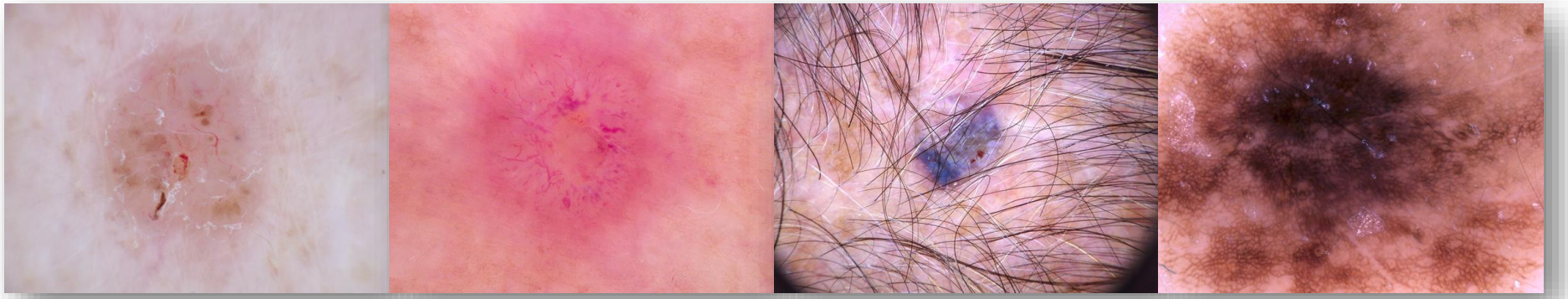
MAIA

CAD System
Deep Learning Approach

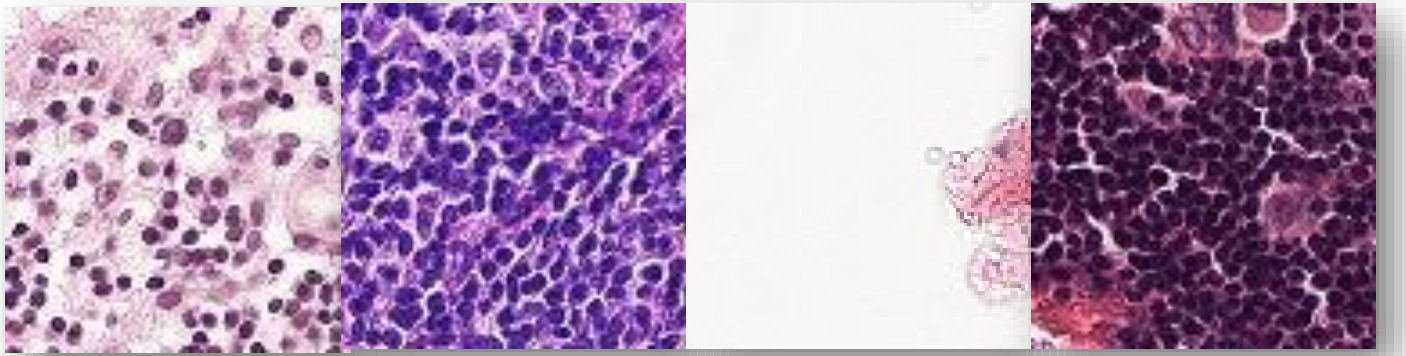
Tewodros Arega, Abdullah Thabit

Project Objectives

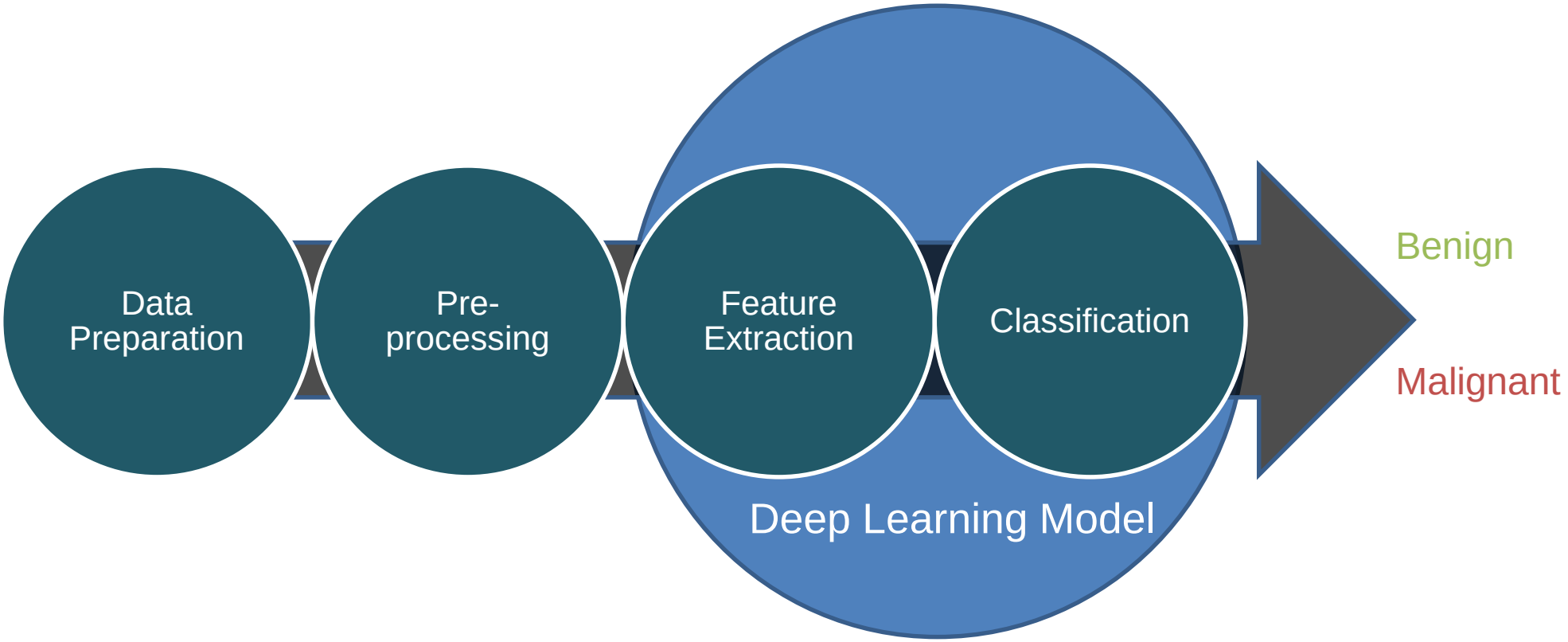
- Build a CAD system to address two main problems:
  - Skin Lesion Classification
    - 6000 images (half benign and half other classes)



  - Histopathology Classification
    - 29494 images (half benign and half malignant)



