Image Classification with Neural Networks

PNEUMONIA DETECTION

GROUP 1 PHASE 4

Project Overview

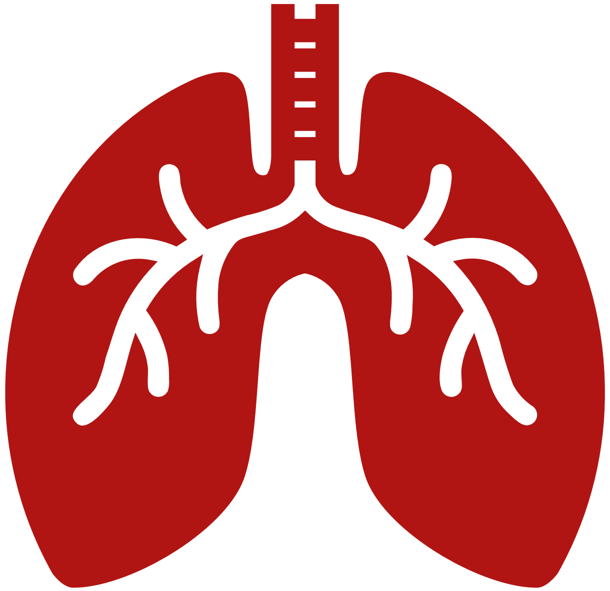
- This project aims to develop a deep neural network model that can accurately classify whether a pediatric patient has pneumonia or not, based on chest X-ray images. This project aims to showcase the practical application of deep learning in the medical domain, specifically in diagnosing pneumonia using medical images. The project is focused on achieving a proof of concept and demonstrating the ability to iterate and improve the model's performance.

What is Pneumonia

Pneumonia is an infection caused by bacteria, viruses, or fungi. It leads to inflammation in the air sacs of one or both lungs. These sacs, called alveoli, fill with fluid or pus, making it difficult to breathe. Chest X-ray, blood tests, and culture of the sputum may help confirm the diagnosis.

Symptoms

- Chest pain when you breathe or cough
- Confusion or changes in mental awareness (in adults aged 65 and older)
- Cough, which may produce phlegm
- Fatigue
- Fever, sweating and shaking chills
- Lower than normal body temperature (in adults older than age 65 and people with weak immune systems)
- Nausea, vomiting or diarrhea* Shortness of breath

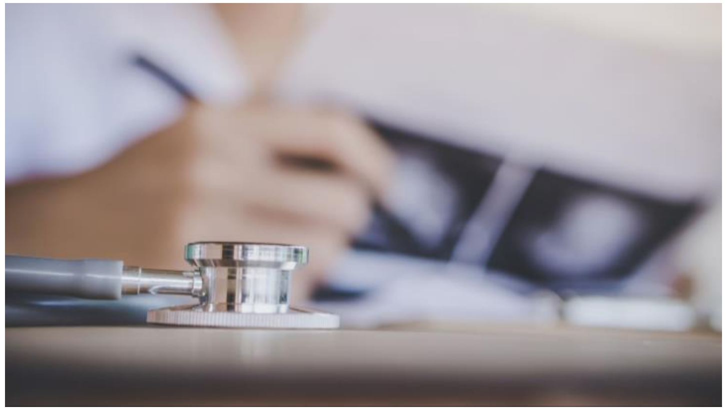


Problem statement

- Pneumonia is a critical health issue in children, requiring quick and accurate diagnosis. Traditional diagnostic methods are limited by time and human errors. By combining deep learning and image classification, diagnosis can be accelerated and made more accurate, improving patient outcomes. Despite being a commonly used imaging technique, chest radiography (CXR) can still result in interpretation errors, with serious consequences for patients and potential legal consequences.

Objective

The primary objective of this project is to create a binary classification model that can distinguish between chest X-ray images of patients with pneumonia and those without pneumonia. Given the complexity of medical image analysis, this task poses a significant challenge, requiring the development of a robust and accurate model.



