



Automatically Annotate Medical Images for downstream analysis

Capstone Project (Spring 2022)

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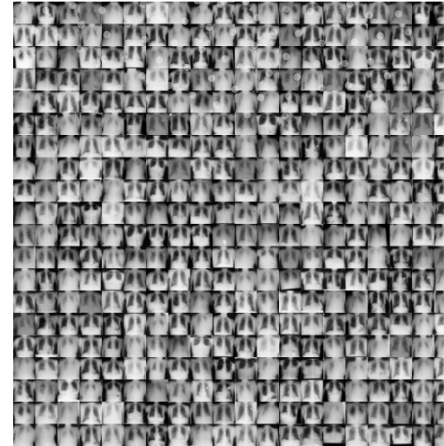
The Goal/Motivation

More and more unlabeled medical images are needed to be annotated for the downstream research analysis. However, manually labeling millions of medical images is impractical. Thus, I want to build an automatic annotator to speed up this process and provide more labeled images for big data analysis.

Data Description

MedMNIST v2: A Large-Scale Lightweight Benchmark for 2D and 3D Biomedical Image Classification

Facts of ChestMNIST



Data Modality: Chest X-ray

Task: Multi-Label (14) Binary-Class (0

Number of Samples: 112,120 (78,46

Source Data:

Xiaosong Wang, Yifan Peng, et al., "Chest
weakly-supervised classification and localizat

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Facts of BreastMNIST



Data Modality: Breast Ultrasound

Task: Binary-Class (2)

Number of Samples: 780 (546 / 78 /

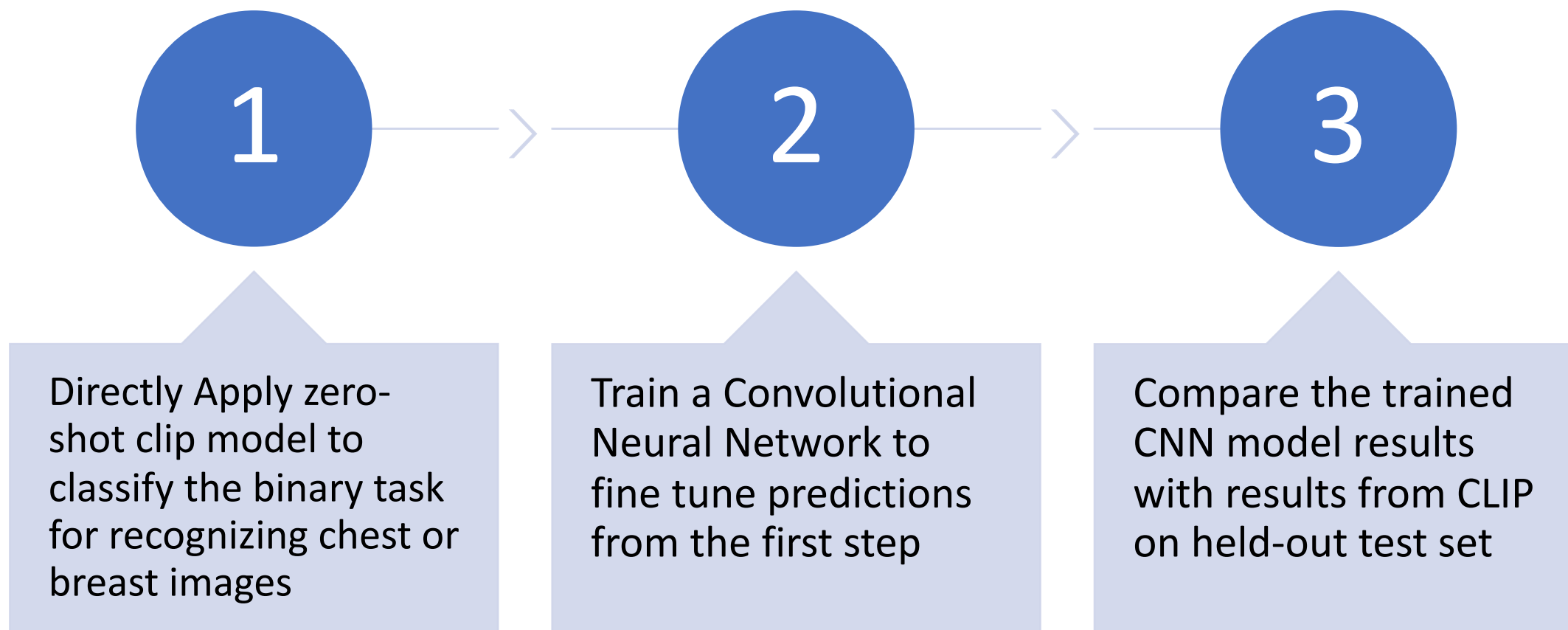
Source Data:

