Lab 4 Report

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TRANSFER LEARNING ON CHEST X-RAY IMAGES FOR COVID-19 DIAGNOSIS

INTRODUCTION:

The COVID-19 pandemic has highlighted the need for rapid and accurate diagnostic tools. Chest X-ray imaging has emerged as a valuable tool for identifying COVID-19 pneumonia. This study investigates the effectiveness of transfer learning with various pre-trained convolutional neural network (CNN) architectures for COVID-19 diagnosis from chest X-ray images.

METHODS:

The Chest X-ray dataset from Kaggle was utilized, consisting of four classes (COVID, Lung_Opacity, Normal, Viral Pneumonia). Data preprocessing involved normalization and a stratified hold-out strategy to split the dataset into 70% for training and 30% for validation. Three transfer learning models were developed using the MobileNetV2 architecture with ImageNet pre-trained weights:

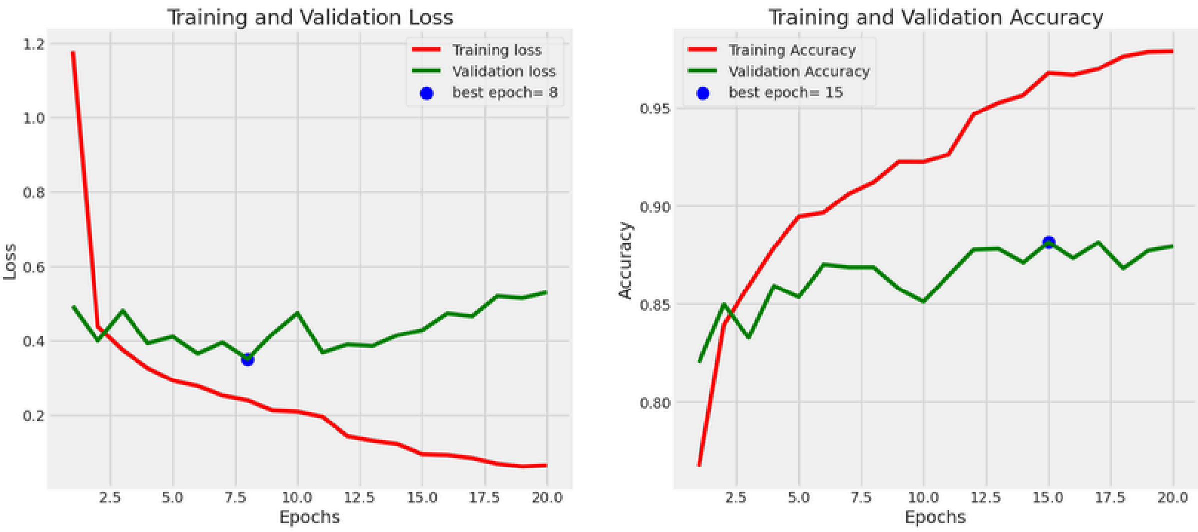
- **Model 1:** Retrained the last 3 fully connected layers.
- **Model 2:** Retrained the last convolutional layer and the 3 fully connected layers.
- **Model 3:** Retrained the last 2 convolutional layers and the 3 fully connected layers.

Each model was trained for 20 epochs with a batch size of 16 and the Adam optimizer with a learning rate of 0.001. Performance metrics, including accuracy, recall, precision, F1-score, and sensitivity, were evaluated on the validation set. Convergence curves and training time were also analyzed.

RESULTS:

All three models achieved high accuracy on the validation set. Model 2, which retrained one convolutional layer along with the fully connected layers, demonstrated the best overall performance with an accuracy of 87.28% and F1-scores exceeding 83% for all classes. Model 1 achieved slightly lower accuracy (86.21%). Model 3, with the highest number of trainable parameters, achieved an accuracy of 83.84%.. All models took close training times of 21 minutes on Two T4 GPUs on Kaggle environment.

