SAMSUNG OCT

CAPSTONE PRESENTATION

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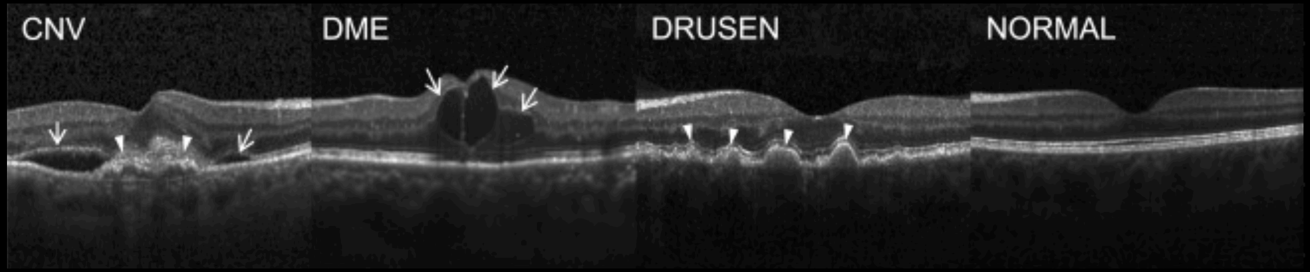
Background

OPTICAL COHERENCE TOMOGRAPHY

So what does this mean? Basically using spooky images of eyeballs to see if they are healthy or not! 👀



Background

WHY A-"EYE"?

COMPLEX PROBLEM SOLVING

Benefit from deep learning models already trained on millions of images.

PERFORMANCE

Meeting human-level performance on classification.

EARLY-DETECTION

Expediting diagnosis of treatable retinal diseases.

Background

BUSINESS PROBLEM

DIAGNOSIS

Expedite the diagnosis of treatable diseases that can lead to blindness.

PREVENTION

Prescribing medication in a timely manner to prevent patient blindness.

GENERALIZATION

Potential for this work to be generalized in other applications of biomedical imaging.

Background

WHO BENEFITS?

RETINAL SPECIALISTS

Support tool for retinal specialists with accurate and timely diagnosis

UNDERSERVED POPULATIONS

Populations without proper access to specialized medical professionals; overpopulated areas where patient-to-staff ratios are high.

Solution

SOLUTION 1

TRANSFER LEARNING W/ INCEPTIONv3

STEP 1

Instantiate base model trained on ImageNet and load pre-trained weights into it without including the top layer.

STEP 2

Freeze all layers in the base model.

STEP 3

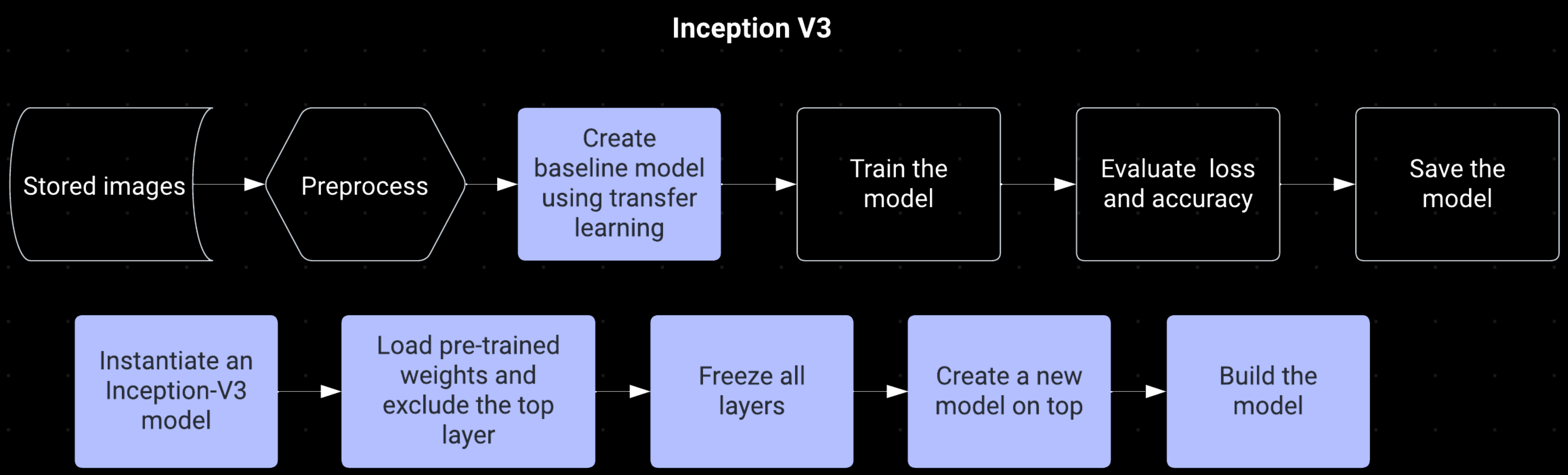
Create an output layer sized to our multi-class classifiers.

