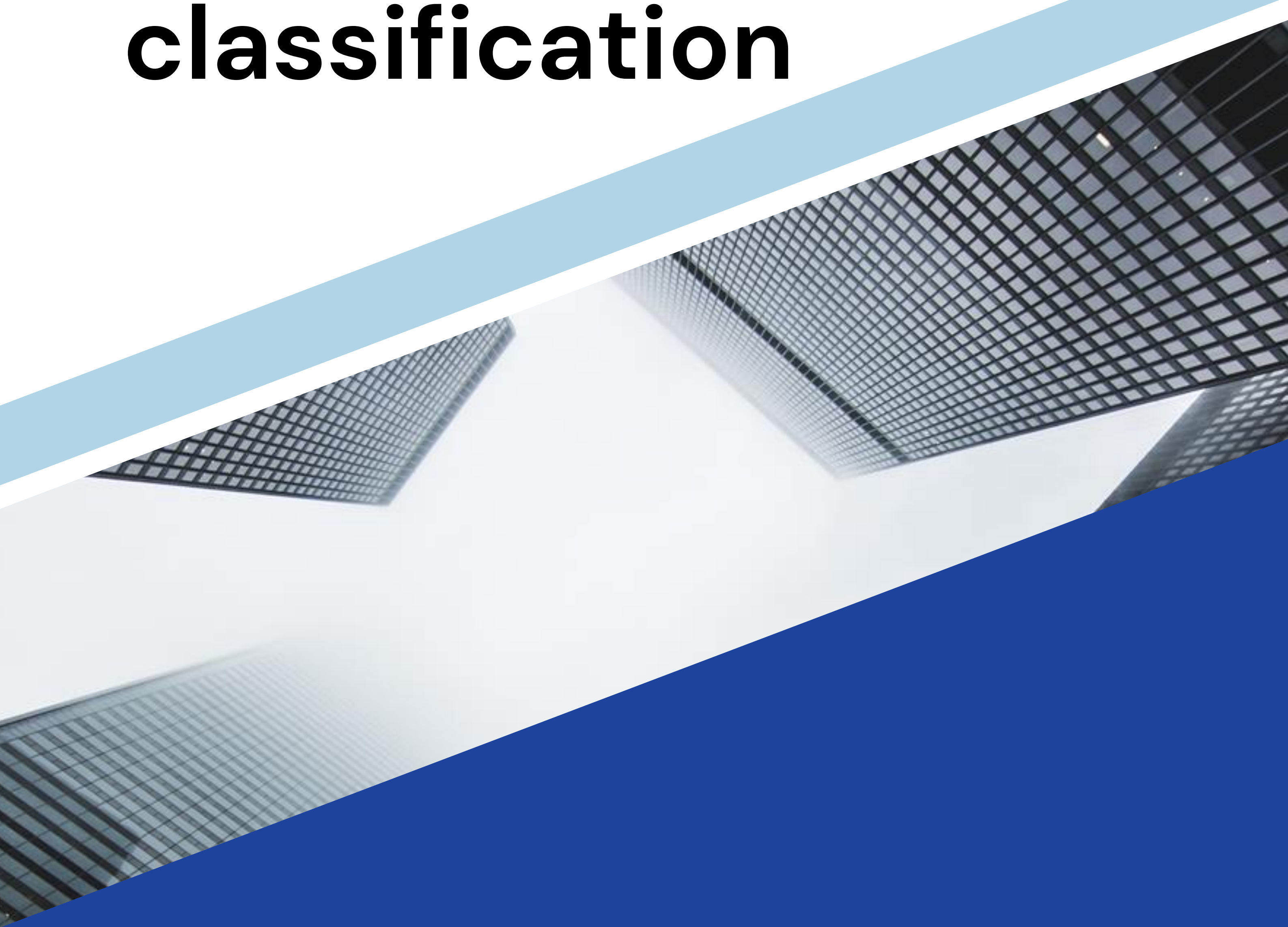
December 2024

Helwan University

Medical image classification



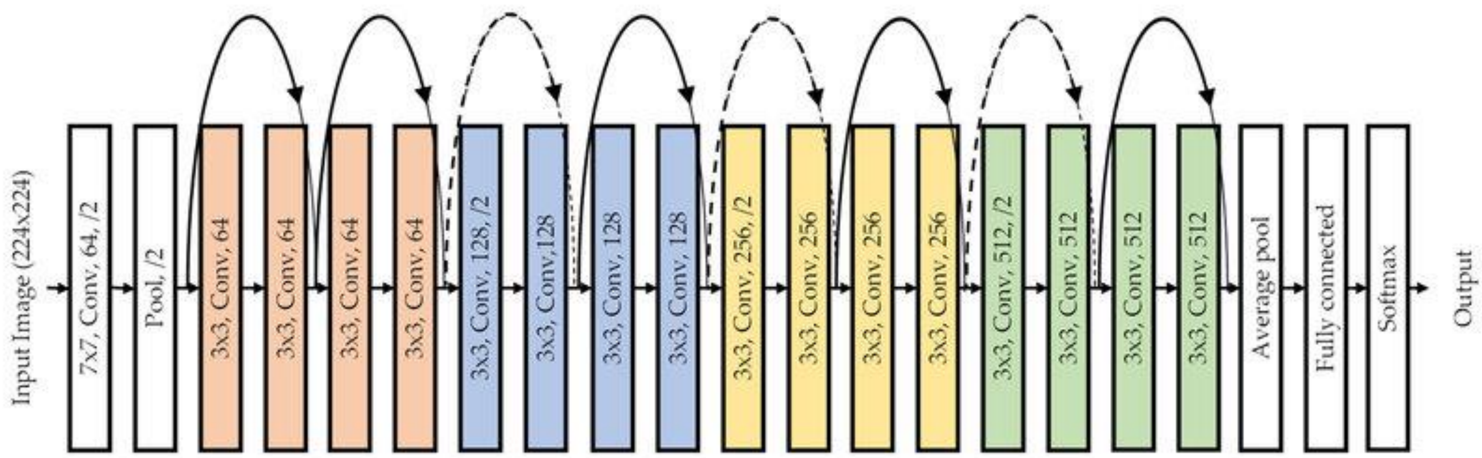
Deep learning project documentation

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:

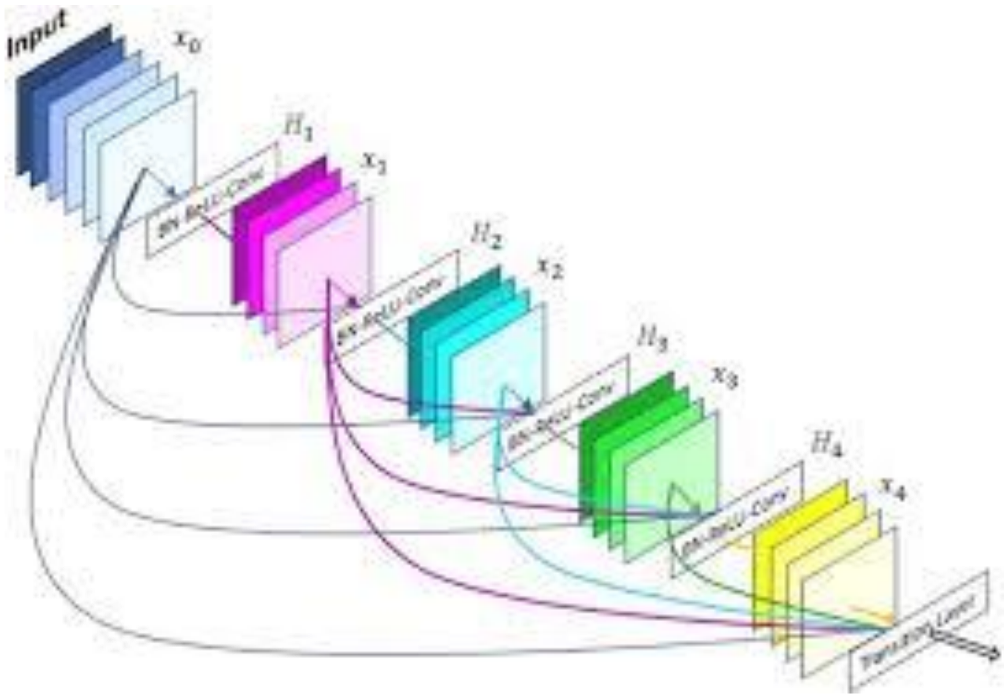


Explanation of the models step by step

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:

