December 2024

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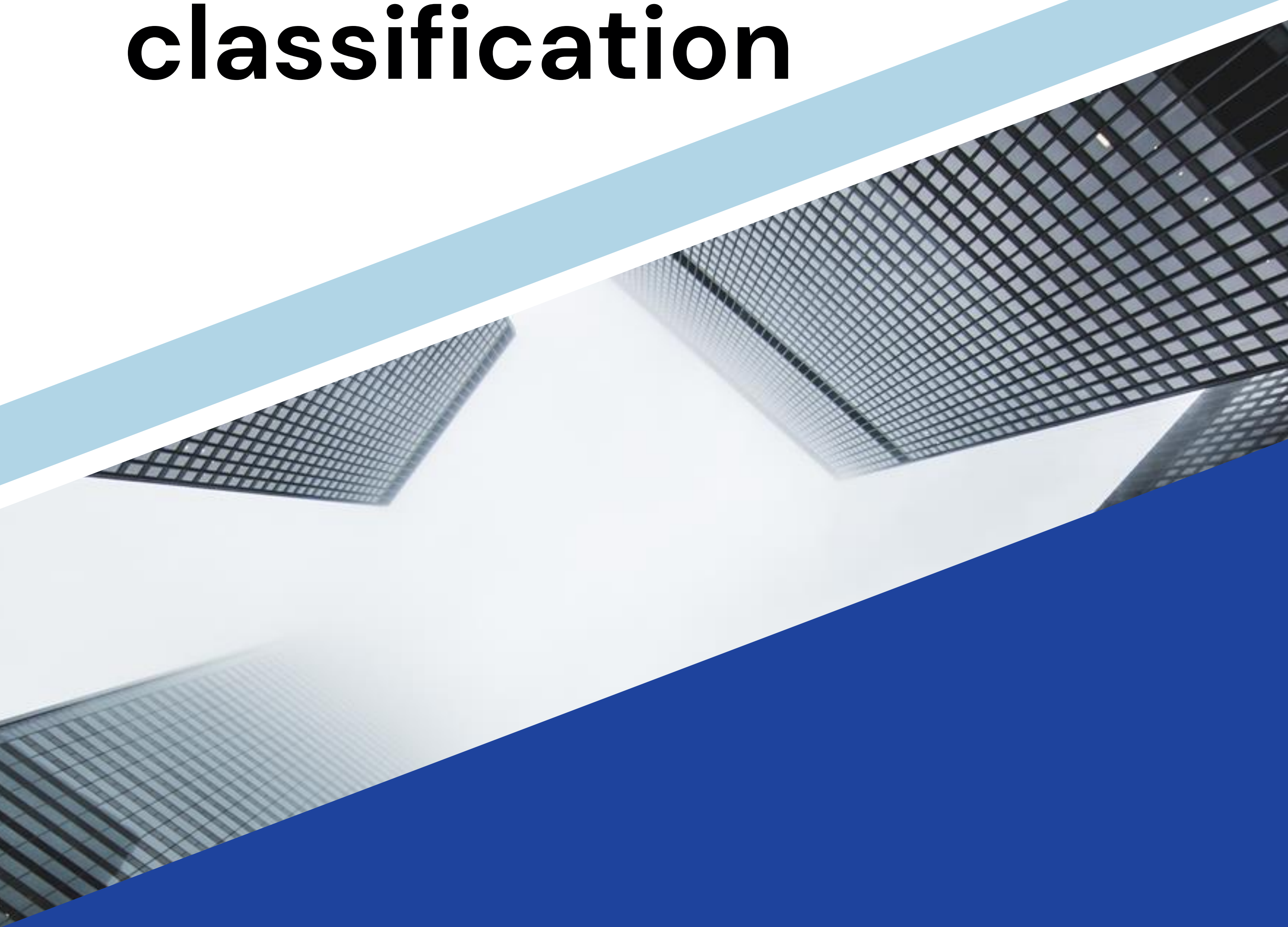
University