Data Understanding

The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (Pneumonia/Normal). There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).

The distributions for each set are as below:

Train Data:

Normal Images: 1341

Pneumonia Images: 3882

Validation Data:

Normal Images: 8

Pneumonia Images: 8

Test Data:

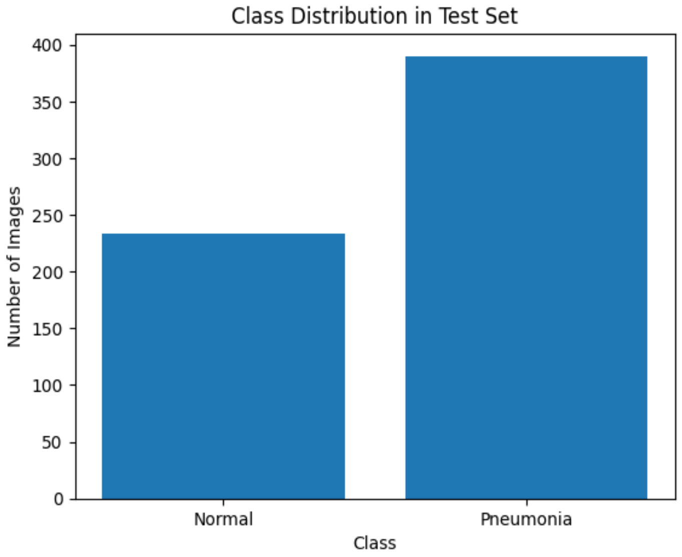
Normal Images: 234

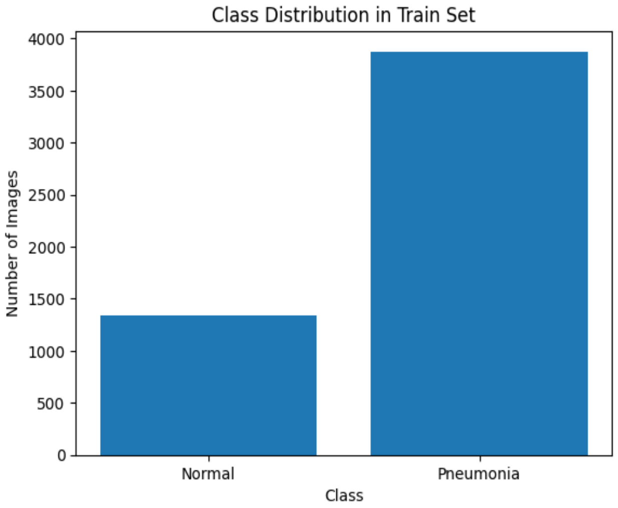
Pneumonia Images: 390

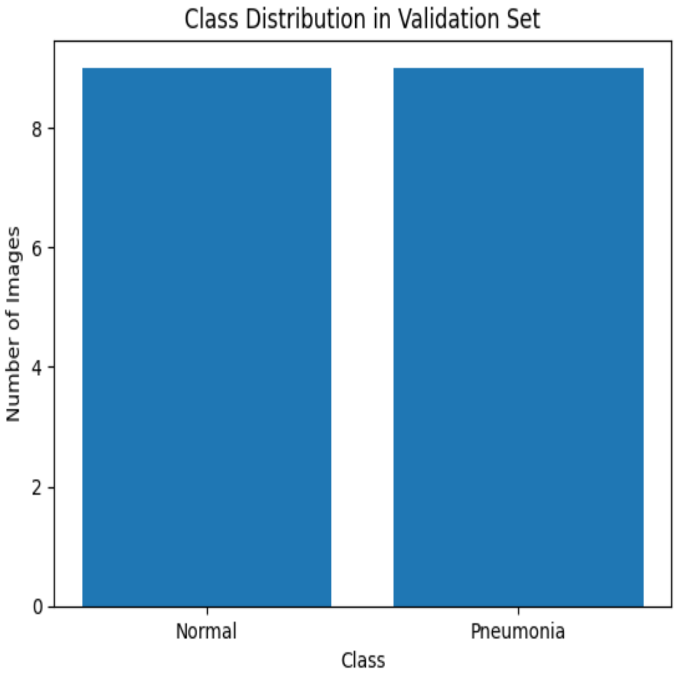
Exploratory Data Analysis (EDA)

1. Class Distribution

- Checking the distribution of images across classes (normal vs. pneumonia). This helps you understand if the classes are imbalanced.