MODEL 1



MODEL 2

MODEL 3

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===============Model 1===============
Confusion Matrix, Without Normalization
[[300  17  42   3]
 [  9 481 112   0]
 [ 11  53 952   3]
 [  1   0   7 126]]
                 precision    recall  f1-score   support

           COVID       0.93      0.83      0.88       362
    Lung_Opacity       0.87      0.80      0.83       602
          Normal       0.86      0.93      0.89      1019
 Viral Pneumonia       0.95      0.94      0.95       134

        accuracy                           0.88      2117
       macro avg       0.90      0.88      0.89      2117
    weighted avg       0.88      0.88      0.88      2117

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===============Model 2===============
Confusion Matrix, Without Normalization
[[331  13  15   3]
 [  6 505  91   0]
 [  9  65 944   1]
 [  0   0   5 129]]
                 precision    recall  f1-score   support

           COVID       0.96      0.91      0.94       362
    Lung_Opacity       0.87      0.84      0.85       602
          Normal       0.89      0.93      0.91      1019
 Viral Pneumonia       0.97      0.96      0.97       134

        accuracy                           0.90      2117
       macro avg       0.92      0.91      0.92      2117
    weighted avg       0.90      0.90      0.90      2117

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===============Model 3===============
Confusion Matrix, Without Normalization
[[338   8  14   2]
 [ 14 512  76   0]
 [ 50  98 869   2]
 [  1   1   6 126]]
                 precision    recall  f1-score   support

           COVID       0.84      0.93      0.88       362
    Lung_Opacity       0.83      0.85      0.84       602
          Normal       0.90      0.85      0.88      1019
 Viral Pneumonia       0.97      0.94      0.95       134

        accuracy                           0.87      2117
       macro avg       0.88      0.89      0.89      2117
    weighted avg       0.87      0.87      0.87      2117