Walid Al-Dhabyani, Mohammed Gomaa, et al
104863, 2020.

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Design Modeling

Three Stages:



Model Architecture Pipeline

1. Select half chest images and half breast images
2. Stratified Split it into training, and test set

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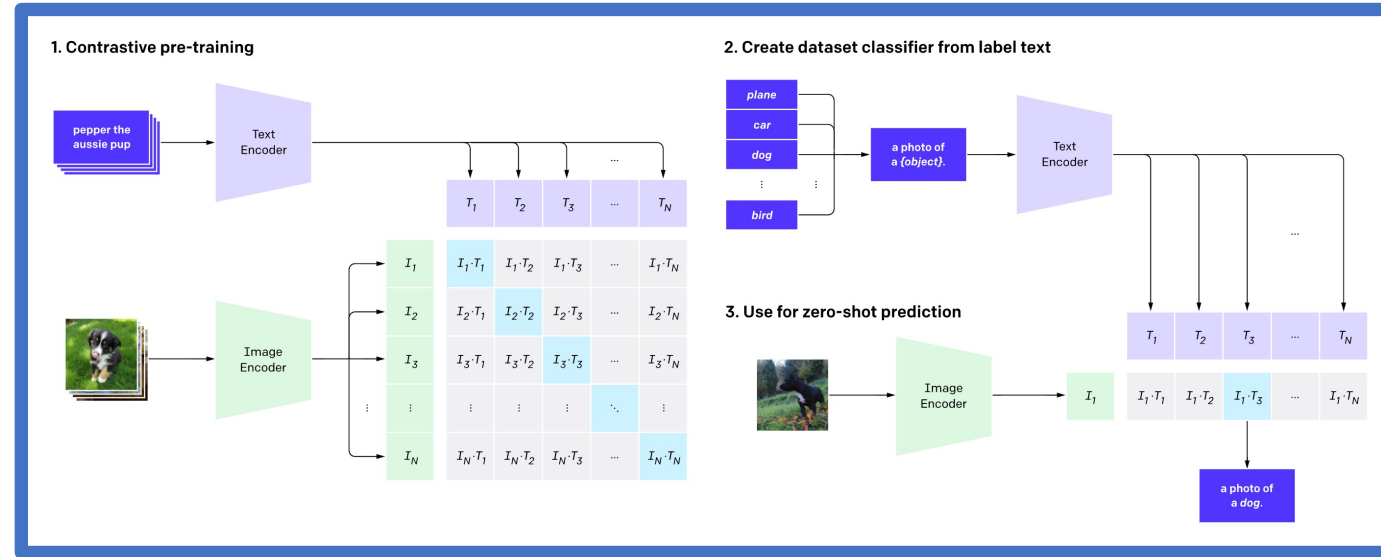
3. Feed training into CLIP