Observations

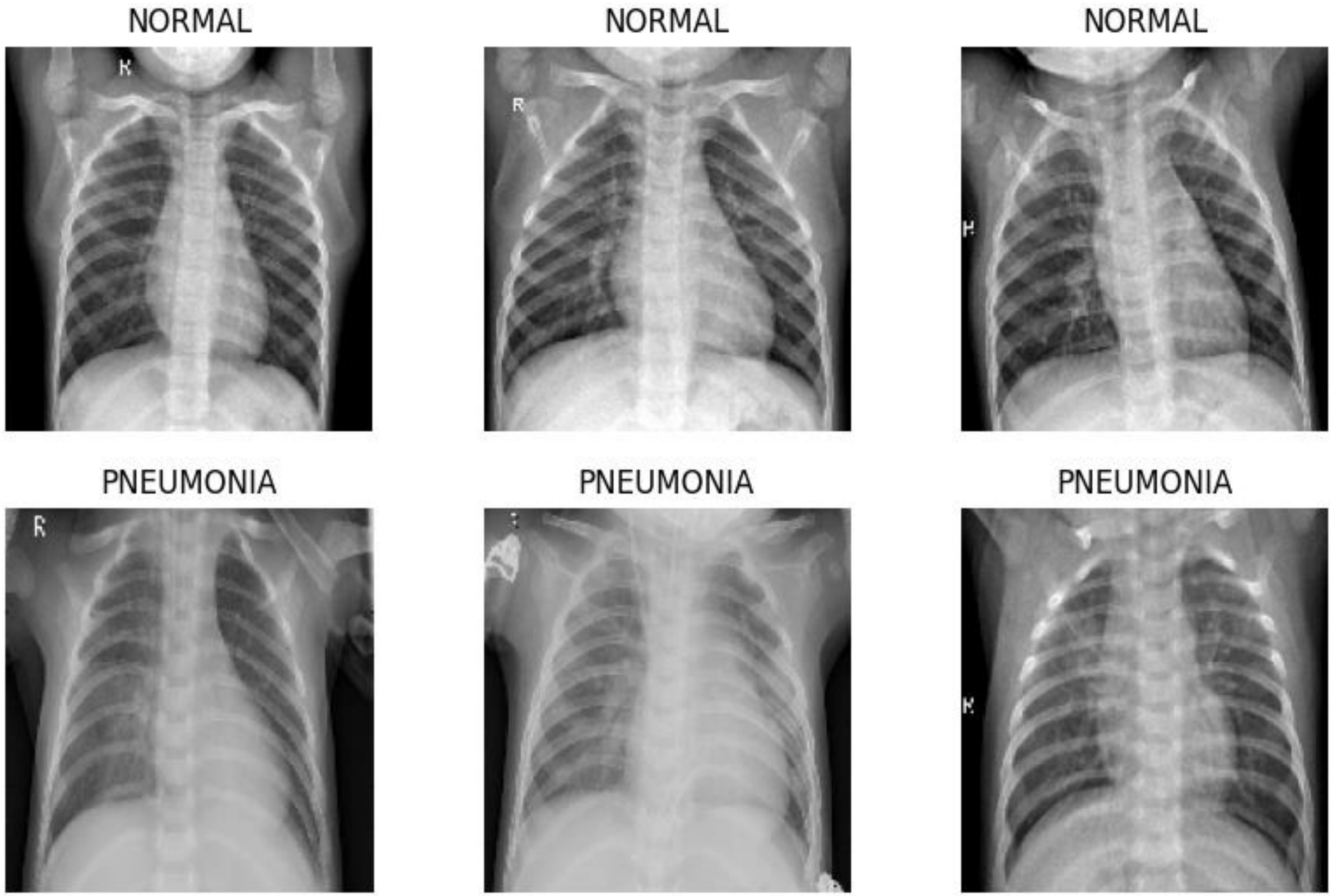
The training set seems to have an imbalanced class distribution, with significantly more pneumonia images than normal images.