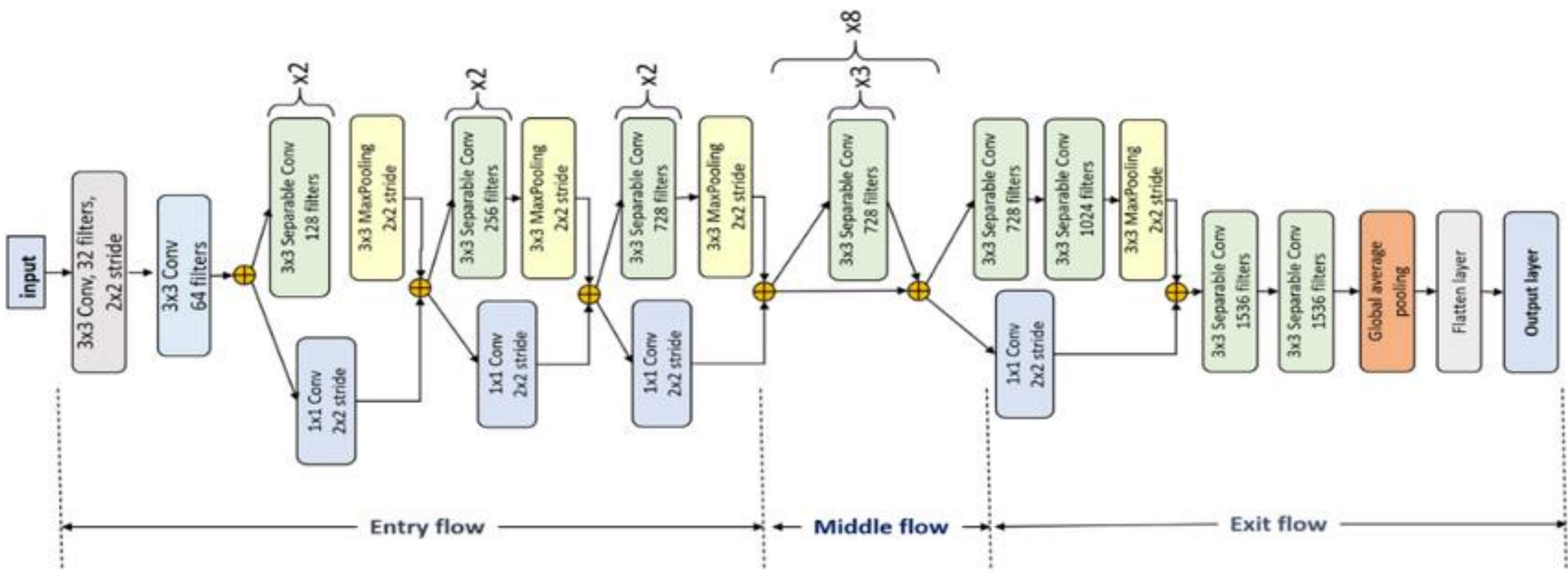


Explanation of the models step by step

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

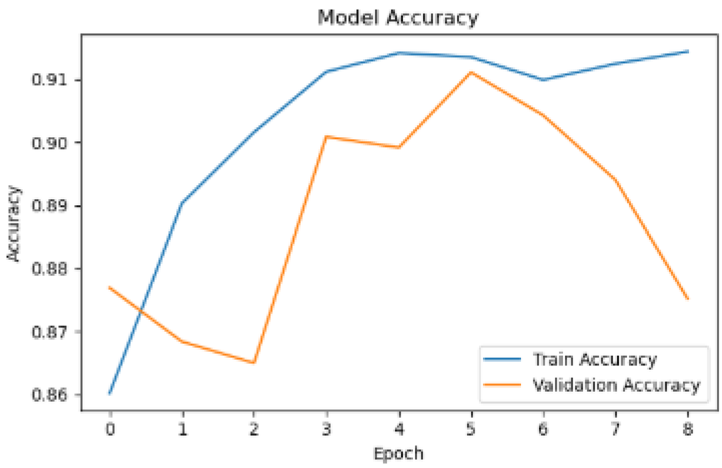
///////	Densenet	Xception	Resnet18
Test Accuracy	0.8964	0.8939	0.8554
Test loss	0.2469	0.2468	0.3367

