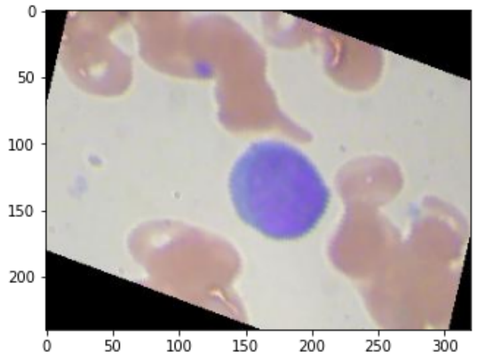
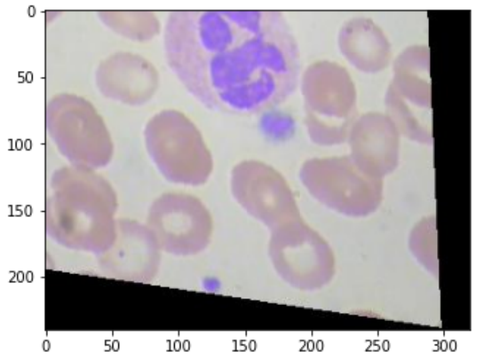
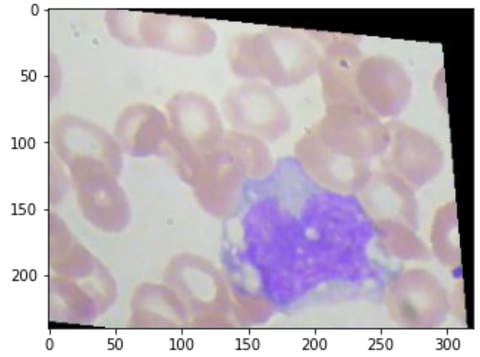
# Comparative Analysis of Blood Cell Image Classification

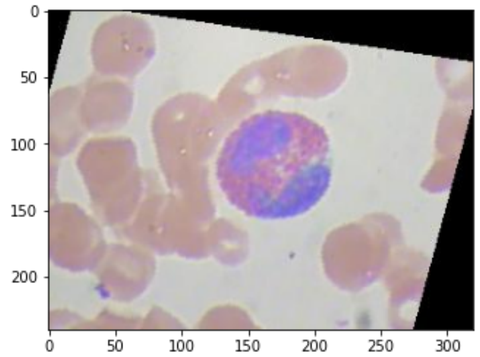
CNNs, Deep Residual and Contrastive Learning based models

Blood Cell Types -




# White Blood Cell Identification is an important task

- Useful for recognizing diseases like Leukemia
- Traditional methods like Flow Cytometry and Fluorescence Microscopy have physical limitations

# Computer Vision Models

INCEPTION RESNET50

RESNET50

INCEPTIONV3

ALEXNET

LENET5

SUPERVISED CONTRASTIVE LEARNING (SIMCLR)

# LeNet 5

- LeNet-5 is one of the earliest pre-trained models proposed in 1998.
- Designed for a 32x32 sized image but modified to work on our images
- It has 5 layers with learnable parameters.
- It has 3 convolution layers, two average pooling layers, and two fully connected layers with a softmax classifier.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 118, 118, 6) | 168 |
| average_pooling2d (AveragePooling2D) | (None, 59, 59, 6) | 0 |
| conv2d_1 (Conv2D) | (None, 57, 57, 16) | 880 |
| average_pooling2d_1 (AveragePooling2D) | (None, 28, 28, 16) | 0 |
| flatten (Flatten) | (None, 12544) | 0 |
| dense (Dense) | (None, 120) | 1505400 |
| dense_1 (Dense) | (None, 84) | 10164 |
| dense_2 (Dense) | (None, 4) | 340 |

Total params: 1,516,952
Trainable params: 1,516,952
Non-trainable params: 0

TRAIN ACCURACY 99.95%

VALIDATION ACCURACY 77.51%

VALIDATION LOSS 0.97

# AlexNet

- AlexNet is a CNN that was originally created in 2012 for an image recognition competition.
- It was designed for the 224×224 images of ImageNet.
- Modified to make it work on smaller, 120x120 images. These modifications include increasing strides and increasing the depth of the network.

