Precision and AUC than the other models.
- ResNet50v2 also necessitated the use of the TPU. Even removing possibly unnecessary epochs, 4.5 hours of training would be needed.
- The VGG and ResNet trained on the GPU for nearly the same amount of time, and achieved nearly as good results.

Metric	VGG-Style	ResNet-Style	ResNet50v2
Loss	0.1901	0.3248	0.1081
Accuracy	0.9434	0.9453	0.9648
Precision	0.9496	0.9029	0.8878
Recall	0.9366	0.8754	0.9849
AUC	0.9914	0.9802	0.9779
# Parameters	327,060	153,076	23,572,996

Accuracy, Precision, Recall, AUC

- While accuracies where high, Recall lagged in ResNet and Precision in ResNet50v2. Unbalanced data can skew performance.



Discussion

- Future iterations of this project could attempt to oversample data from minority classes.
- Validation data alone is not enough to gauge the performance of a model. My validation data mirrored the makeup of my training data. Therefore, for those classes where there were many images, a greater number were also in the validation data. This skewed the results.
- Another place for improvement is a better strategy for saving models. I attempted to checkpoint models, and this worked only partially. Models were lost or corrupted.
- Data shows that pre-trained model did not perform substantially better on this task than the other models, relative to resource expended.

Conclusion

- Using two models trained from scratch as well as fine-tuned pre-trained model, RenNet50v2, it is clear that the pre-trained model did not perform substantially better using the same resources.
- Models trained on other image recognition tasks need to be carefully evaluated for whether they can be successfully adapted to other classification projects.
- An accuracy of over .96 on this task is possible. Further gains can be made through optimization and longer training.
- There may be space in the doctor's office for trained neural networks in diagnosing pathologies.