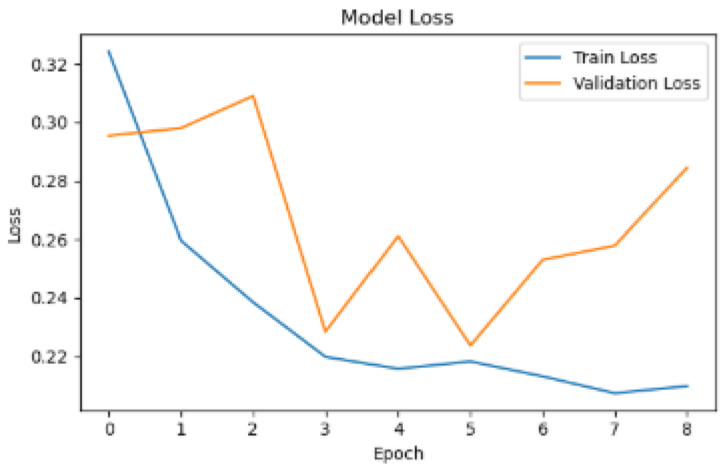
Graphs of models

2024

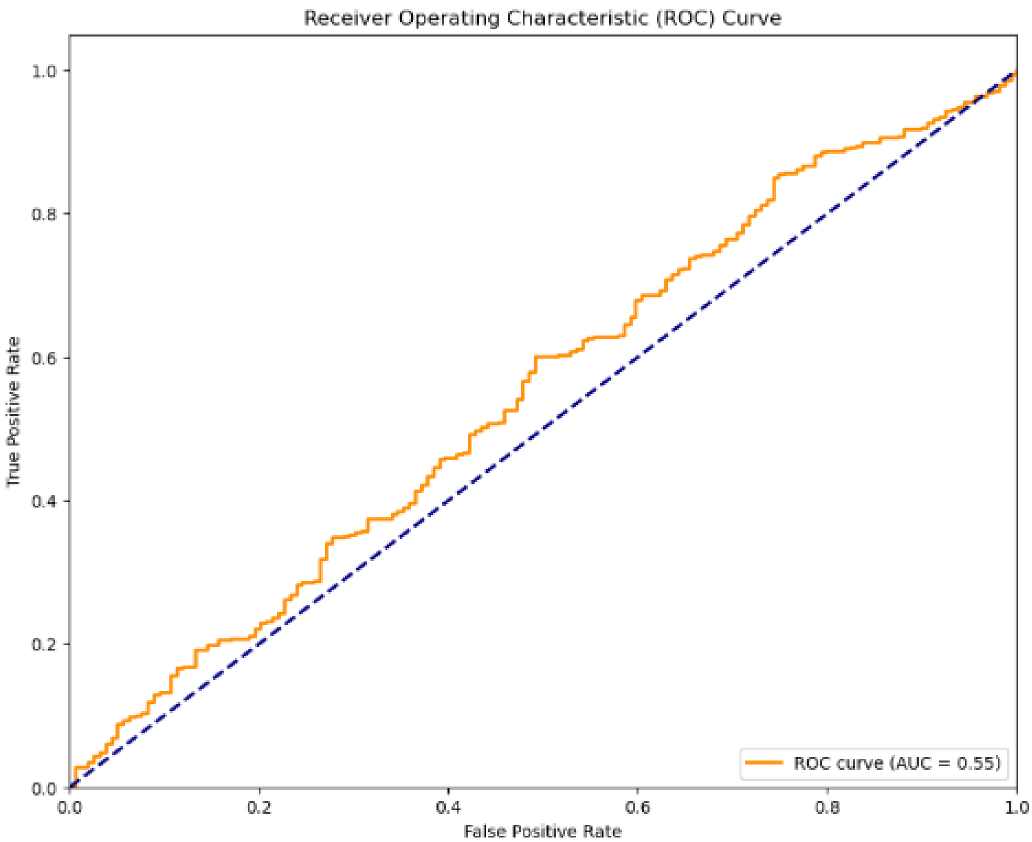
Xception model

Accuracy and loss curve



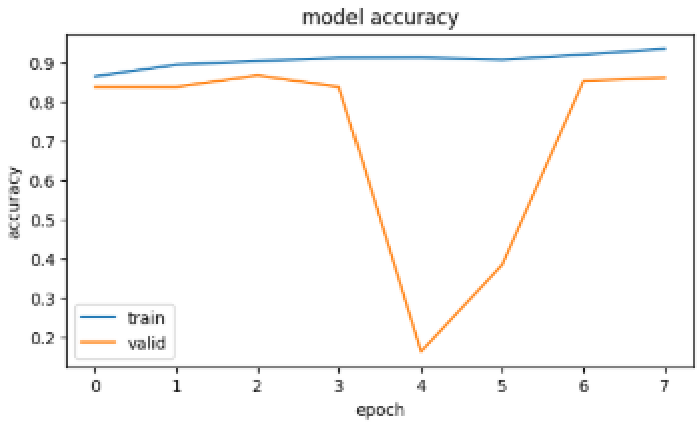


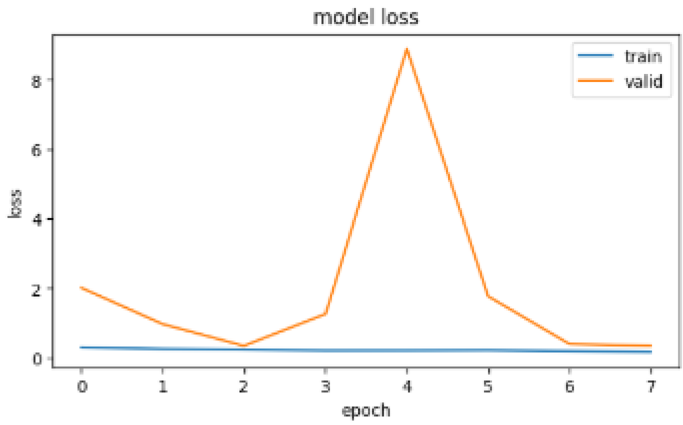
AUC & ROC



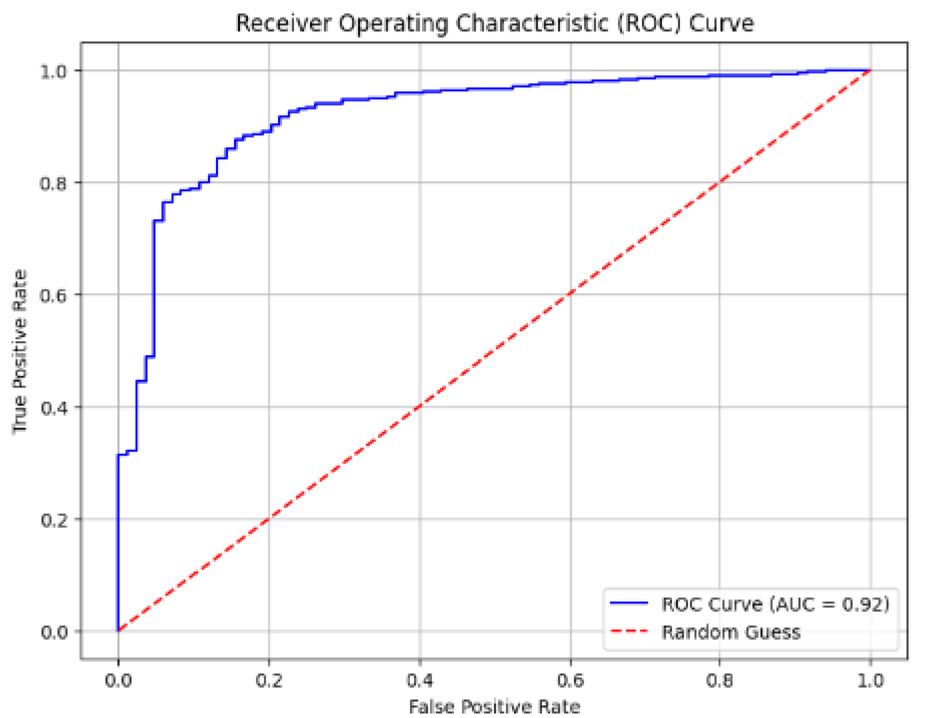
Resnet18 model

Accuracy and loss curve



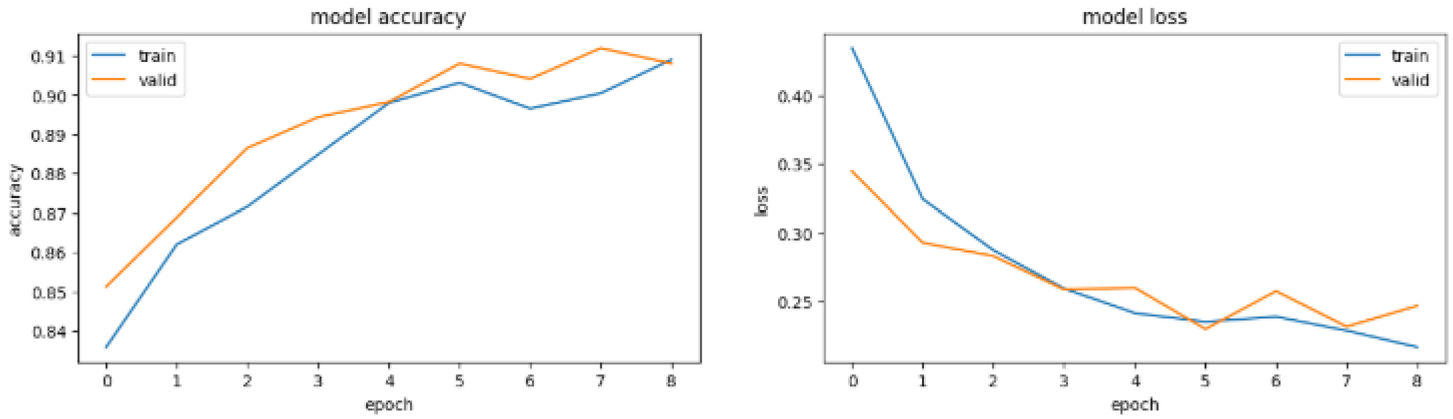


AUC & ROC

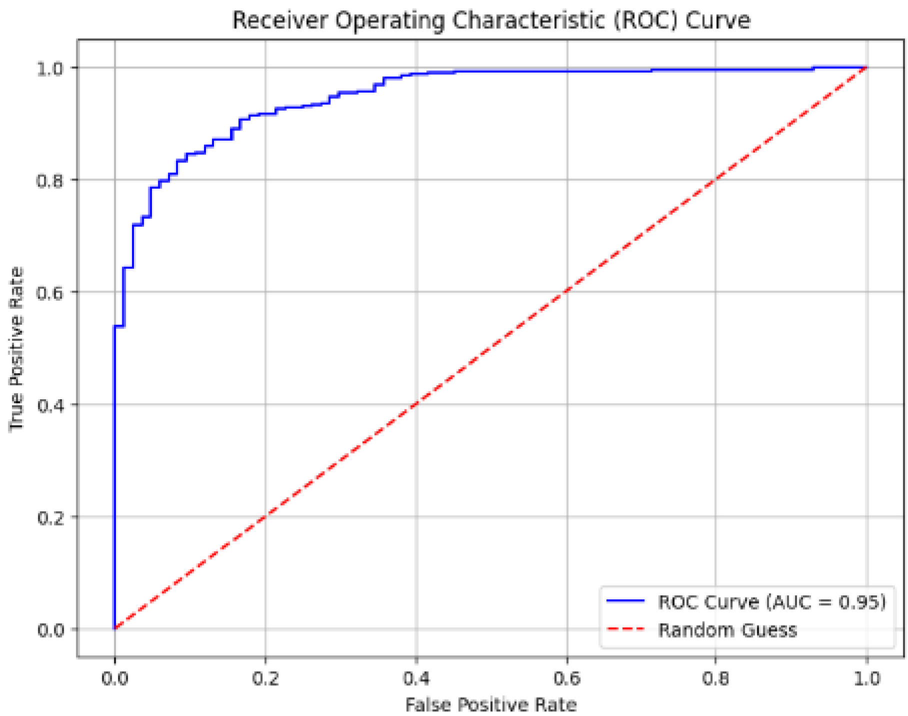


Densenet model

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:

Xception achieved the second-highest test accuracy of 0.8939, indicating its strong performance on the given task.