STEP 4

Build a model on a limited training set.

Solution

TRANSFER LEARNING W/ INCEPTIONv3



Solution

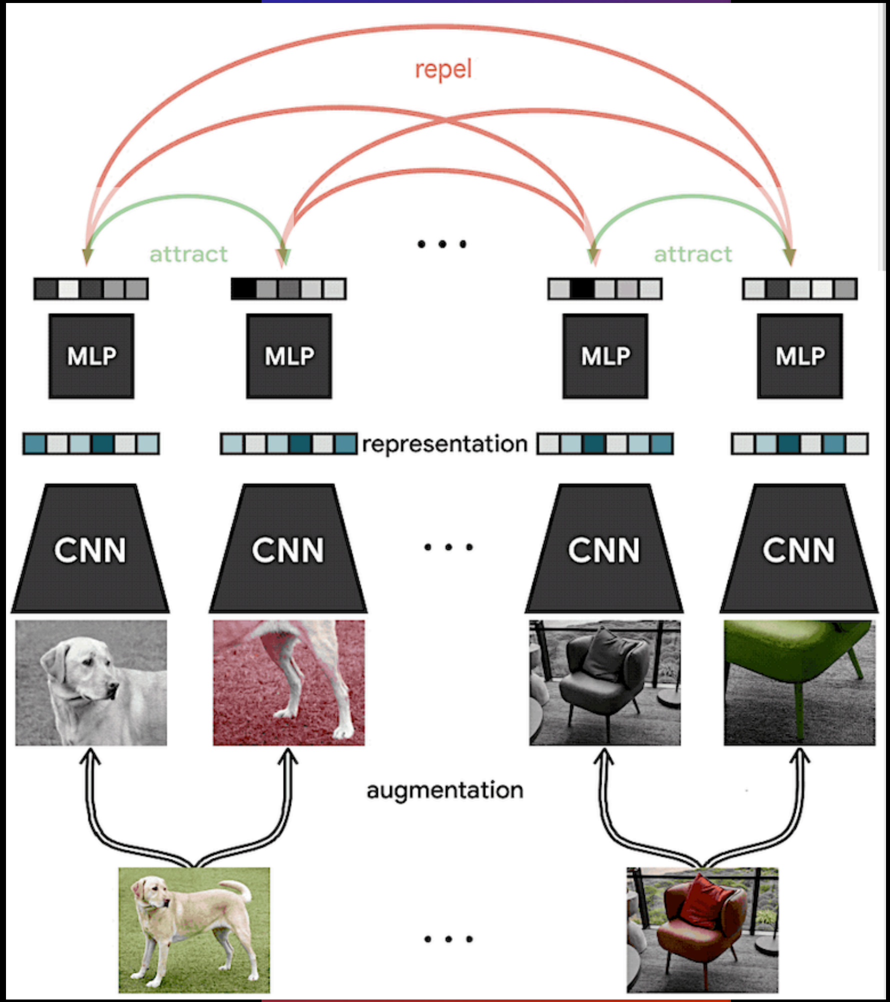
SOLUTION 2

SEMI-SUPERVISED LEARNING W/ SIMCLRv2