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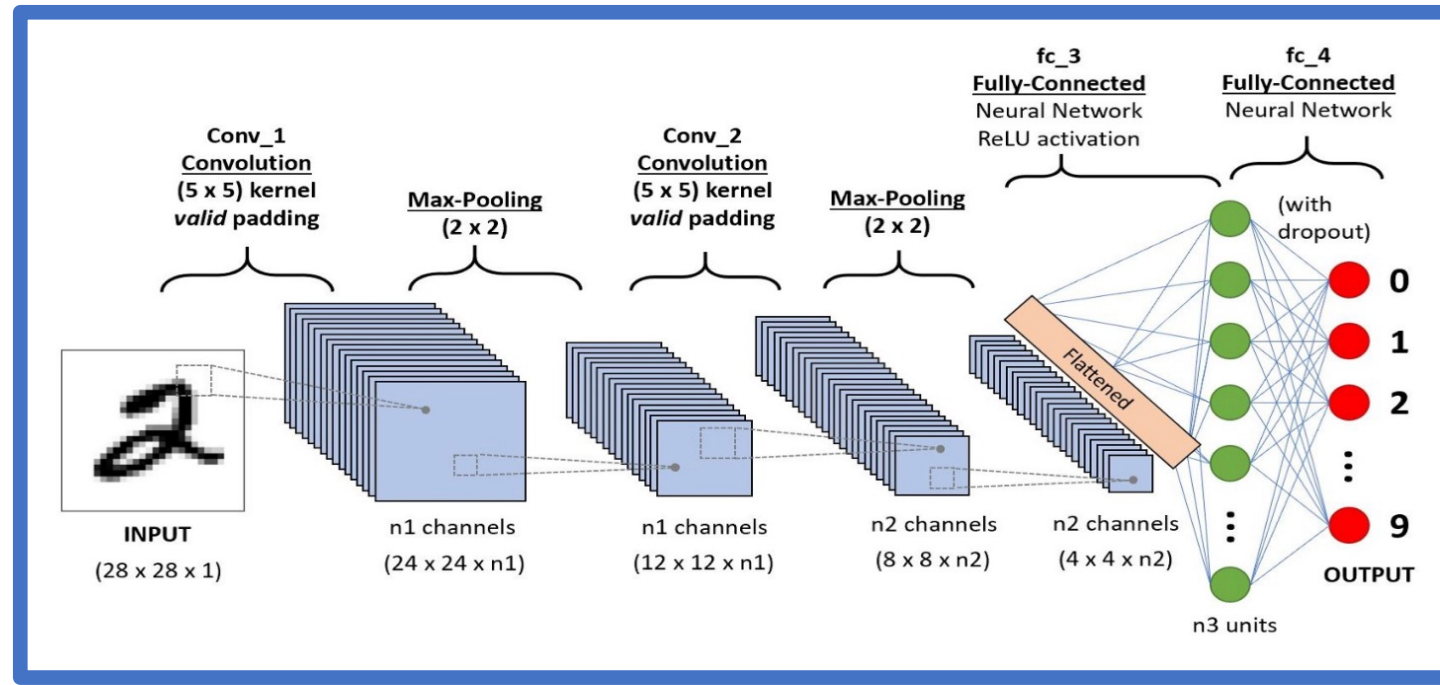
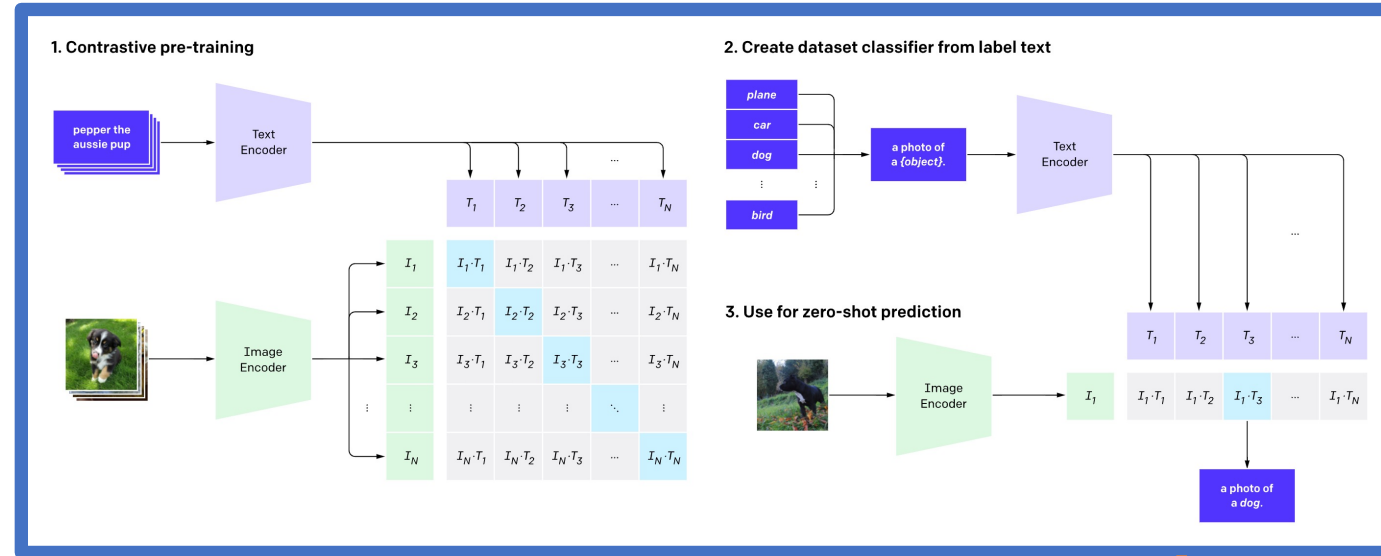