Medical image classification



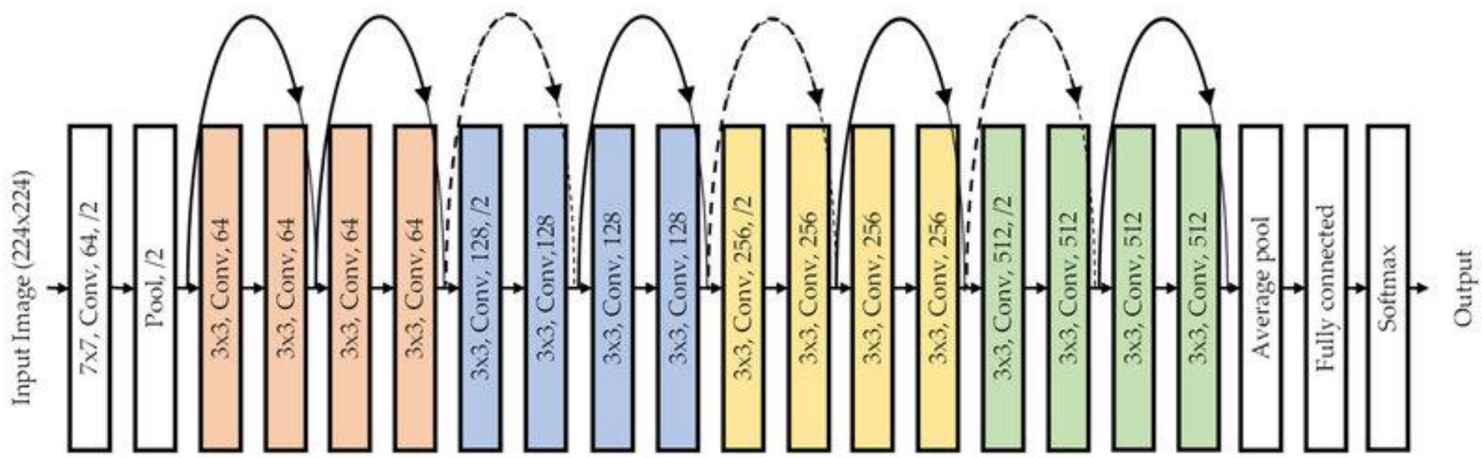
Deep learning project documentation

Explanation of the models step by step

ResNet (ResNet18) Architecture:

1. The ResNet architecture is built upon the concept of residual learning, which helps to address the problem of vanishing gradients in very deep neural networks.
2. The ResNet18 model consists of an initial convolutional layer, followed by a series of residual blocks.
3. Each residual block contains two convolutional layers, with a shortcut connection that bypasses the two layers and adds the input to the output of the block.
4. This shortcut connection allows the network to learn residual mappings, which can be easier to optimize than learning the original, unreferenced mappings.
5. The residual blocks are followed by a global average pooling layer and a fully connected layer for classification.

Diagram:

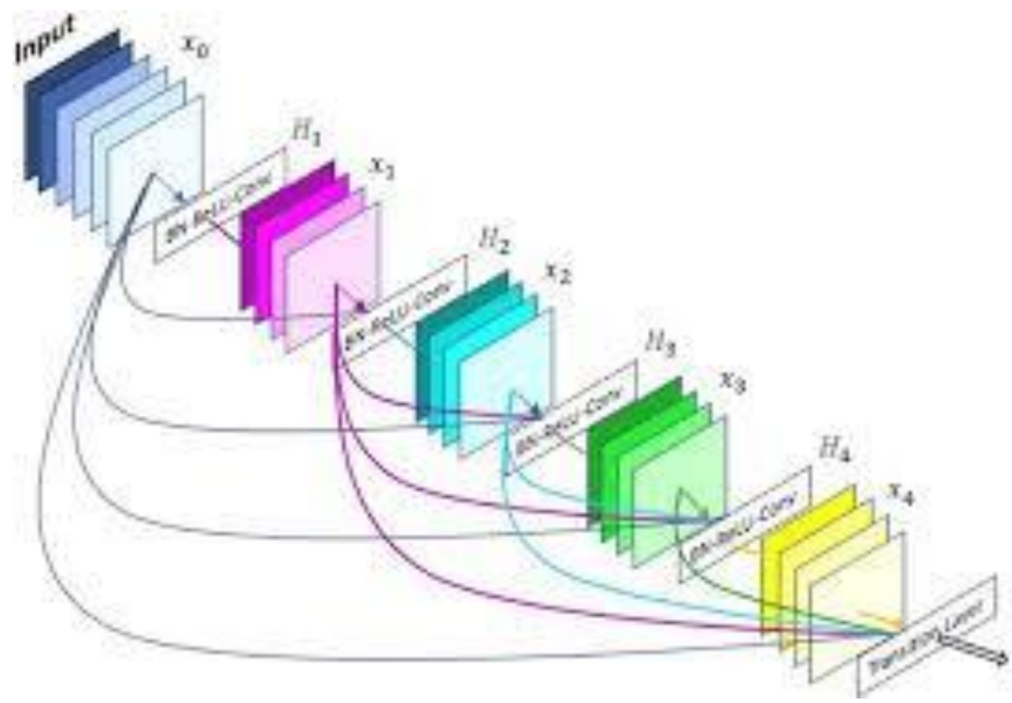


Explanation of the models step by step

DenseNet (DenseNet121) Architecture:

1. The DenseNet architecture is characterized by its dense connectivity pattern, where each layer is connected to all subsequent layers.
2. The DenseNet121 model starts with an initial convolutional layer, followed by a series of dense blocks.
3. Each dense block contains several convolutional layers, where the input of each layer is the concatenation of the outputs of all preceding layers within the same block.
4. The dense connectivity allows the network to reuse features learned in earlier layers, which can improve the flow of information and gradients through the network.
5. Between the dense blocks, there are transition layers that reduce the spatial dimensions of the feature maps using average pooling.
6. The final layers of the DenseNet121 model include a global average pooling layer and a fully connected layer for classification.

Diagram:

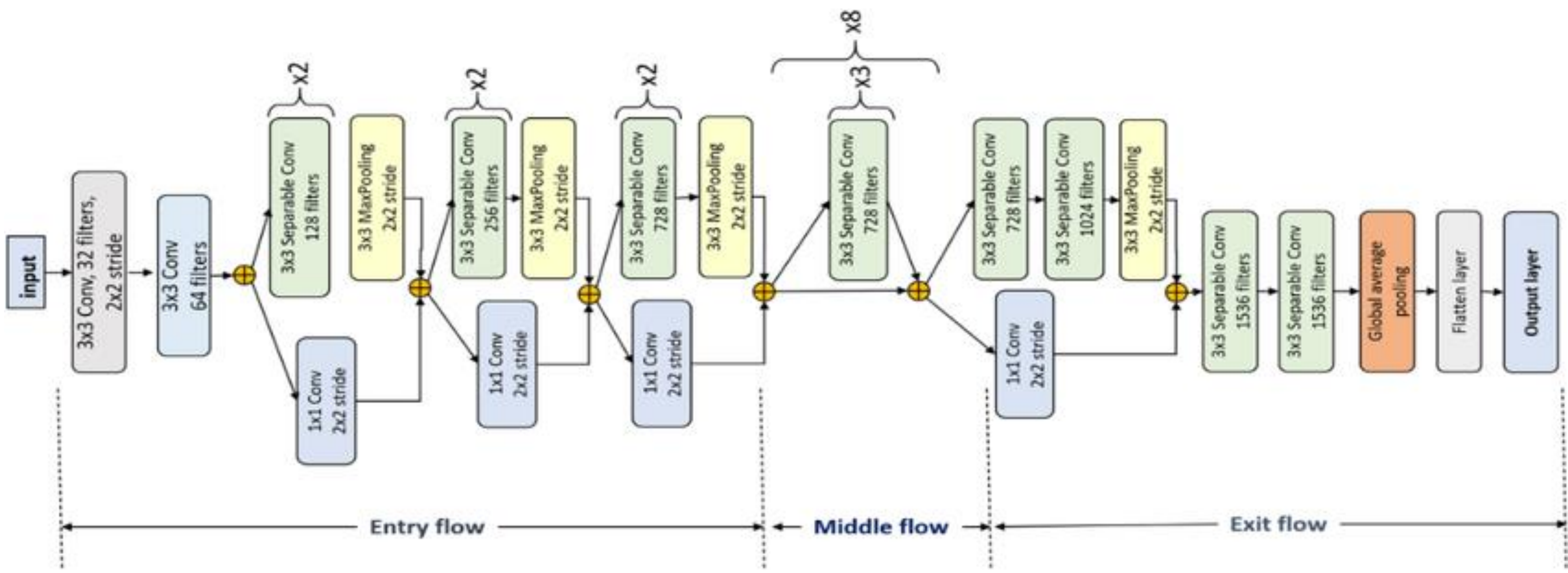


Explanation of the models step by step

Xception Architecture:

1. The Xception architecture is an evolution of the Inception module, which aims to improve the modeling of cross-channel correlations.
2. The key component of Xception is the depthwise separable convolution, which is a factorized convolution operation that splits the standard convolution into two parts: a. Depthwise convolution: Applies a single filter per input channel. b. Pointwise convolution: Applies a 1x1 convolution to combine the output of the depthwise convolution.
3. The Xception model starts with an initial convolutional layer, followed by a series of Xception blocks.
4. Each Xception block consists of several depthwise separable convolution layers, with residual connections between the input and output of the block.
5. The final layers of the Xception model include global average pooling and a fully connected layer for classification.

Diagram:



Diffrence between the models

1. ResNet focuses on residual learning to address the vanishing gradient problem in deep networks.
2. Xception utilizes depthwise separable convolutions to improve the modeling of cross-channel correlations.
3. DenseNet employs a dense connectivity pattern to encourage feature reuse and improve information flow.

Links for the research papers

ResNet (ResNet18) Architecture:

Xception Architecture:

DenseNet (DenseNet121) Architecture:

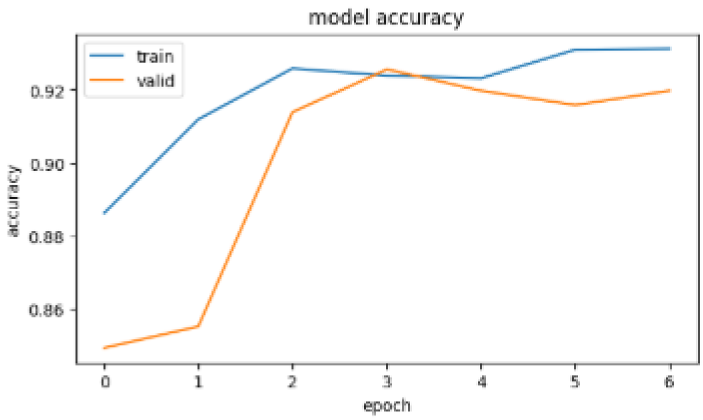
Compare between models

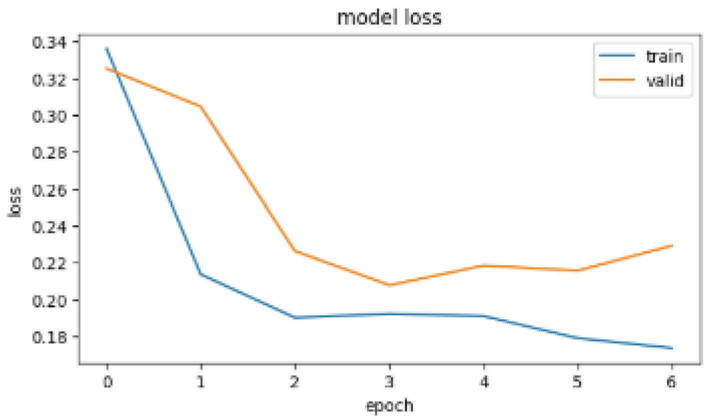
///////	Densenet	Xception	Resnet18
Test Accuracy	0.8964	0.9121	0.8554
Test loss	0.2469	0.1965	0.3367