CAD System Framework



Histopathology Classification

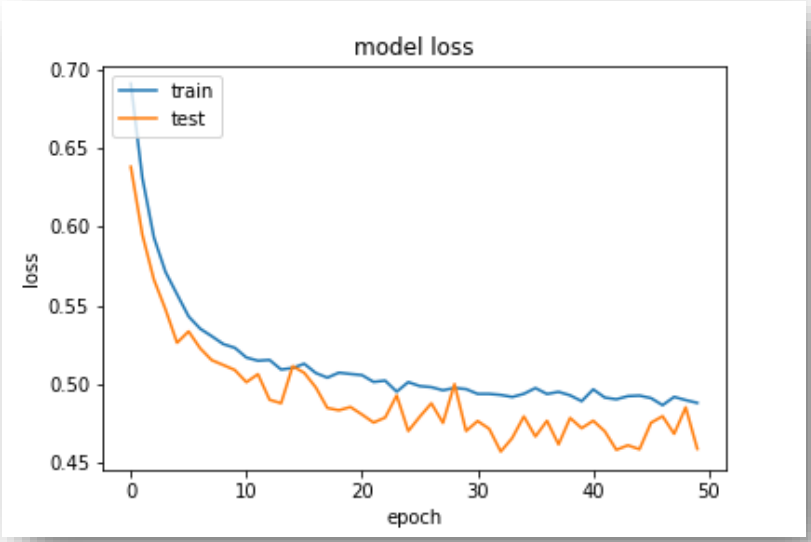
First Experiment: Transfer Learning

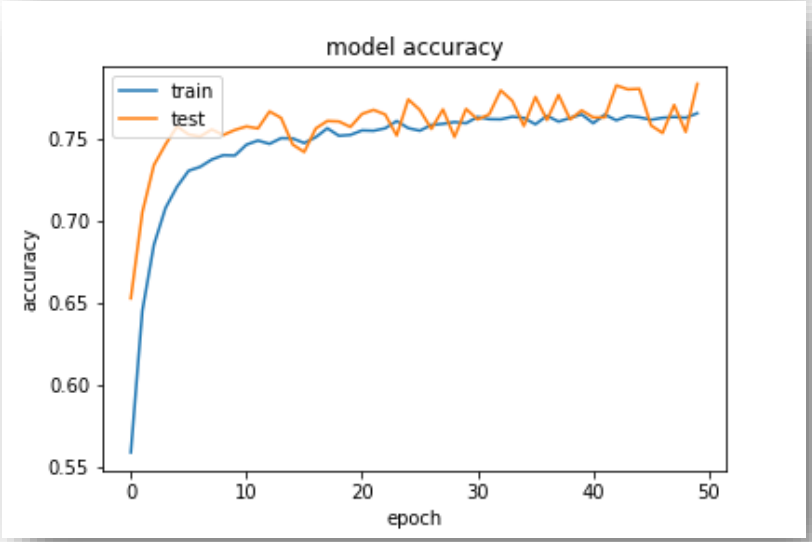
- VGG16
- Resnet50

- **Initial Hyperparameters:**
- Optimizer: Adadelta
- Lr= 0.001
- Epochs = 50

- The models Performed about the same
- VGG16 (acc) = 77.9%
- Resnet50= 78.1%

- Training Loss is high meaning the models couldn't learn the dataset very well