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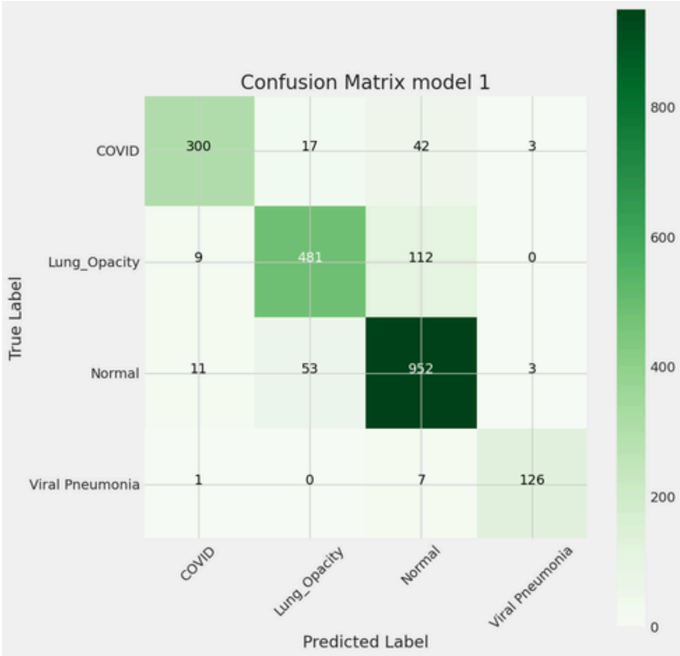
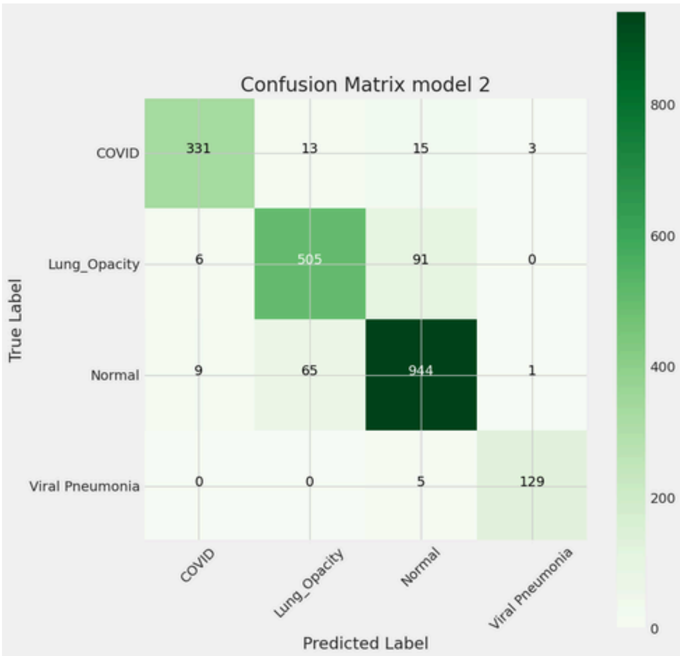
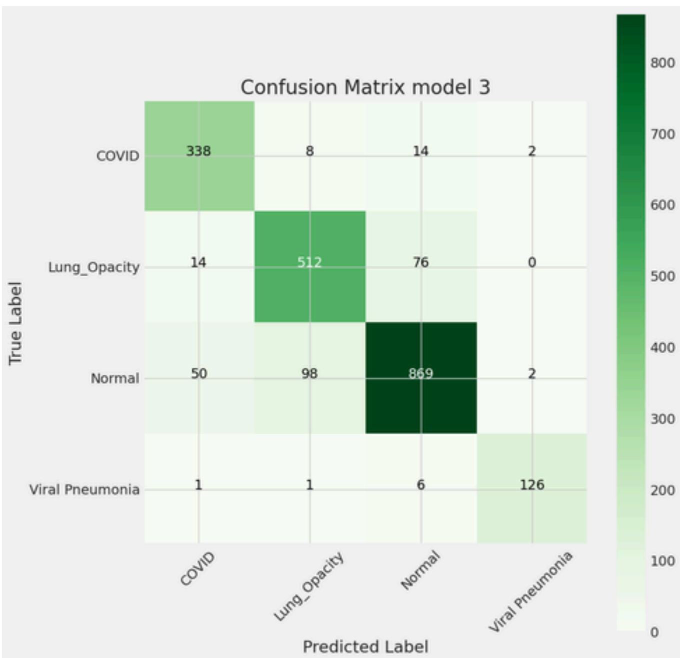

Confusion Matrix model 1
True Label
Predicted Label
COVID
Lung_Opacity
Normal
Viral Pneumonia
300 17 42 3
9 481 112 0
11 53 952 3
1 0 7 126
0
200
400
600
800


Confusion Matrix model 2
True Label
Predicted Label
COVID
Lung_Opacity
Normal
Viral Pneumonia
331 13 15 3
6 505 91 0
9 65 944 1
0 0 5 129
0
200
400
600
800


Confusion Matrix model 3
True Label
Predicted Label
COVID
Lung_Opacity
Normal
Viral Pneumonia
338 8 14 2
14 512 76 0
50 98 869 2
1 1 6 126
0
100
200
300
400
500
600
700
800

DISCUSSION

The study demonstrates the effectiveness of transfer learning with pre-trained CNNs for COVID-19 diagnosis from chest X-ray images. Retraining a limited number of layers, particularly one convolutional layer along with the fully connected layers, achieved a balance between accuracy and training efficiency. The results suggest that transfer learning can provide a valuable tool for supporting healthcare professionals in COVID-19 diagnosis and management.

Further research could explore:

- **Fine-tuning hyperparameters and exploring different optimizers.**
- **Employing data augmentation techniques to improve model generalization (Like the lungs mask).**
- **Investigating the performance on external datasets and in clinical settings.**
- **Comparing with other pre-trained CNN architectures and transfer learning approaches.**

CONCLUSION

Transfer learning with pre-trained CNNs offers a promising approach for accurate and efficient COVID-19 diagnosis from chest X-ray images. The findings contribute to the development of reliable AI-powered tools to support healthcare efforts in combating the pandemic.