Graphs of models

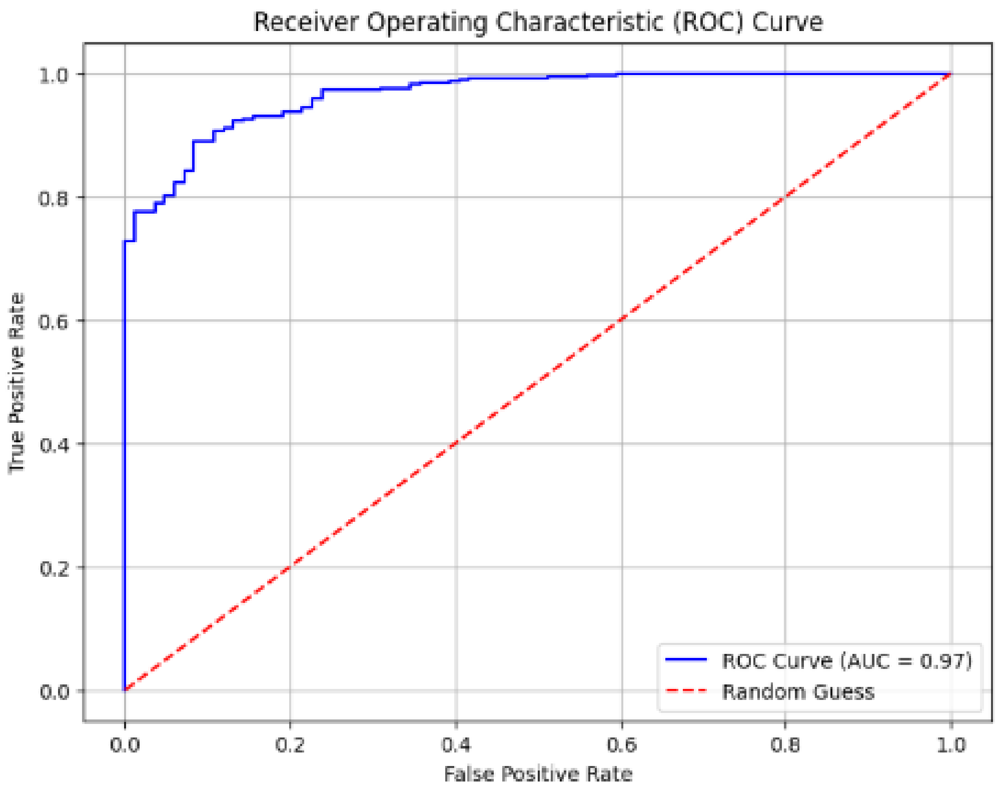
Xception model

Accuracy and loss curve





AUC & ROC



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