TRAIN ACCURACY 98.64%

VALIDATION ACCURACY 85.89%

VALIDATION LOSS 0.6378%

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d_3 (Conv2D) | (None, 118, 118, 32) | 896 |
| max_pooling2d_3 (MaxPooling 2D) | (None, 59, 59, 32) | 0 |
| conv2d_4 (Conv2D) | (None, 57, 57, 32) | 9248 |
| max_pooling2d_4 (MaxPooling 2D) | (None, 28, 28, 32) | 0 |
| conv2d_5 (Conv2D) | (None, 26, 26, 64) | 18496 |
| max_pooling2d_5 (MaxPooling 2D) | (None, 13, 13, 64) | 0 |
| dropout_3 (Dropout) | (None, 13, 13, 64) | 0 |
| flatten_1 (Flatten) | (None, 10816) | 0 |
| dense_4 (Dense) | (None, 128) | 1384576 |
| dropout_4 (Dropout) | (None, 128) | 0 |
| dense_5 (Dense) | (None, 4) | 516 |

Total params: 1,413,732
Trainable params: 1,413,732
Non-trainable params: 0

# ResNet50

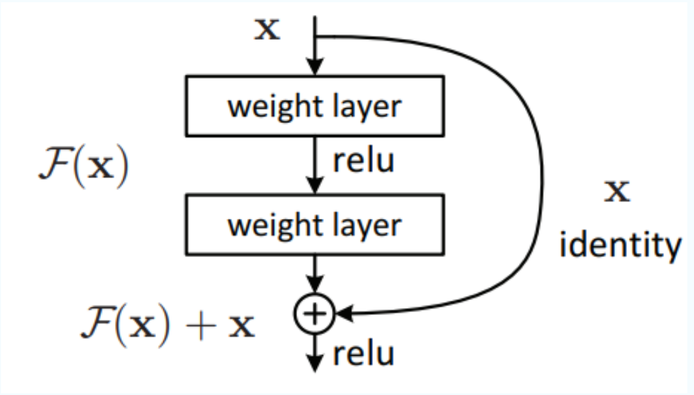
- ResNet-50 is a convolutional neural network that is 50 blocks deep
  - This depth can only be efficiently implemented through Residual Building Block structures because of network degradation
- The Residual Building Blocks can effectively skip one or more layers and help combat the exploding/vanishing gradient problem
- Since ResNet was conceived in 2015, the presence of Residuals in CNNs have been present in nearly every modern architecture
- We're using pretrained weights as a baseline. (ImageNet)

TRAIN ACCURACY 97.46%

VALIDATION ACCURACY 88.55%

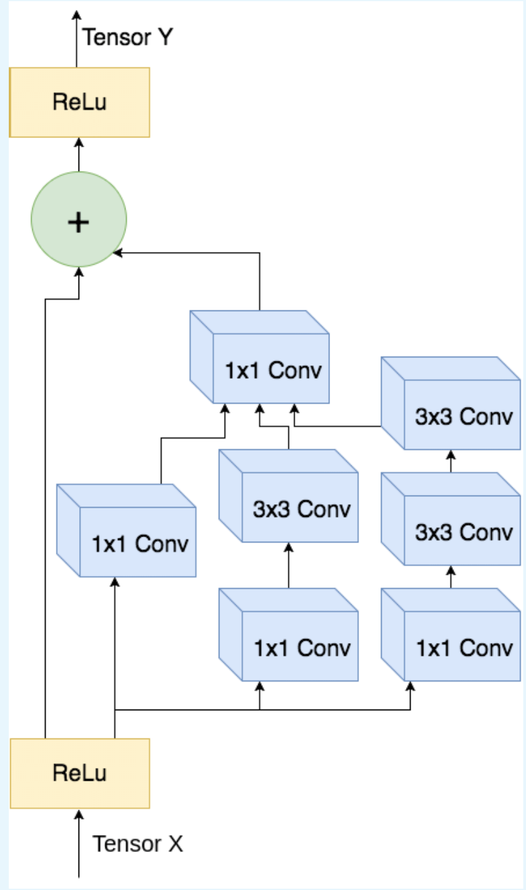
VALIDATION LOSS 0.33

A Residual Block



# InceptionResNet V2

- This architecture has a very clear residual structure along with 3 paths for different types of convolutions mixed together in a final 1x1 convolution
- Clear inspiration from ResNet
- Our best performer
- We're using pretrained weights as a baseline. (ImageNet)