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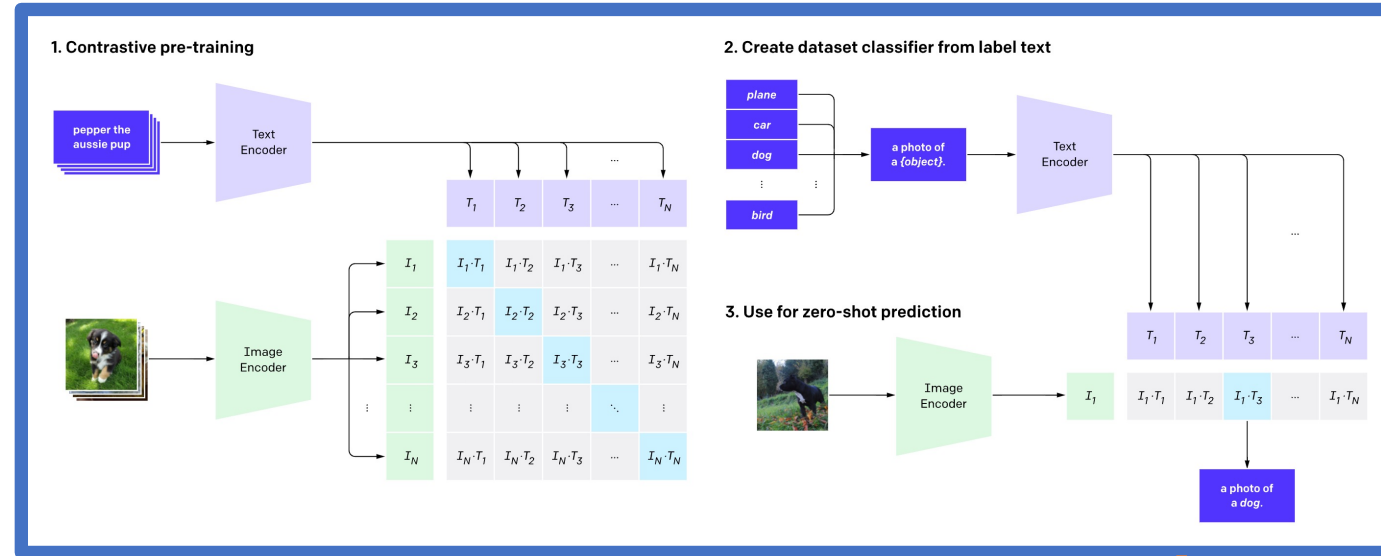