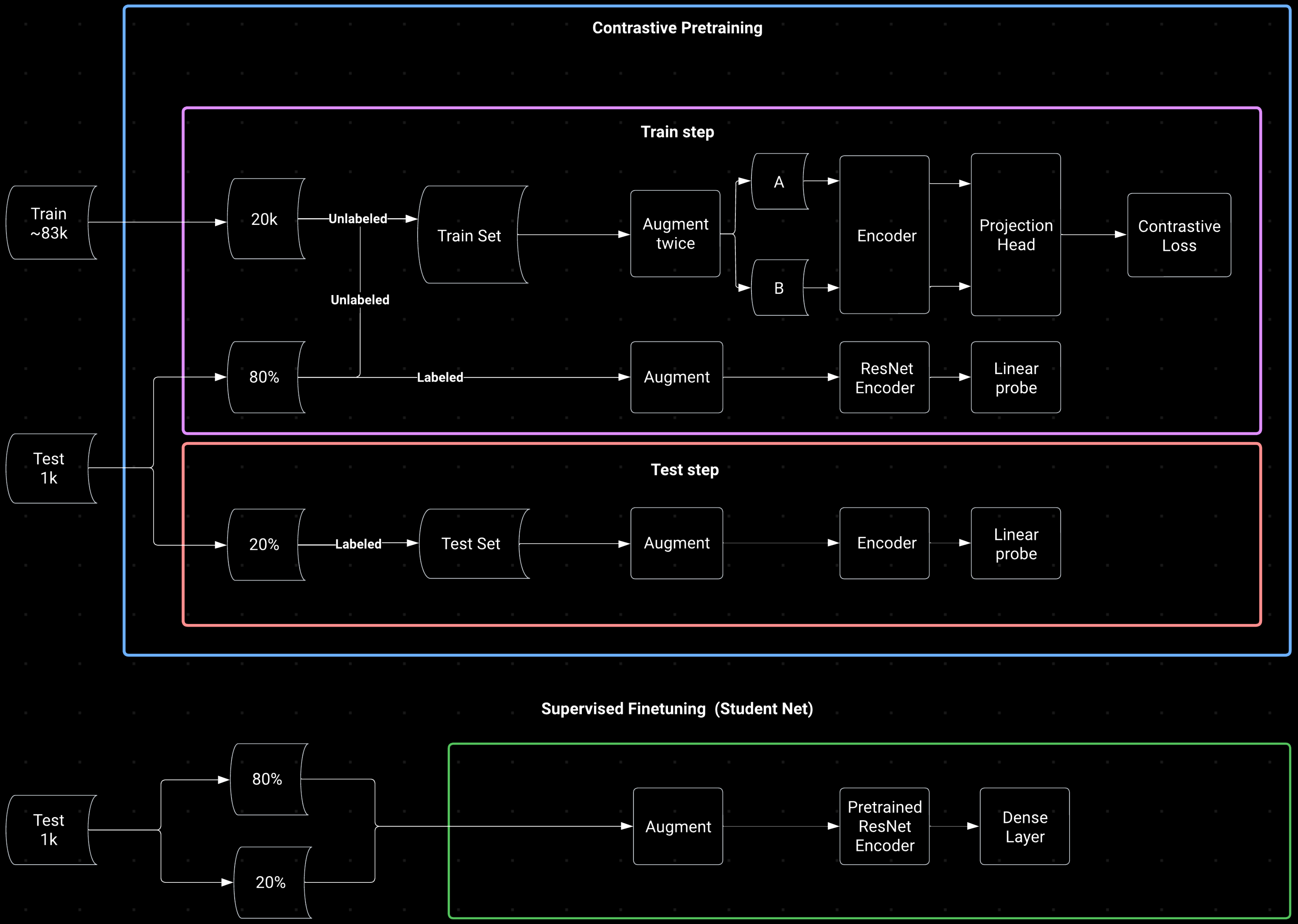
Semi-supervised learning utilizes a large unlabeled dataset and a much smaller labeled dataset.

The SimCLR model uses contrastive learning between image positive pairs to train a "Teacher Net".