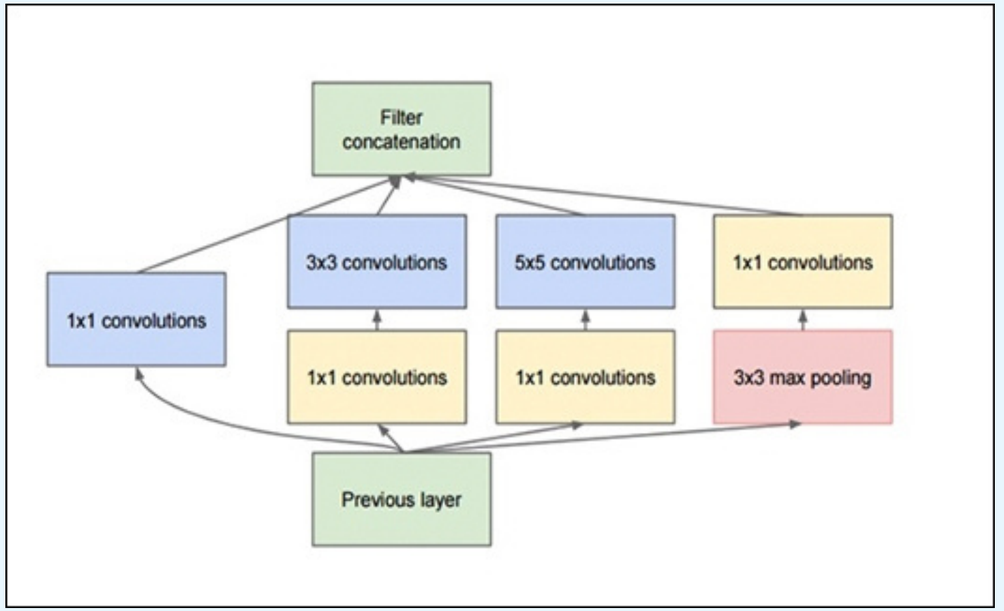

TRAIN ACCURACY 99.41%

VALIDATION ACCURACY 99.50%

VALIDATION LOSS 0.0209

# Inception V3

- Inceptionv3 can have deeper layers while keeping the number of parameters from growing too large.
- Inception v3 architecture has h 1x1, 3×3, and 5×5 convolution with max pooling.
- All the convolutions are performed, and the model picks the what’s best
- We're using pretrained weights as a baseline. (Imagenet)




TRAIN ACCURACY 99.38%

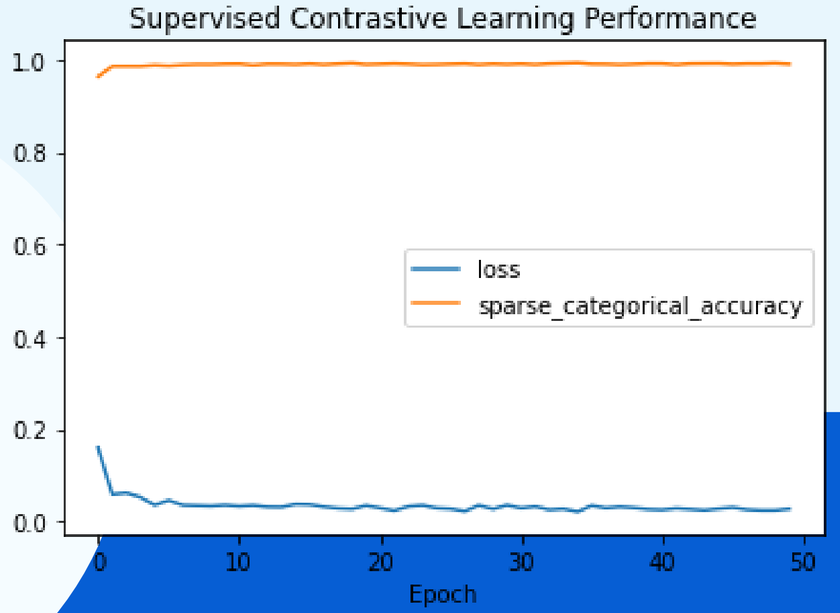
VALIDATION ACCURACY 95.03%

VALIDATION LOSS 0.24

# Supervised Contrastive Learning (ResNet + SupCon Loss Function)

Pranay Khosla

- Contrastive learning is usually a self-supervised learning technique that uses the difference between two images to learn the similarity and dissimilarities between the two images.
- SIMCLR is a supervised learning method that can leverage labeled data along with contrastive learning to learn the model.
- Fully supervised