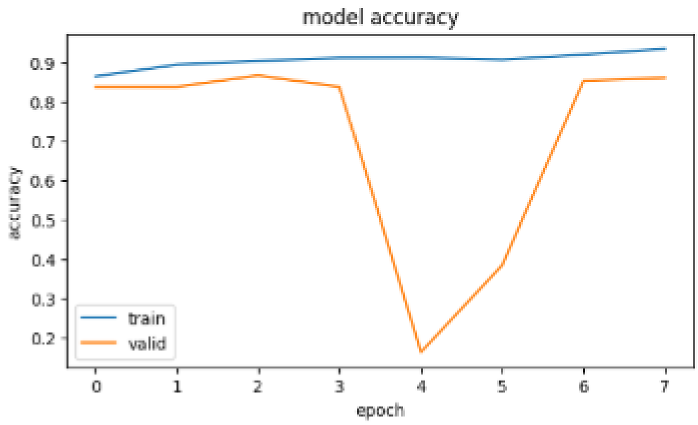
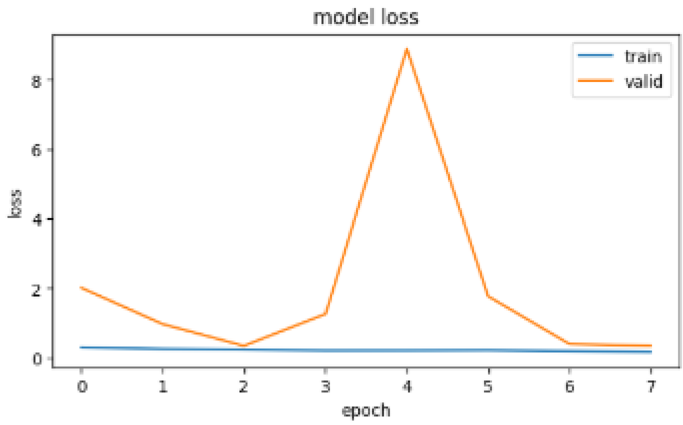
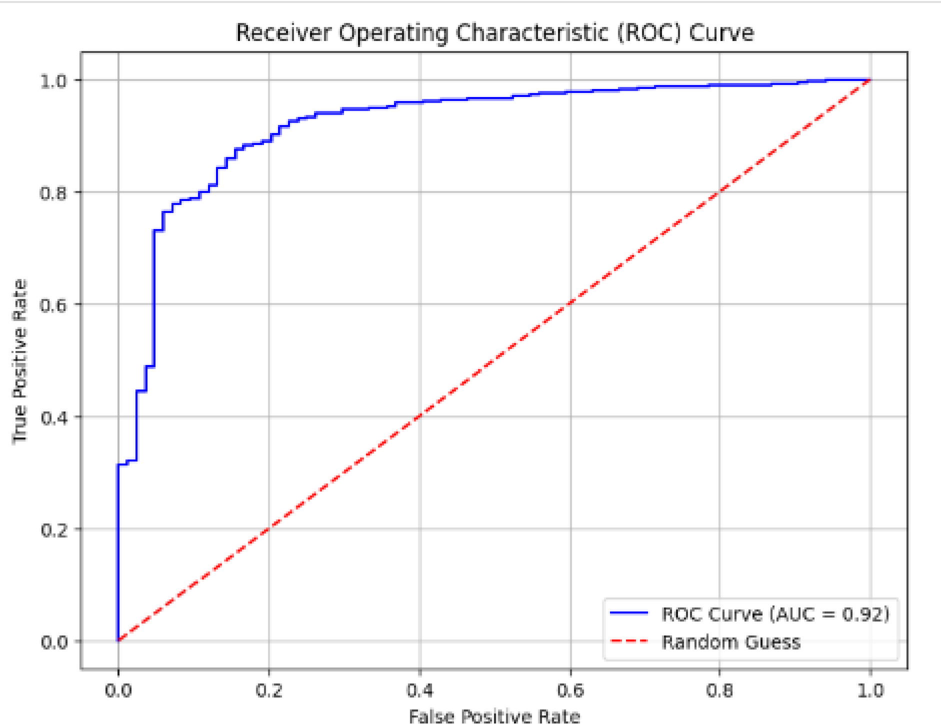
Resnet18 model