A fine-tuned "Student Net" is produced from the "Teacher Nets" embedded ResNet - training on only labeled data.

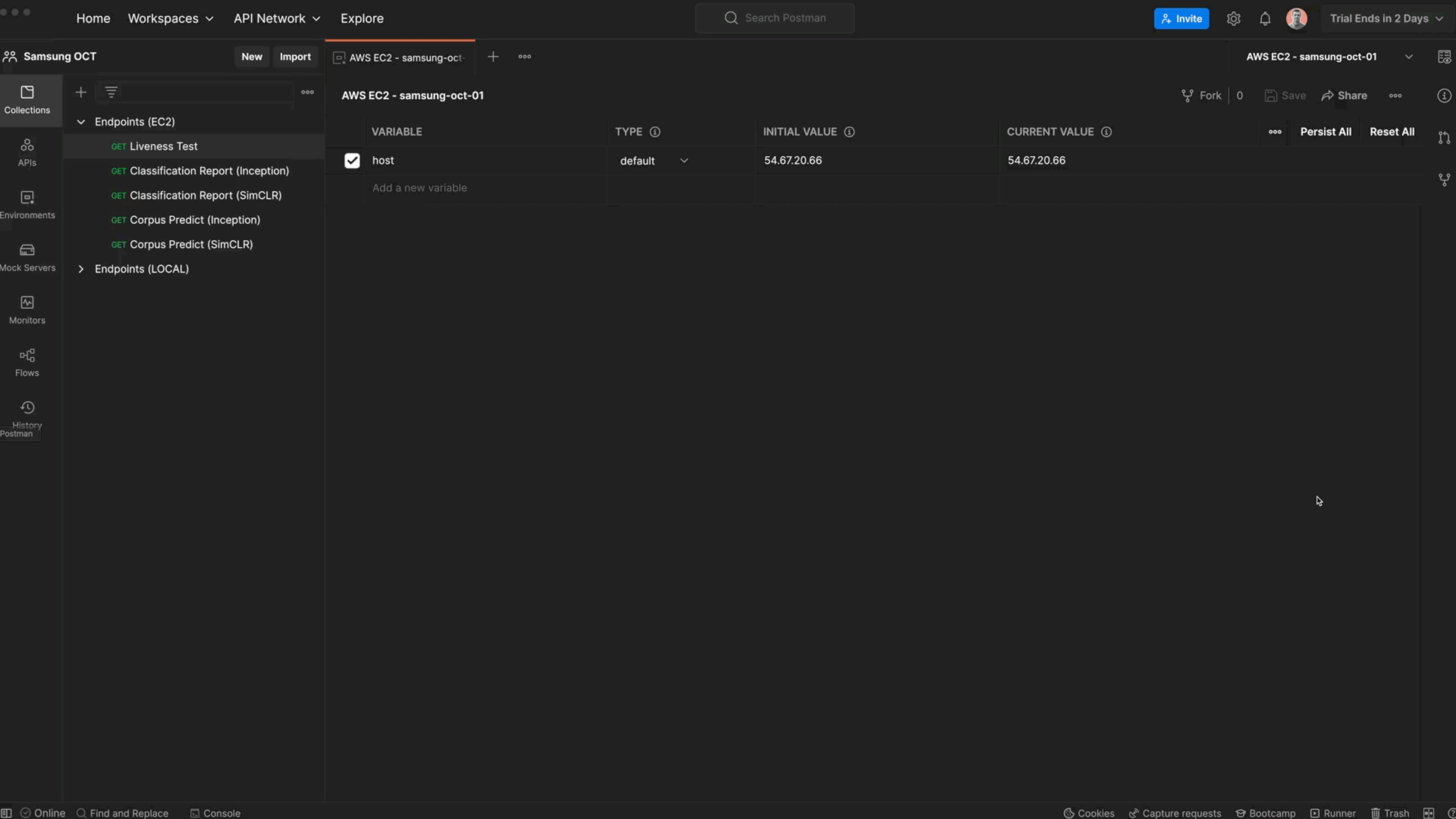


Solution



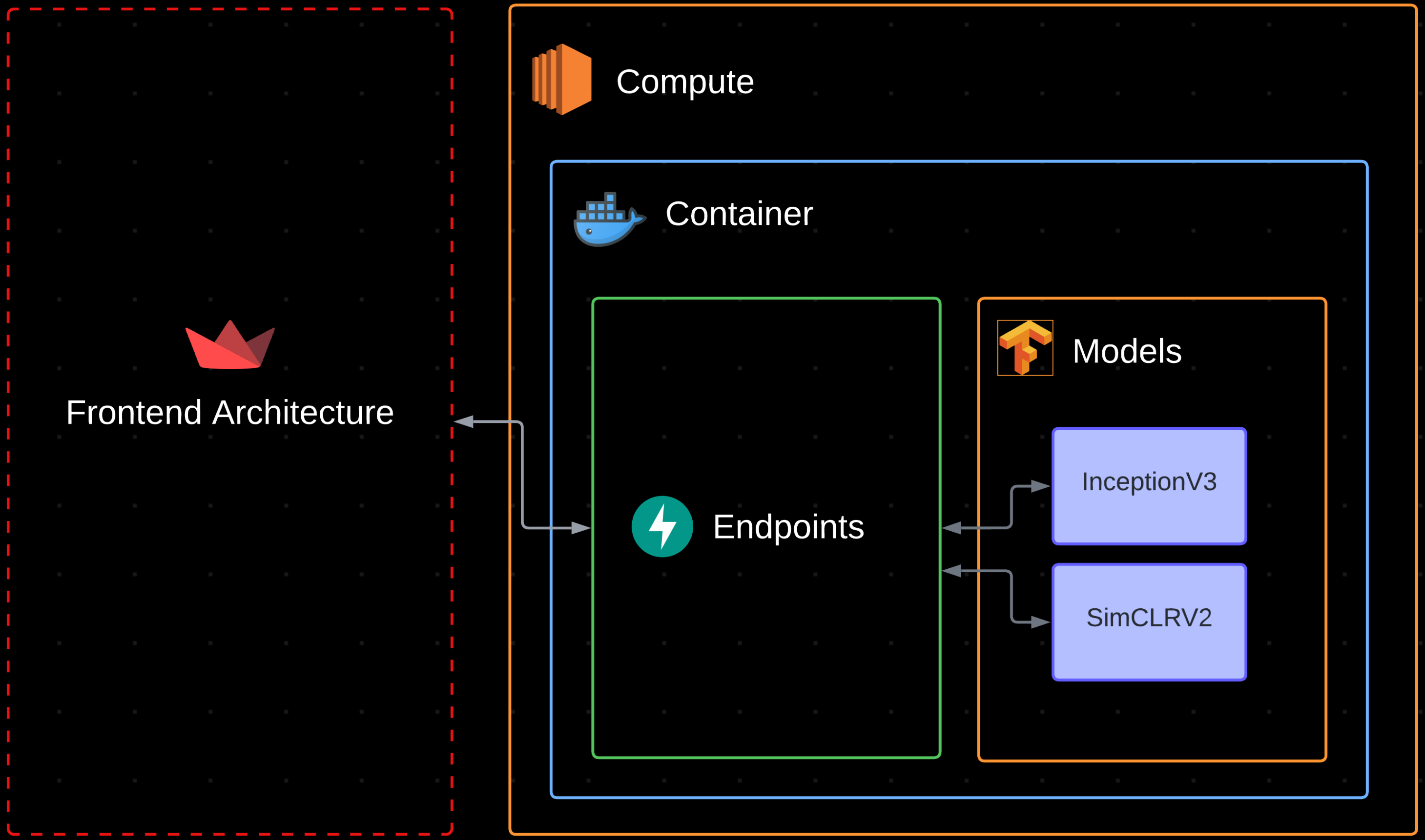
Contrastive Pretraining
Train step
Train
~83k
20k
Unlabeled
Train Set
Augment
twice
A
B
Encoder
Projection
Head
Contrastive
Loss
Unlabeled
80%
Labeled
Augment
ResNet
Encoder
Linear
probe
Test
1k
Test step
20%
Labeled
Test Set
Augment
Encoder
Linear
probe
Supervised Finetuning (Student Net)
Test
1k
80%
20%
Augment
Pretrained
ResNet
Encoder
Dense
Layer