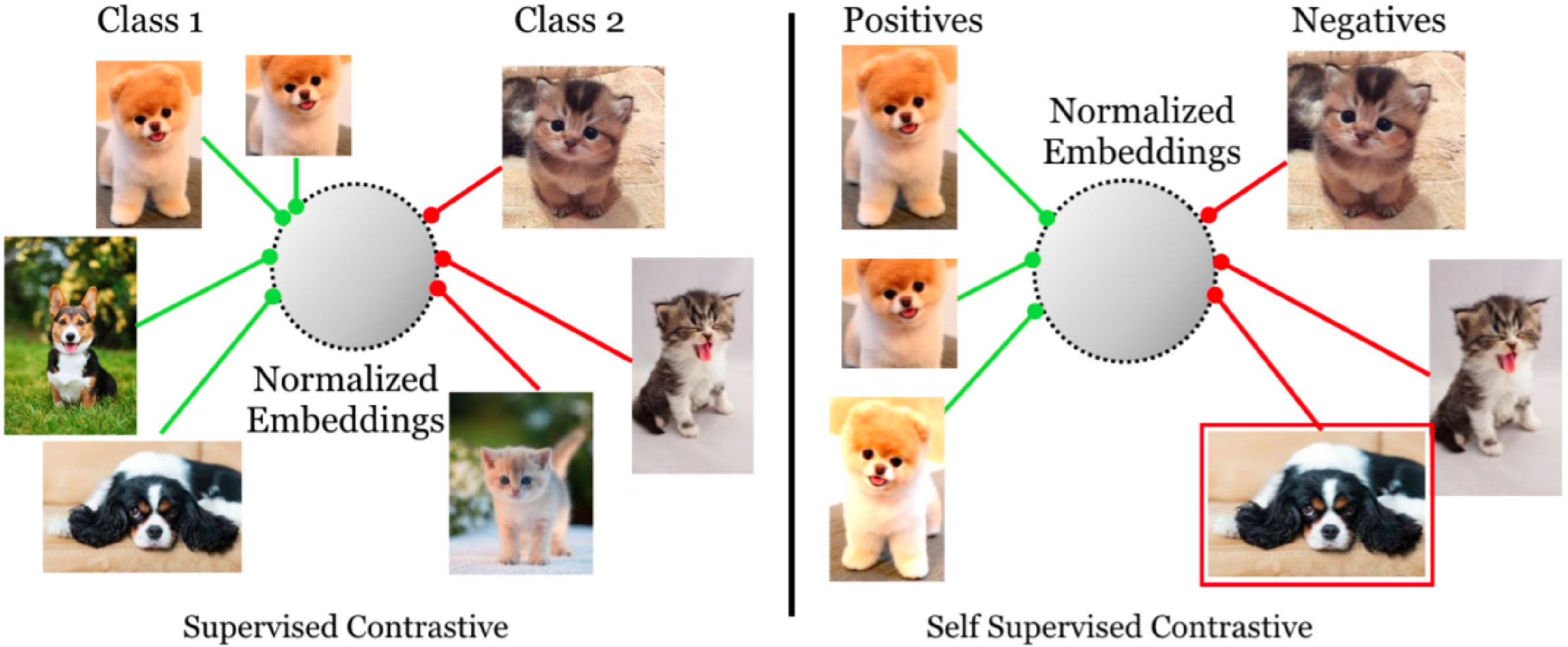

TRAIN ACCURACY 99.06%

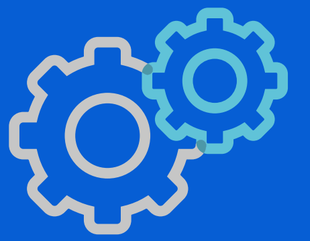
VALIDATION ACCURACY 92.73%

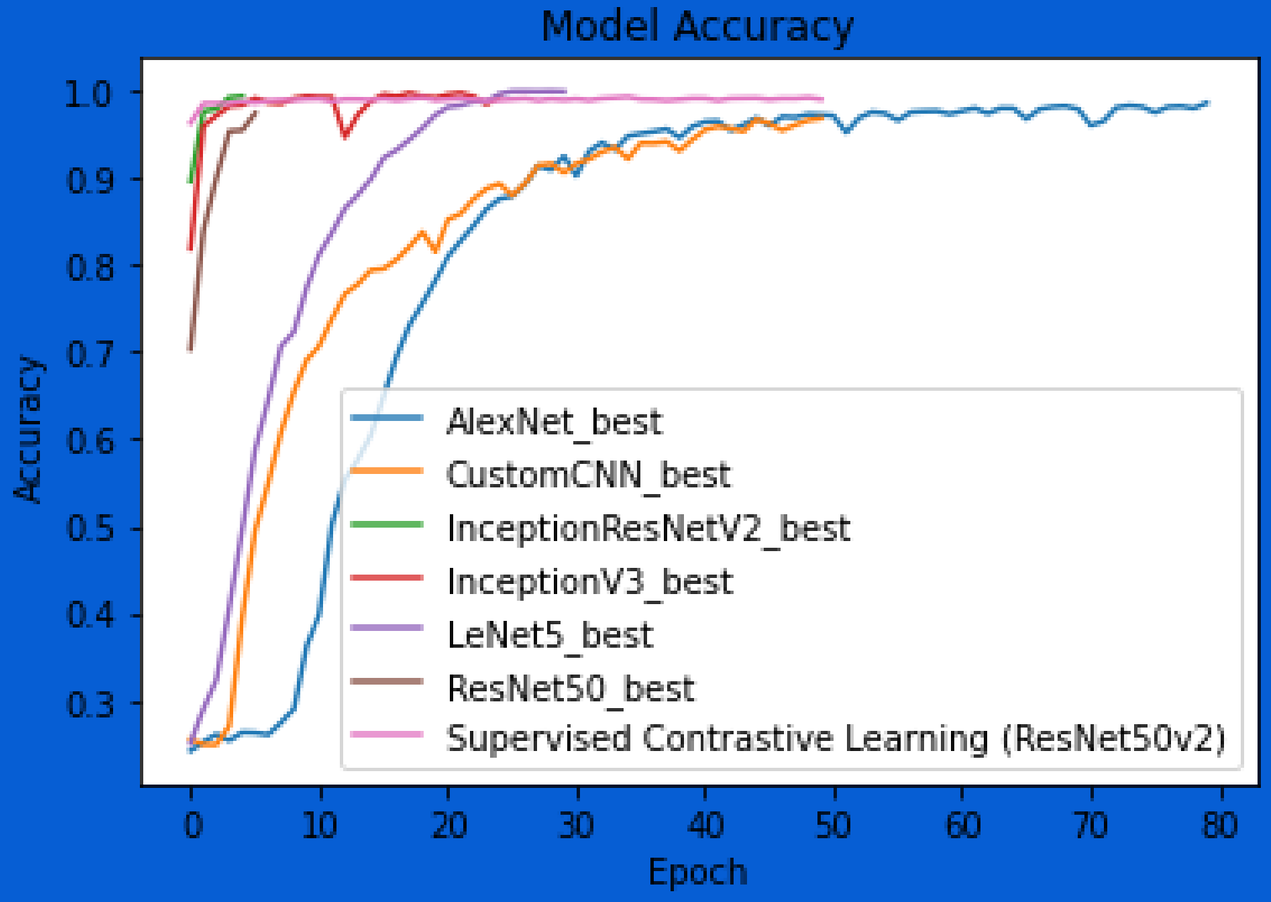
LOSS 0.0273

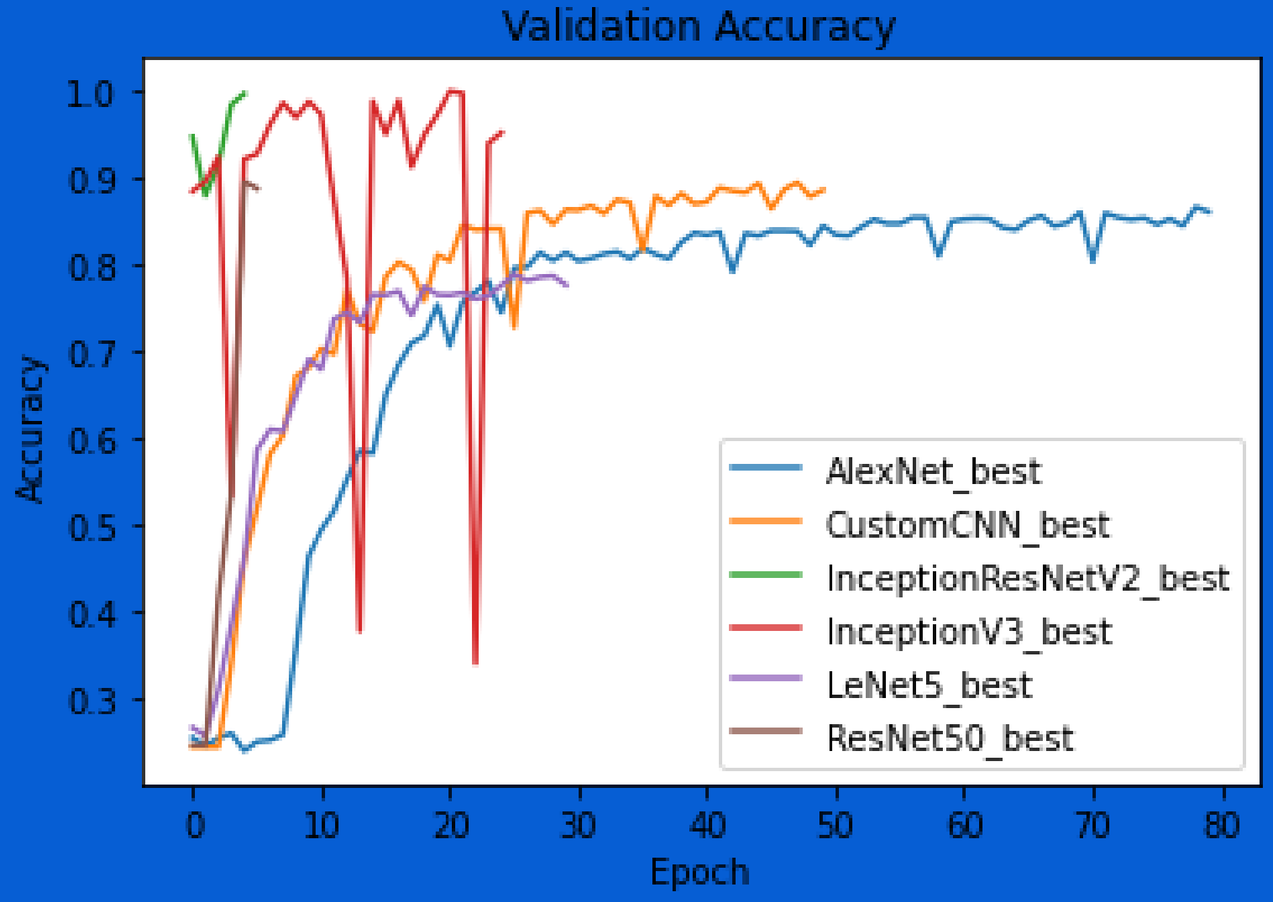
# Contrastive Learning (SupCon Loss)

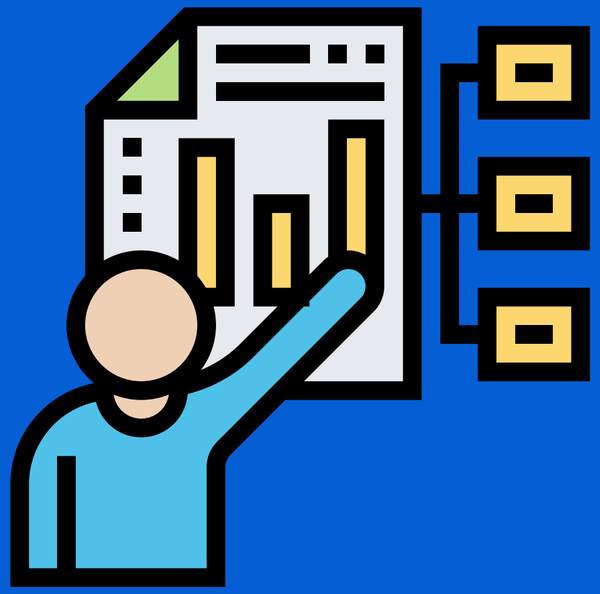
Clusters of points belonging to the same class are pulled together in embedding space, while simultaneously pushing apart clusters of samples from different classes.






Model Accuracy
Accuracy
Epoch
AlexNet_best
CustomCNN_best
InceptionResNetV2_best
InceptionV3_best
LeNet5_best
ResNet50_best
Supervised Contrastive Learning (ResNet50v2)


Validation Accuracy
Accuracy
Epoch
AlexNet_best
CustomCNN_best
InceptionResNetV2_best
InceptionV3_best
LeNet5_best
ResNet50_best



# Conclusion

Need to improve parameters further to prevent overfitting.

## Best Model Accuracy:

## 99.95%

LeNet50 (Overfit)

## Best Validation Accuracy

## 99.50%

InceptionResNetV2

**99.5%** INCEPTIONRESNETV2

**RealTesting** Best Overall Network for Blood Cell Classification

# Next Steps

# Sources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# Questions?