Accuracy and loss curve





AUC & ROC



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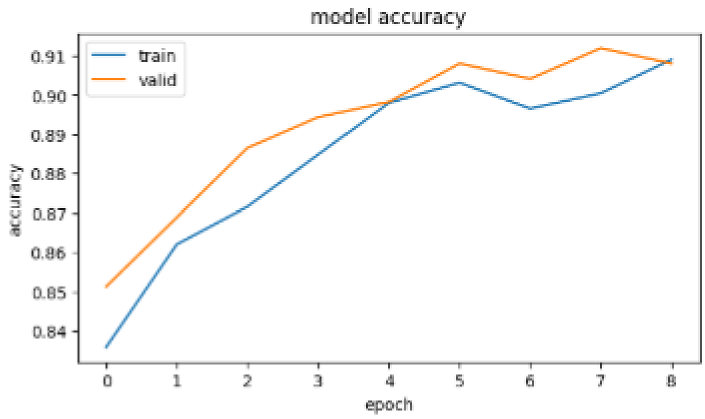
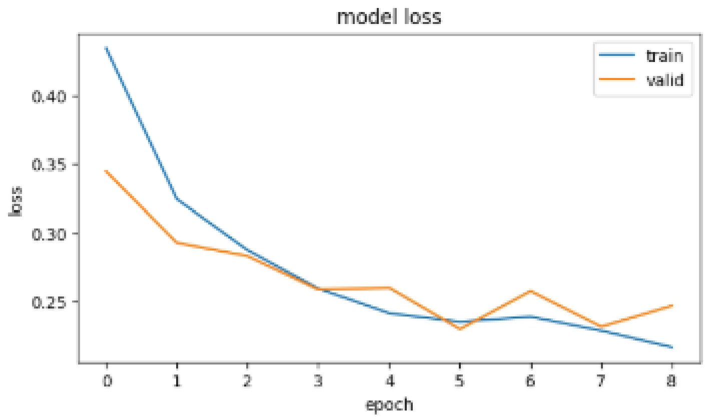
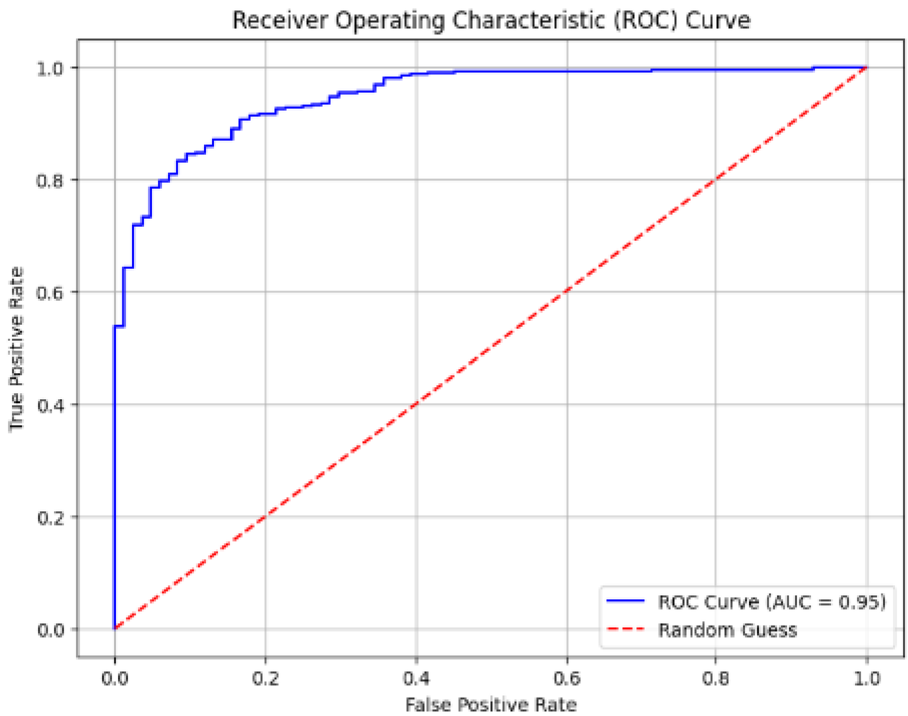
Densenet model

Accuracy and loss curve





AUC & ROC



Pros and Cons for the models

ResNet (ResNet18):

Pros:

ResNet is a widely-used and well-established architecture that is known for its ability to effectively train very deep neural networks.
The ResNet18 model is relatively lightweight and efficient, making it suitable for deployment on resource-constrained devices.

Cons:

The test accuracy of 0.8554 is the lowest among the three models, indicating that it may not be the optimal choice for this specific medical image classification task.
ResNet18 may not be able to capture all the necessary features and nuances in the complex medical images as effectively as the other two models.