DEMO


Home
Workspaces
API Network
Explore
Search Postman
Invite
Trial Ends in 2 Days
Samsung OCT
New
Import
AWS EC2 - samsung-oct-
AWS EC2 - samsung-oct-01
Collections
APIs
Environments
Mock Servers
Monitors
Flows
History
Postman
Endpoints (EC2)
GET Liveness Test
GET Classification Report (Inception)
GET Classification Report (SimCLR)
GET Corpus Predict (Inception)
GET Corpus Predict (SimCLR)
Endpoints (LOCAL)
AWS EC2 - samsung-oct-01
Fork
0
Save
Share
VARIABLE
TYPE
INITIAL VALUE
CURRENT VALUE
Persist All
Reset All
host
default
54.67.20.66
54.67.20.66
Add a new variable
Online
Find and Replace
Console
Cookies
Capture requests
Bootcamp
Runner
Trash

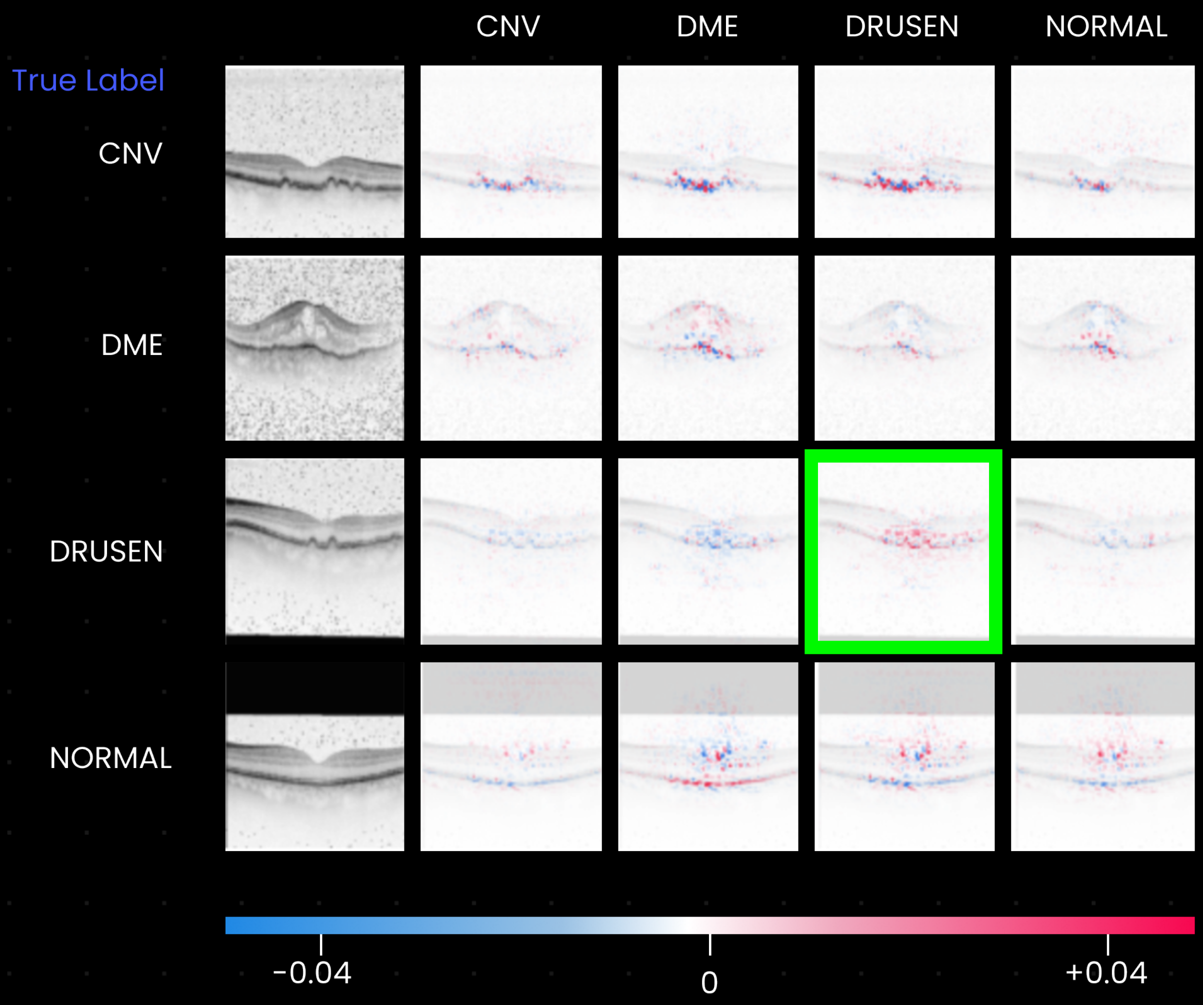
Solution

SOLUTION ARCHITECTURE DIAGRAM



EXPLAINABILITY & INTERPRETABILITY

- Explainability in AI — a lot of AI algorithms or methods are uninterpretable by human standards
- Explainability methods help reveal under the “black box” and can reveal why a classifier has specified certain labels to specific features
- Shapley Values are one such method in which features are given values of importance in a classification
  - I.e., if this feature didn’t exist, by how much does our classification change?
- Here we can see weighted average contributions per feature per potential label



THANK YOU
THANK YOU
THANK YOU

THANK YOU

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THANK YOU

APPENDIX

WEB RESOURCES

[Dataset]
[Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning]
[SimCLR github repo]
[SimCLRv2 - Big Self-Supervised Models are Strong Semi-Supervised Learners]
[Project Github Repository]

Project Approach

Unsupervised learning using InceptionV3 w/ Softmax (4) classification head