Xception is known for its efficient use of depthwise separable convolutions, which can lead to reduced model complexity and improved computational efficiency.

Cons:

Xception is a relatively newer architecture compared to ResNet and DenseNet, and its performance may be more sensitive to hyperparameter tuning and dataset characteristics.
The test loss of 0.2468 is slightly higher than DenseNet, suggesting that there may be some room for improvement in the model's ability to minimize the loss function.

Pros and Cons for the models

DenseNet (DenseNet121):

Pros:

DenseNet121 achieved the highest 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

DenseNet (DenseNet121):

1. Superior Performance:
   DenseNet121 achieved the highest test accuracy of 0.8964 and the lowest test loss of 0.2469 among the three models.
   This indicates that DenseNet121 is the most effective at correctly classifying the medical images into the respective disease categories.
2. Improved Feature Reuse:
   The dense connectivity pattern in DenseNet helps to improve the flow of information and gradients through the network.
   This leads to better feature reuse, where the network can leverage features learned in earlier layers more effectively.
   This is particularly beneficial for complex medical image data, where the network needs to capture a wide range of relevant visual features.
3. More Effective Learning:
   The dense connectivity in DenseNet also contributes to more effective learning, as it allows the network to learn representations that are a composite of features from multiple layers.
   This can help the network better understand the intricate patterns and relationships within the medical images, leading to more accurate disease detection.
4. Scalability:
   DenseNet architectures, such as DenseNet121, are designed to be scalable, with the ability to increase depth and complexity as needed.
   This means the DenseNet model can potentially be further optimized and refined for even better performance on this medical image classification task, if required.

References

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