The validation set appears to have a very small number of images for both classes. This could potentially affect the model's ability to generalize effectively.

The test set seems to have a more balanced distribution compared to the training set, with a relatively smaller number of pneumonia images compared to normal images.

2. Sample Images

- Visualization of a few sample images from each class to get an idea of the data.



Observations

Normal images show healthy lungs without any signs of infection or abnormalities. Lung structures are well-defined, and the diaphragm appears intact.

Pneumonia images depict lung infections with visible signs such as white patches (consolidation), increased density, hazy lung tissue (infiltrates), and more visible airways (air bronchograms).

Data Preprocessing

The images were loaded in grayscale.

Data Augmentation: Data augmentation techniques were applied to diversify the training data. This includes techniques like resizing, rotation, and flipping.

Resizing/Rescaling: The pixel values of the images were normalized to the range [0, 1] using the rescaling factor (1/225).

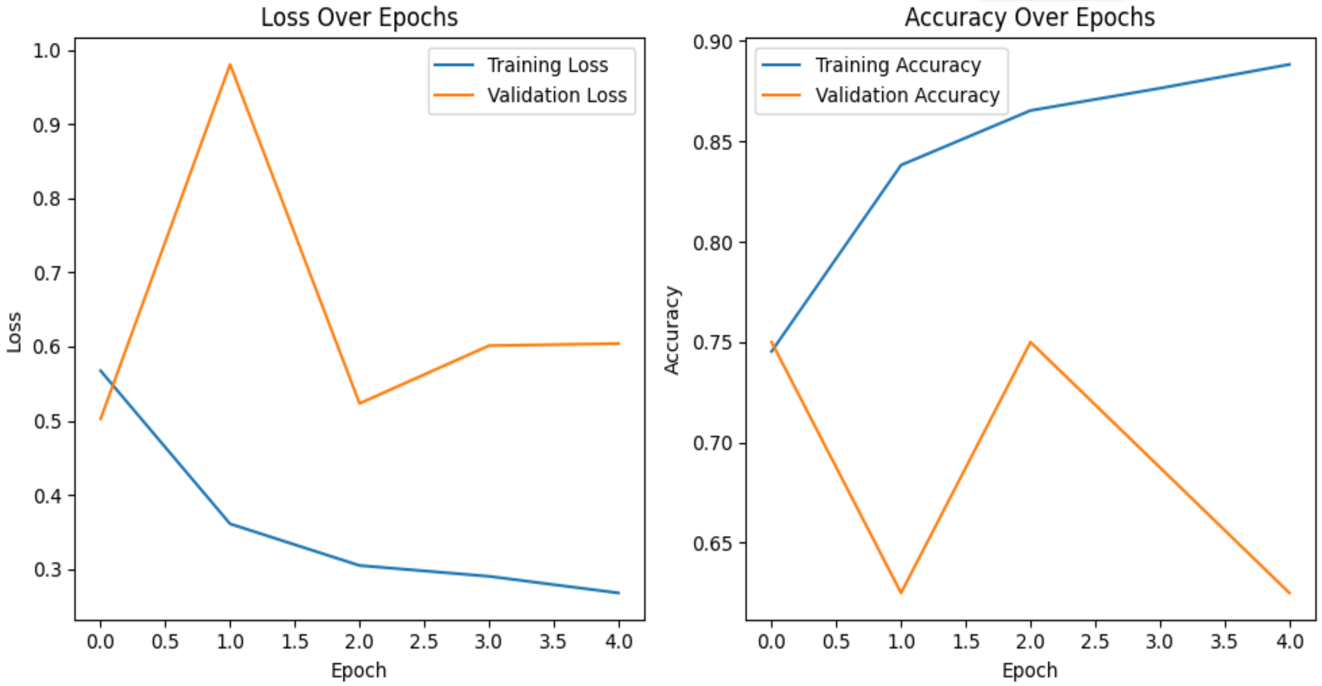
Handling Class Imbalance: Use of class weights to give more importance to the underrepresented class.