- Freeze the convolutional layer and retrain a new classification head for our classes

SimCLR

- Image augmentation
  - Classification augmentation (for supervised learning)
  - Contrastive augmentation (stronger than the above)
- Supervised learning baseline using ResNet50
- Self-supervised learning using contrastive pre-training
- Supervised fine tuning

Semi-Supervised Learning w/ SimCLRv2

Training step uses Nonlinear MLP as projection head on top of the ResNet encoder

- Train the weights of the ResNet using:
    - unlabeled data set
    - 2 different augmentation of each image in this set
- These augmented images are positive pairs (A/B) and are pushed through their own projection heads (1,2) where a contrastive loss is calculated between the pairs
- Contrastive loss is sparse categorical cross entropy between contrastive labels and similarities (between augmented pairs)

Test step uses Linear Probe

- Train a single dense layer on top of the encoder's features
    - encoder weights are frozen post contrastive loss
- Probe loss is sparse categorical cross entropy
- Supervise fine-tuning of the pre-trained encoder above

OCT Image Classification – Project Brief

Project:

The OCT (Optical Coherence Tomography) is an imaging method used to diagnose the patient's retinal health into four categories: Normal, CNV, DME, and DRUSEN.

Goal:

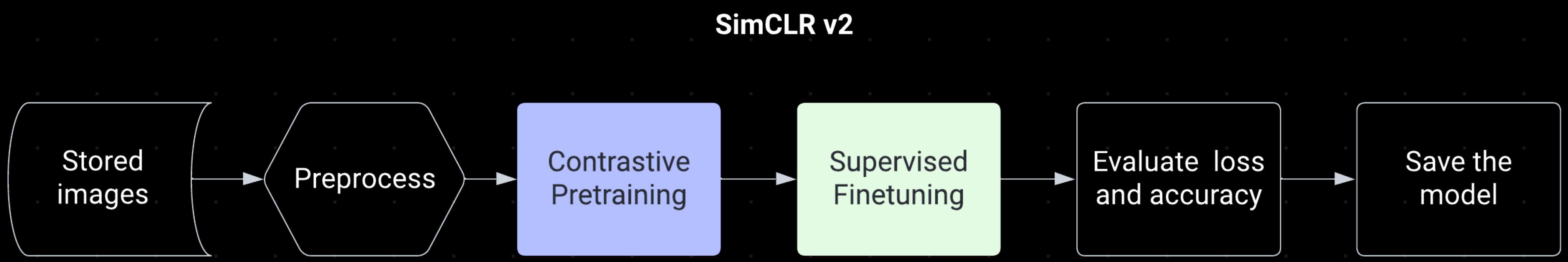
1. create a baseline: reproduce the SOTA classification accuracy by training a Deep CNN (Supervised Learning)
2. improve the classification accuracy over the baseline in part 1 using the self-supervised method described in SimCLR paper.