Pros and Cons for the models

Xception:

Pros:

Superior Performance
Highest accuracy (0.9121) among all tested models
Lowest loss value (0.1965)
Better feature extraction capabilities
Strong performance on medical imaging tasks
Efficient Architecture
Depthwise separable convolutions reduce computational complexity
Better parameter utilization than traditional CNNs
More memory-efficient than DenseNet
Optimized processing of spatial and channel-wise features
Medical Imaging Specific Benefits
Excellent at capturing fine-grained medical details
Good at handling multiple scales of features
Strong transfer learning capabilities for medical domains
Better adaptation to medical imaging contexts
Implementation Advantages
Good balance between performance and resource usage
Easier to deploy in practical medical settings
Scalable architecture
Effective feature reuse through the network

Pros and Cons for the models

Xception:

Cons:

Model Complexity
More complex than ResNet18
Requires careful hyperparameter tuning
May need more training time to converge
Complex architecture may be harder to modify
Resource Requirements
Higher computational requirements than simpler architectures
May need more GPU memory during training
Could be challenging to deploy on resource-limited devices
Requires good hardware for optimal performance
Training Considerations
More sensitive to initialization
May require careful learning rate scheduling
Could be more difficult to debug when issues arise
Needs proper batch size selection for stable training
Practical Limitations
May be overkill for simpler medical classification tasks
Could be harder to interpret decision-making process
Requires more expertise to fine-tune effectively
More challenging to maintain and update

Pros and Cons for the models

DenseNet (DenseNet121):

Pros:

DenseNet121 achieved the second test accuracy of 0.8964 and the lowest test loss of 0.2469 among the three models.
The dense connectivity pattern in DenseNet helps to improve the flow of information and gradients, which can lead to better feature reuse and more effective learning.

Cons:

DenseNet121 is a larger and more complex model compared to ResNet18, which may require more computational resources and memory for training and deployment.
The performance of DenseNet may be more sensitive to the specific characteristics of the medical image dataset, and it may require more extensive hyperparameter tuning to achieve optimal results.

Advantage of a specific architecture

Xception model

- Superior Performance Metrics:

Highest accuracy of 0.9121 (compared to DenseNet: 0.8964 and ResNet: 0.8554)
Lowest loss of 0.1965 (compared to DenseNet: 0.2469 and ResNet: 0.3367)
This significant improvement in both metrics indicates better overall model reliability

- Architectural Benefits:

Depthwise Separable Convolutions:

    More efficient processing of spatial and channel-wise features separately
    Particularly beneficial for medical images where both spatial details (lesions, structures) and channel relationships are important
    Reduces computational complexity while maintaining high accuracy

- Medical Imaging Specific Advantages:

Better Feature Extraction:

    The extreme version of inception modules helps in capturing both fine-grained and large-scale features
    Crucial for detecting subtle medical conditions in images
    More effective at handling various scales of medical abnormalities

Advantage of a specific architecture

Xception model

- Computational Efficiency:

Despite high accuracy, Xception is computationally efficient due to:

Optimized parameter usage through depthwise separable convolutions

Better parameter utilization compared to traditional CNNs

More efficient than DenseNet while achieving better accuracy

- Transfer Learning Benefits:

Pre-trained Xception shows excellent transfer learning capabilities:

Better adaptation to medical imaging domain

Strong feature extraction capabilities that transfer well to medical contexts

Good generalization ability for medical image classification tasks

- Practical Implementation Advantages:

Balance of Performance and Resources:

Better accuracy-to-computational-cost ratio

More efficient memory usage compared to DenseNet

Easier to deploy in practical medical settings

References

https://paperswithcode.com/task/medical-image-classification

https://towardsdatascience.com/understanding-and-visualizing-resnets-442284831be8

https://www.geeksforgeeks.org/residual-networks-resnet-deep-learning/

https://www.geeksforgeeks.org/resnet18-from-scratch-using-pytorch/

https://viso.ai/deep-learning/xception-model/

https://ieeexplore.ieee.org/document/10604438

https://paperswithcode.com/method/xception