4. Feed Training and prediction into CNN

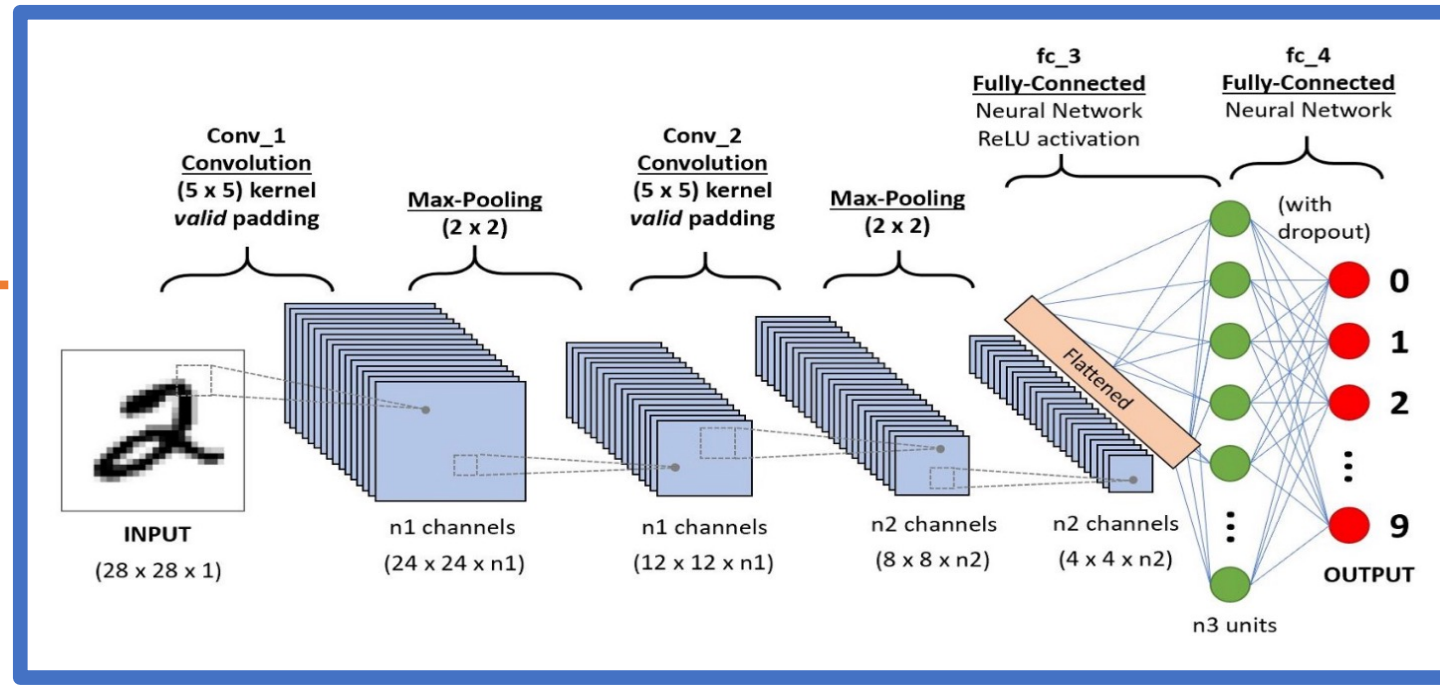
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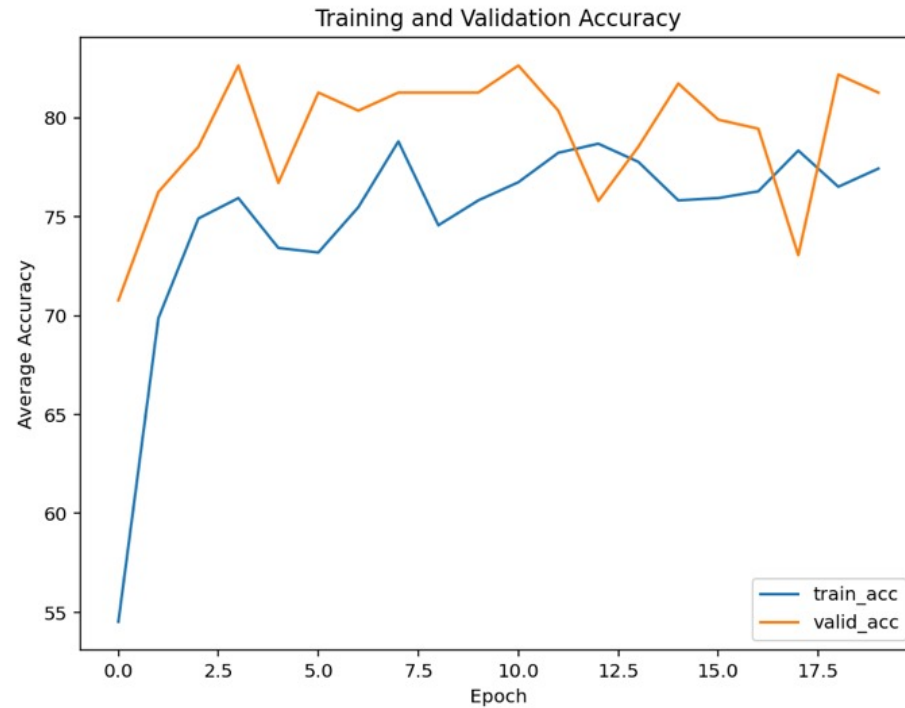