Data source: https://data.mendeley.com/datasets/rscbjbr9sj/2

Data will be hosted on AWS

Appendix

Semi-Supervised Learning w/ SimCLRv2

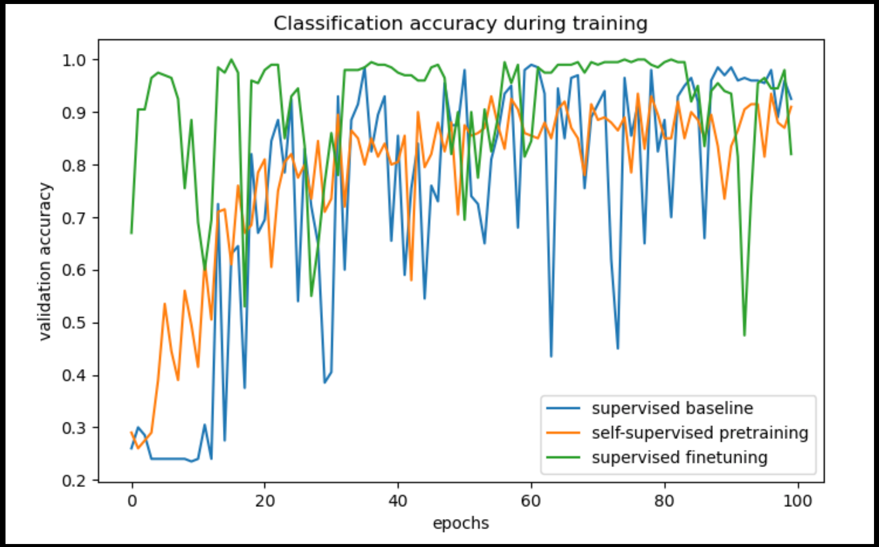


Appendix

Metrics – Training Performance (Accuracy)

Inceptionv3

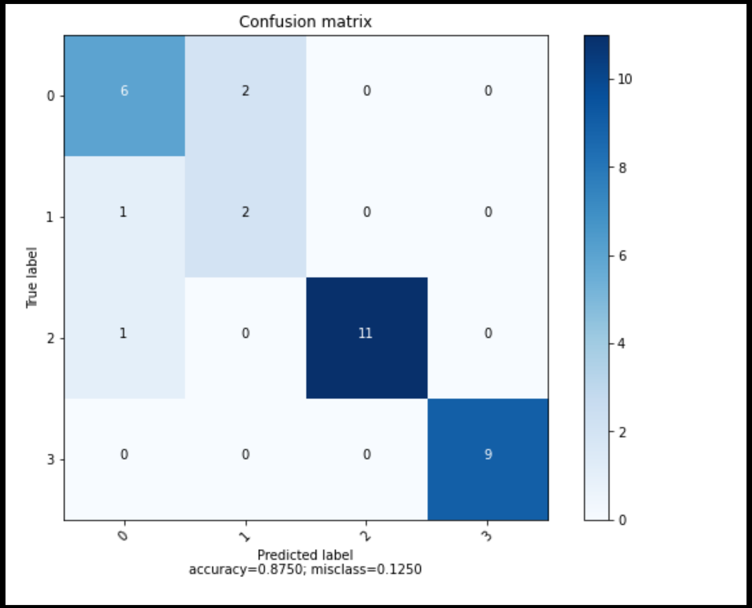
SimCLRv2



Appendix

Metrics – Confusion Matrices

Inceptionv3



SimCLRv2