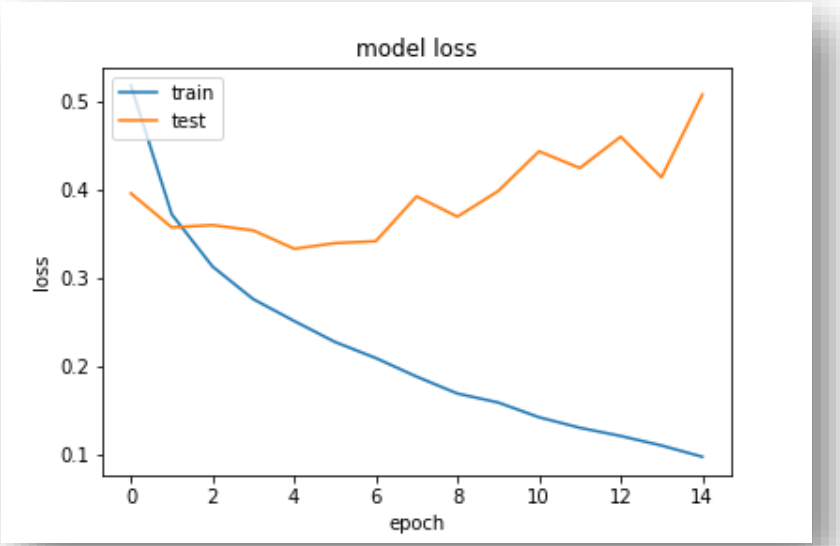
Histopathology Classification

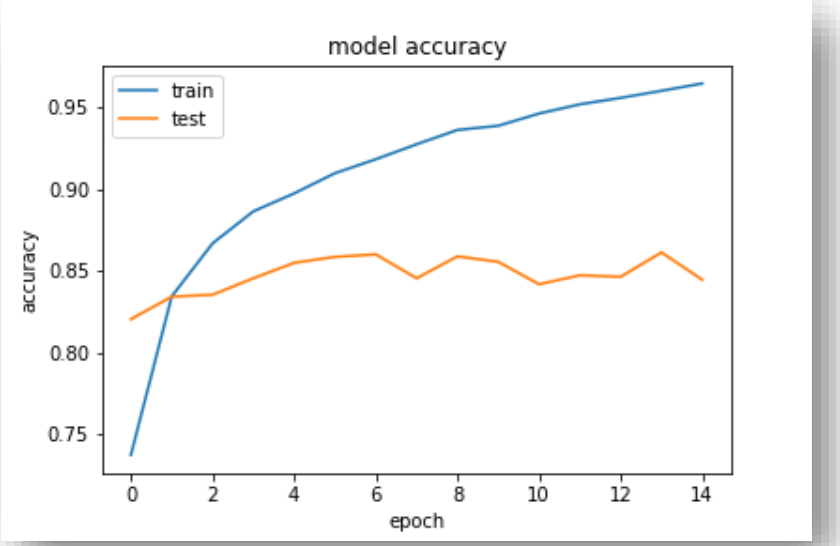
Switch to fine tuning:

- Vgg16
- Resnet50
- Densenet161

- VGG16 = 80%
- Resnet50= 81%
- Densenet161 = 84%

- Training loss now goes very low, but there is big over fitting from the first epochs!!

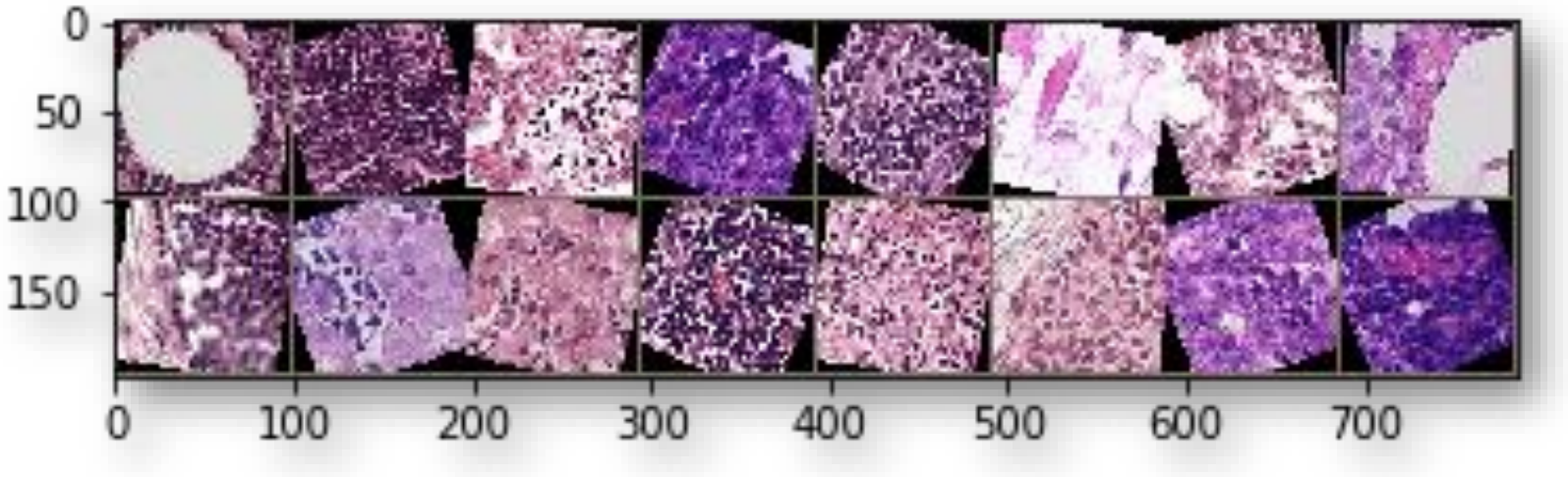




Histopathology Classification

Apply Augmentation:

- Contrast and Saturation
- Rotation
- Flipping



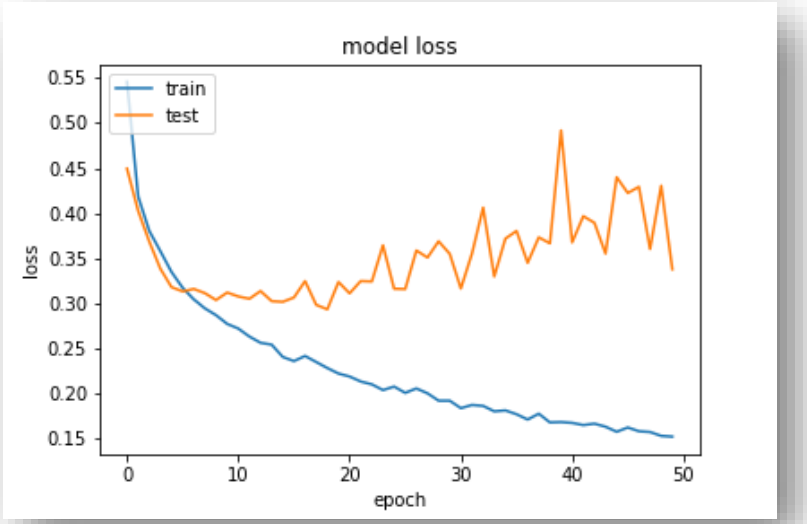
Histopathology Classification

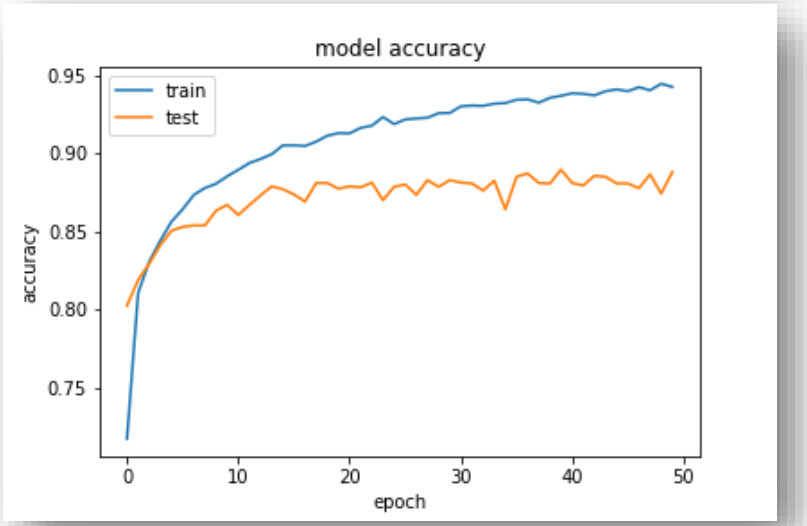
Apply Augmentation:

- Vgg16
- Densenet161
- Resnet50
- Resnet34
- InceptionV3

- The models Performance increased
- Vgg16 = 86%
- Resnet34 = 86%
- Resnet50 = 86%
- Densenet161 = 87%
- InceptionV3 = 56% (failed)