4. Feed Training and prediction into CNN



5. Apply the trained model on the test to compare with results from CLIP only

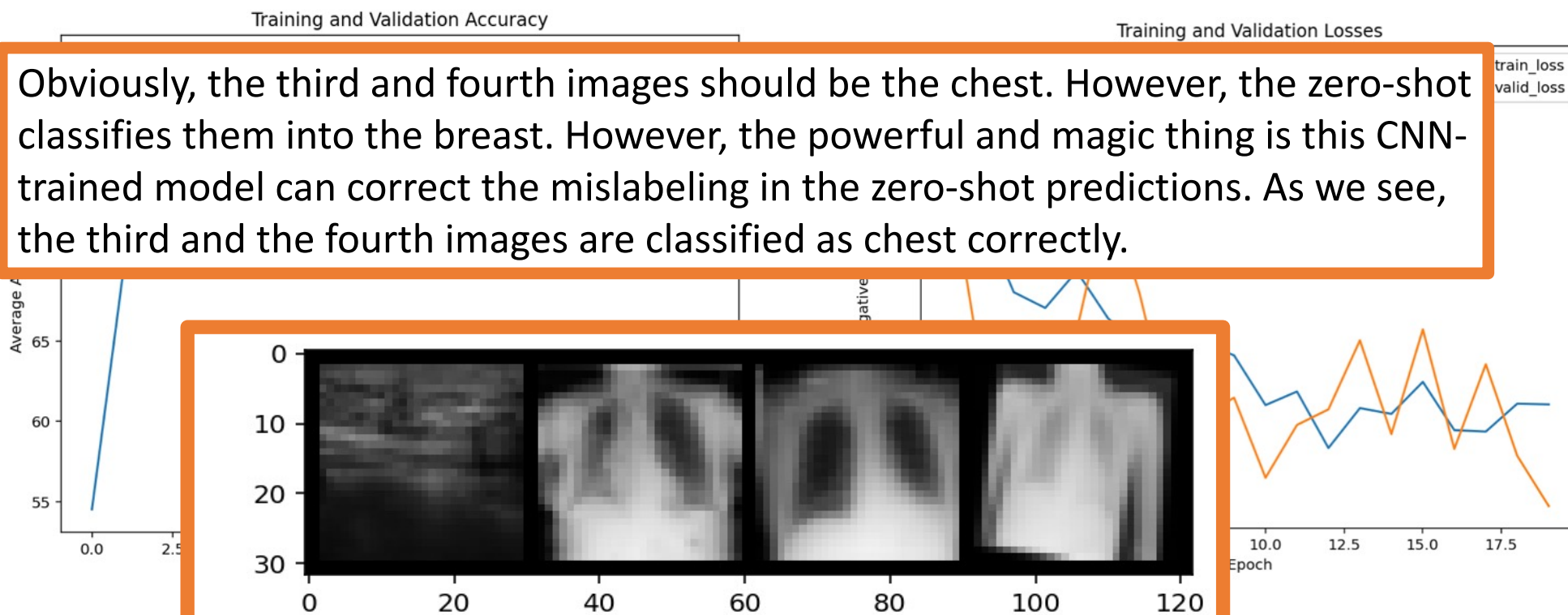
Training and Comparison Results



I got 95.72% accuracy on the test set by using trained CNN;