The ImageDataGenerator from Keras was used for image data augmentation and preprocessing, which also facilitates feeding data into the model during training.

MODELLING

Model 1 - Baseline Convolutional Neural Network (CNN) model

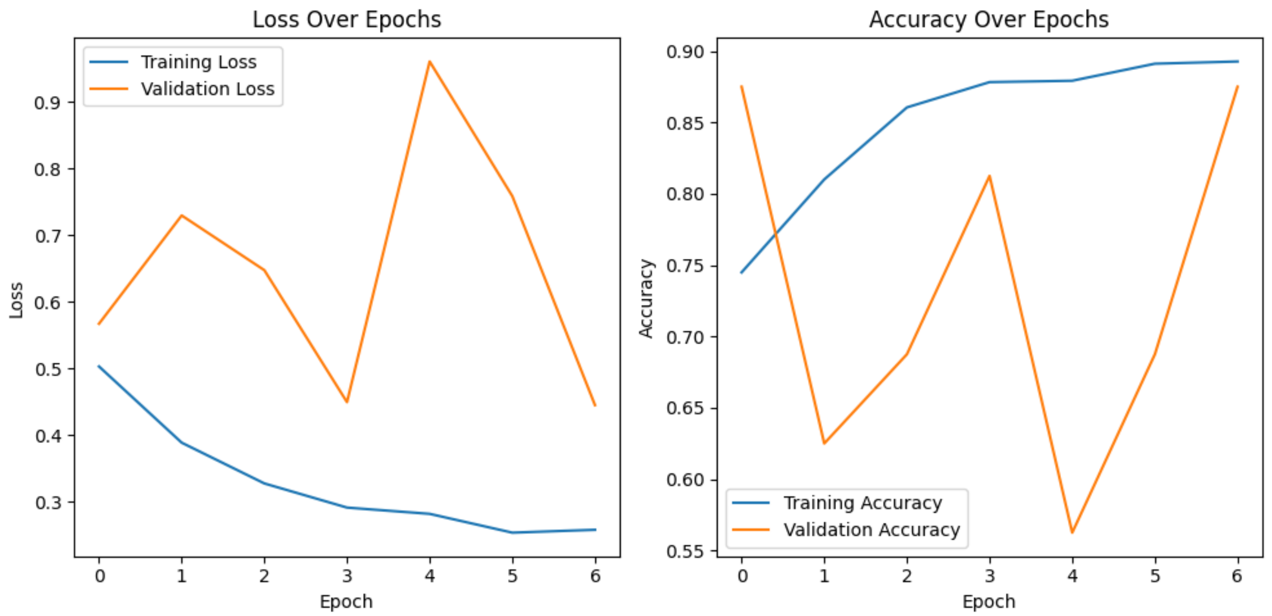
- The test accuracy is about 78% whereas the test loss is about 42%. The test loss is quite high and the accuracy can be improved.




```
39/39 [==============================] - 9s 225ms/step - loss: 0.4213 - accuracy: 0.7772
Original Model - Test Loss: 0.42126357555389404
Original Model - Test Accuracy: 0.7772436141967773
```