- Overfitting reduced, but still present

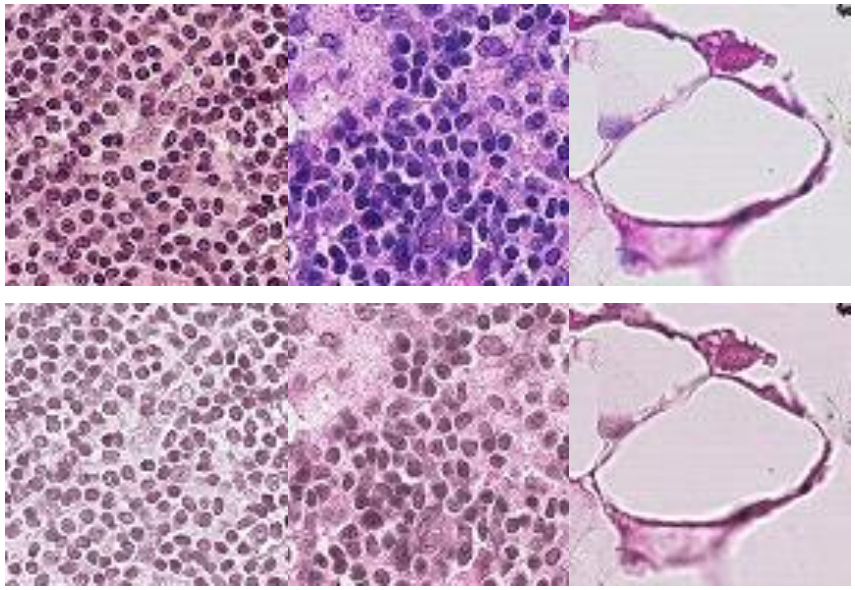




Histopathology Classification

Apply Stain Normalization:

Macenko stain normalization *'A method for normalizing histology slides for quantitative analysis'*

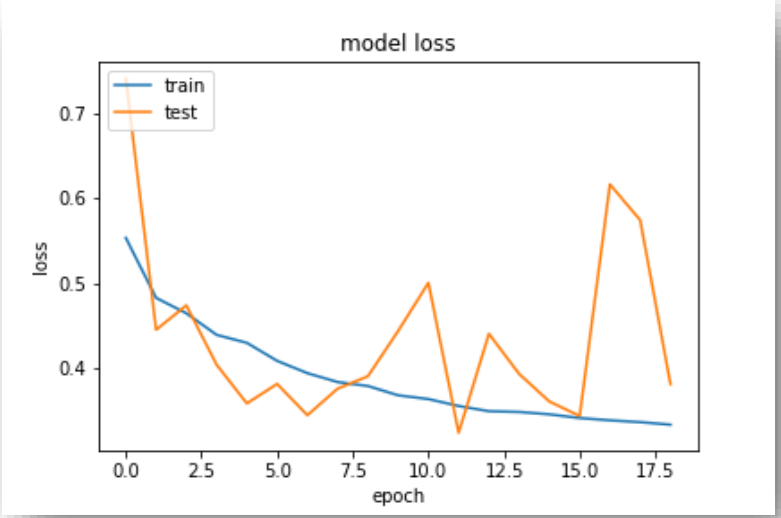


Histopathology Classification

Apply Stain Normalization with two setups:

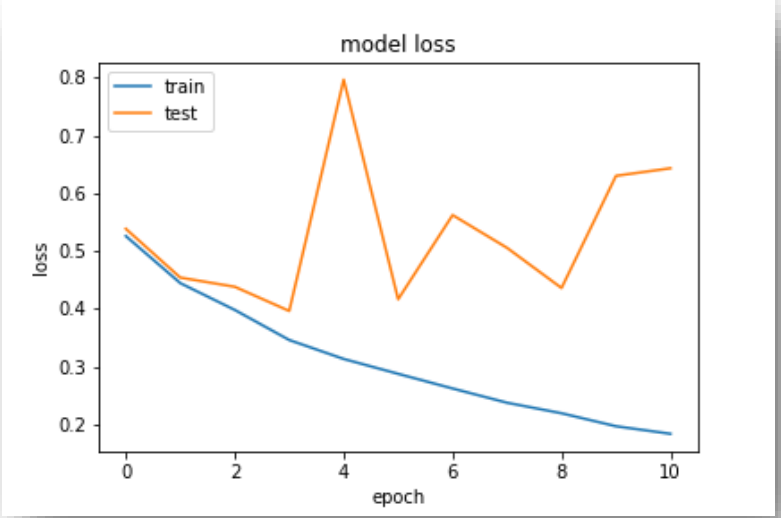
- With Augmentation
- Without Augmentation