I Got 82.05% accuracy on the test set by using CLIP only

Training and Comparison Results



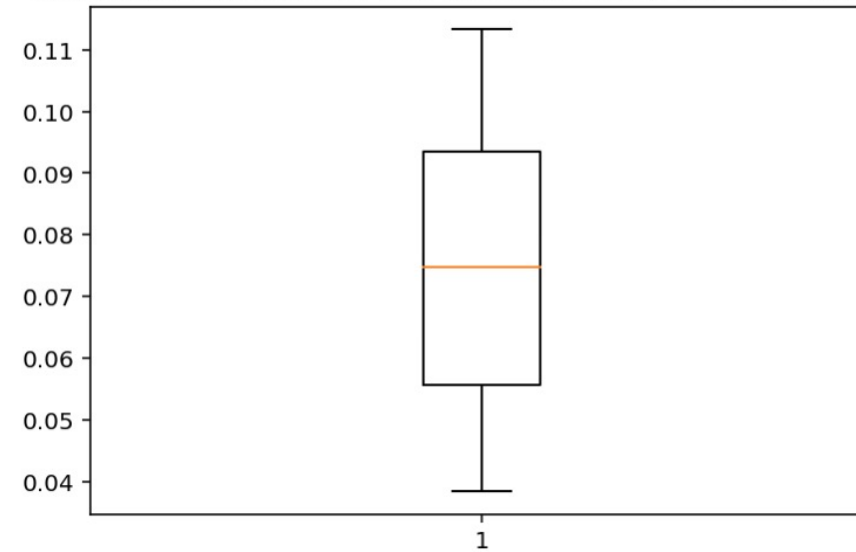
I got 9
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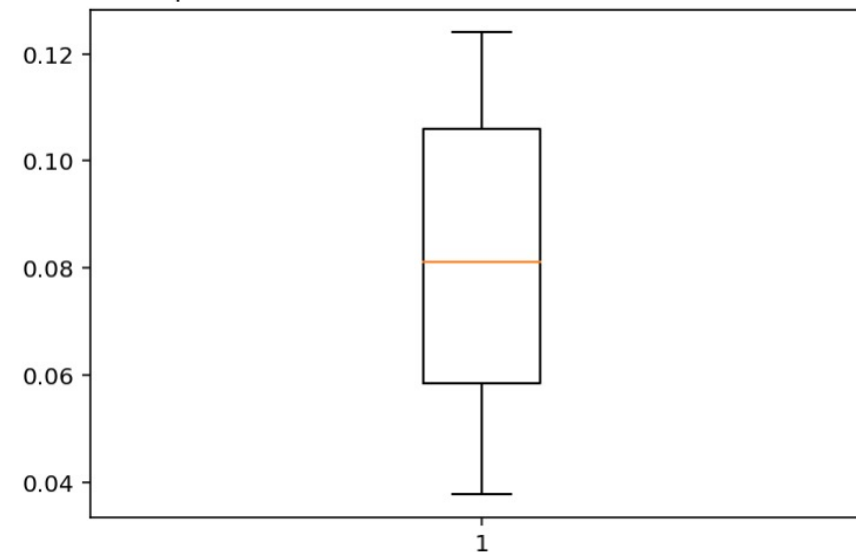
ng trained

Run model
comparison for
30 times to see
generalized
improvement

Boxplot for difference of new model accuracy and CLIP accuracy



Boxplot for difference of new model F1 and CLIP F1



Conclusion

- After these two stages, the trained CNN model can correct mislabel generated by CLIP because CNN is powerful enough to learn the general pattern from majority correct labels and images. The average accuracy improvement is 6%.
- The Two-Stage model can be used to annotate the chest or breast images for production automatically. Then the labeled medical images can be analyzed in the downstream tasks for more research and use cases.

Next Steps

- Employ Monai pre-trained medical image models in the current zero-shot CLIP architecture
- Once the open AI releases and publish its training codes which are used to train their zero-shot learning models between images and texts, I will plan to use those codes to train on all medical dataset in the MedMNIST benchmark dataset and fine-tune them.
- I will plan to test more pairwise datasets, like Blood and Derma, and use different kinds of CNN models



Thanks, Q&A