Model 2 - CNN with Dropout

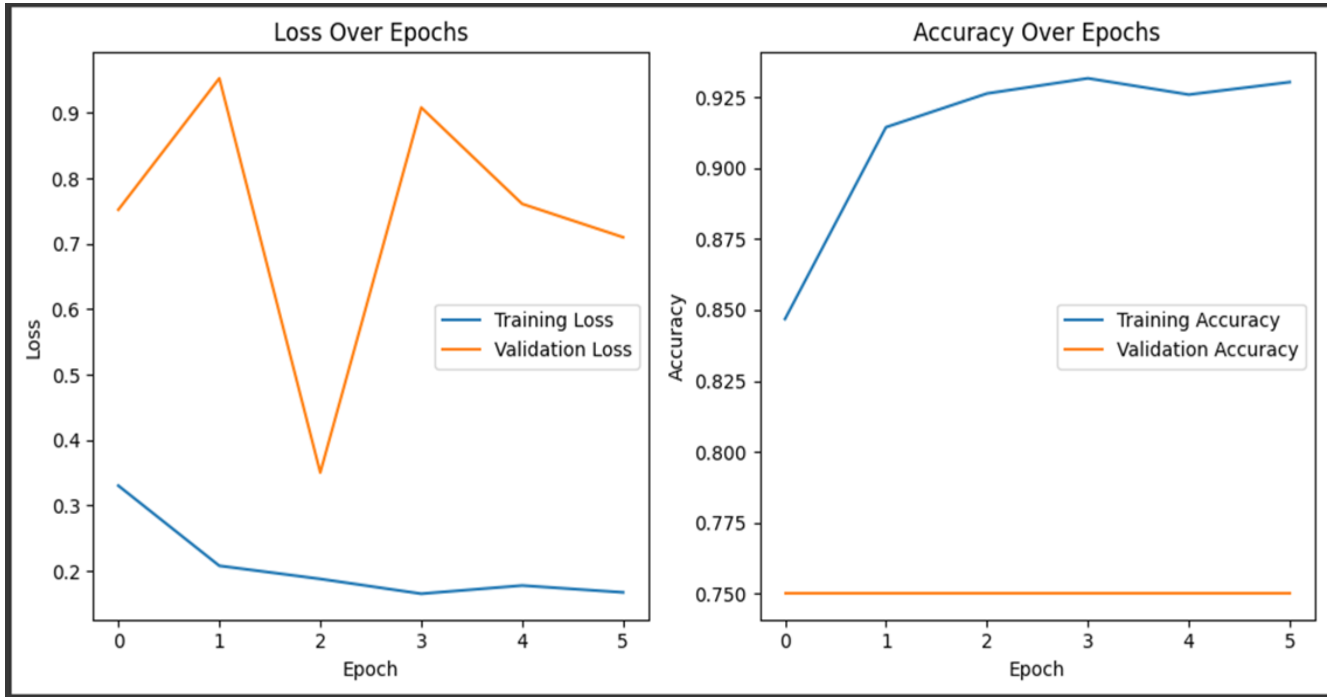
The test accuracy is about 80% whereas the test loss is about 44%. Improvements are observed on both the loss and accuracy of both validation and training sets, this can be attributed to tuning our first model by adding an optimizer and two regularization techniques, early stopping and dropout




```
39/39 [==============================] - 6s 146ms/step - loss: 0.4356 - accuracy: 0.7997
Model_2 - Test Loss: 0.43557998538017273
Model_2 - Test Accuracy: 0.7996794581413269
```