- Applied on Resnet34



- The models Performance decreased
- Without Augmentation = 82%
- With Augmentation = 84%

- Stain normalization led to corrupting the features extracted with the deep learning model, and led to a worse performance



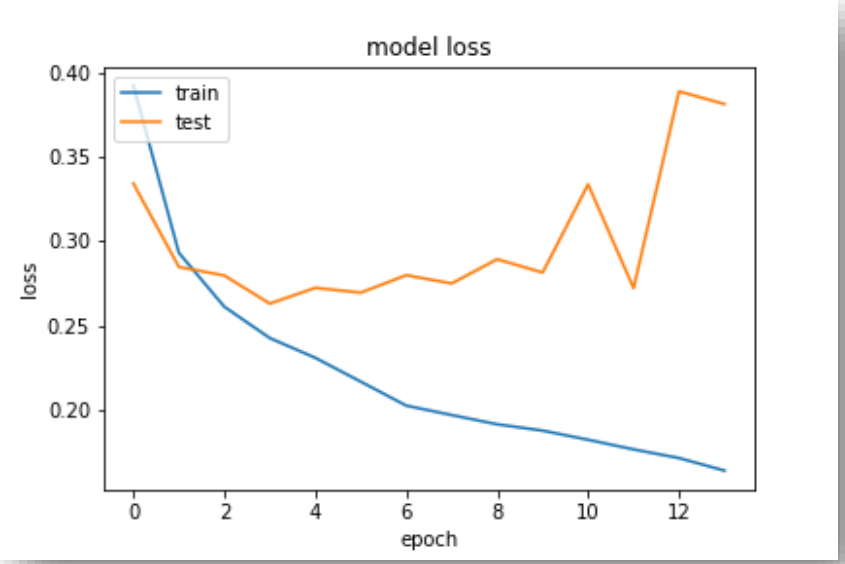
Histopathology Classification

Hyperparameter tuning:
- Applied on Resnet34

Parameters	Range of options
Optimizer	Adadelta, Adam, SGD
Lr	0.001 – 0.00001
Weight decay(Adam)	0.01 – 0.0001
Momentum (SGD)	0.5 – 0.9
Lr_scheduler	Factor=0.5,0.9 Patience =2, 5
Batch size	6, 16, 32, 64

- Best parameters found:
- Optimizer = SGD
- Lr = 0.001
- Momentum = 0.9
- Lr_scheduler = No
- Batch size = 16

- Resnet34 = 88.9%
- SGD with these parameters converge faster and to a lower loss value, but at the expense of oscillation in loss function!



Histopathology Classification

Apply best parameters on all networks:

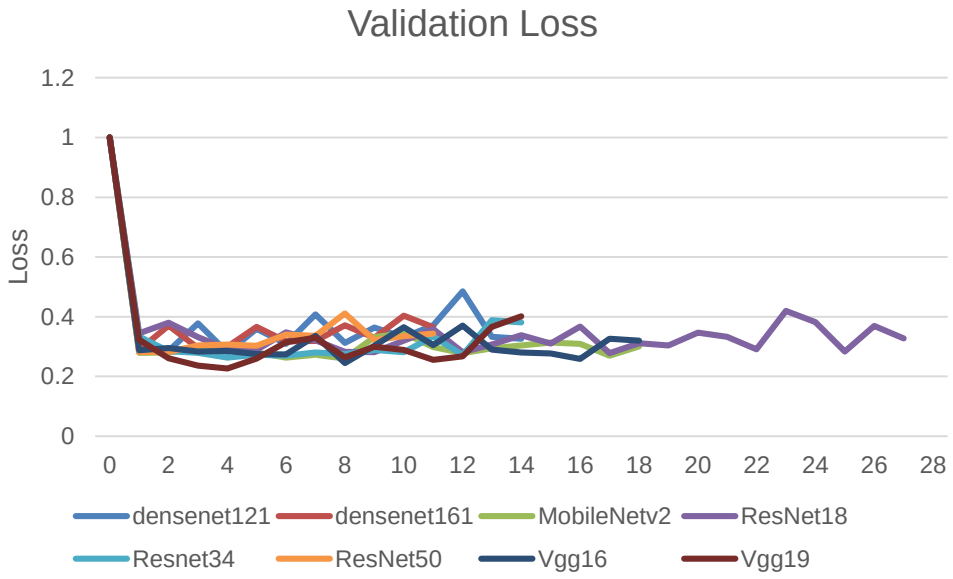
- MobileNetV2
- ResNet18
- ResNet34
- ResNet50
- DenseNet121
- DenseNet161
- Vgg16
- Vgg19

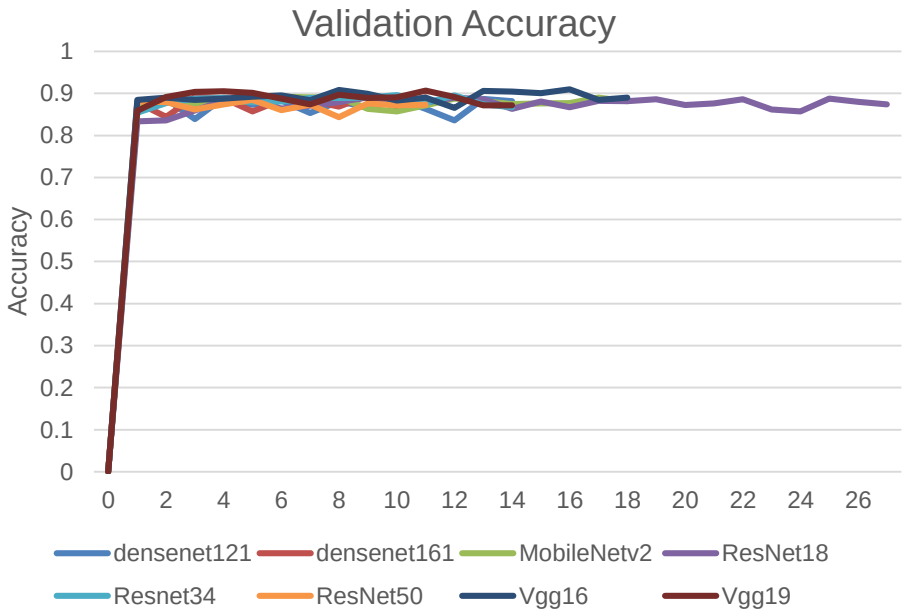
- Best model: VGG19
- AI models have higher sensitivity than specificity with VGG19 having a balanced sensitivity to specificity ratio and a high accuracy

Model	Accuracy(%)	Sensitivity(%)	Specificity(%)
MobileNetV2	89.0	91.5	86.8
ResNet18	88.2	95.0	83.2
ResNet34	89.0	91.6	86.5
ResNet50	88.0	91.7	85.0
DenseNet121	89.0	91.8	86.5
DenseNet161	87.9	90.3	85.6
Vgg16	90.8	93.2	88.7
Vgg19	**90.5**	**90.7**	**90.2**

Histopathology Classification

Best Model: VGG19





Training Metrics	
Accuracy	93.7%
Per-class Accuracy	93.3% , 93.9%

Validation Metrics	
Accuracy	90.5%
Per-class Accuracy	90.3% , 90.8%

Universitat de Girona

Histopathology Classification

Best Model: VGG19