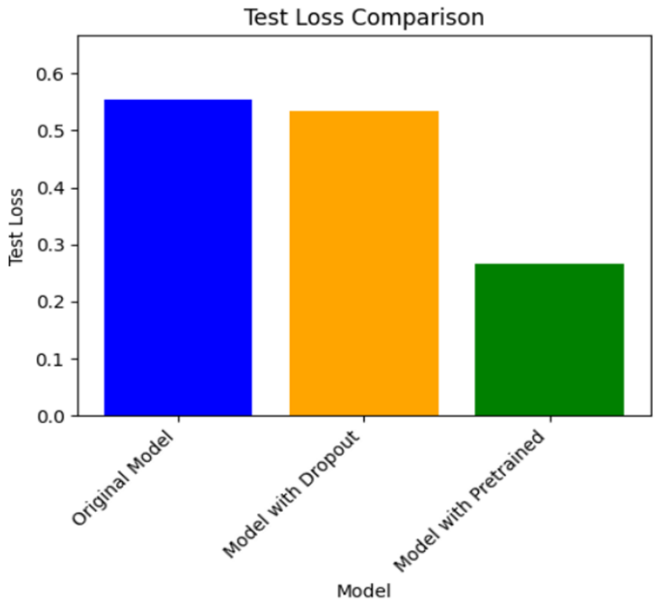
Model 3 - Transfer Learning through the VGG16

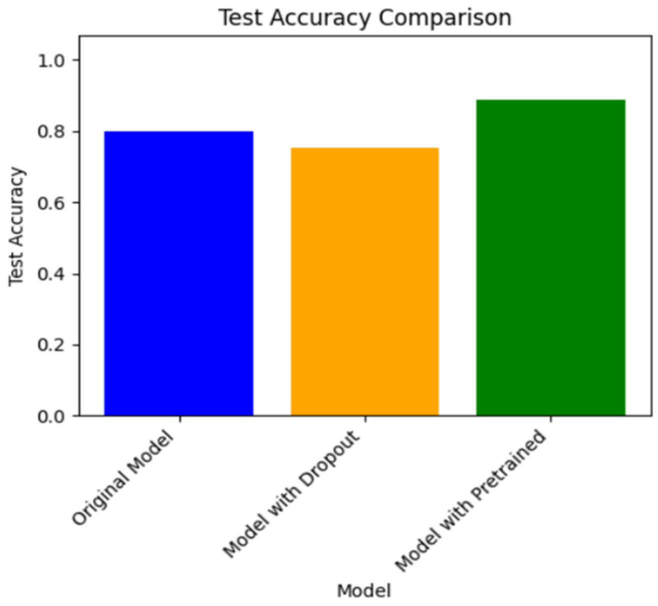
- The test accuracy is about 89% whereas the test loss is about 28%.
- The pretrained model far supersedes our previous models in terms of minimizing the loss, but is slightly edged out in terms of validation accuracy by our second model.




```
39/39 [==============================] - 7s 185ms/step - loss: 0.2801 - accuracy: 0.8798
 Model_3 - Test Loss: 0.28011810779571533
 Model_3 - Test Accuracy: 0.879807710647583
```

Understanding Variations in Test Results





- Original Model - The original model's test accuracy of 0.78 and test loss of 0. 42
- Model with Dropout - The model with dropout exhibited improvements with a test accuracy of 0.80 and test loss of 0.44
- Model with Pretrained(preferred model) - The model with transfer learning from a pre-trained base model yielded impressive results with a test accuracy of 0.87 and a test loss of 0.28

Conclusions

The models exhibit variations in test results due to their architectures and training techniques:

- **Original Model**: The initial model's moderate accuracy and loss might be due to its simpler architecture, limiting its ability to capture complex patterns. Overfitting, caused by insufficient regularization, could also have played a role.

- **Model with Dropout**: Introducing dropout improved accuracy and reduced loss. This technique added randomness during training to prevent overfitting, leading to better generalization.

- **Model with Pretrained Base**: Leveraging a pre-trained VGG16 base resulted in impressive accuracy and lower loss. It harnessed existing image features for improved discrimination and benefited from extensive prior learning for strong generalization.

In conclusion, choosing an appropriate model complexity, implementing effective regularization, and utilizing pre-trained features can significantly impact model performance and accuracy.

Recommendations

The developed deep learning model will offer several advantages to the healthcare industry:

Efficient Diagnosis: The model can rapidly process and analyze chest X-ray images to provide a binary diagnosis (pneumonia or non-pneumonia). This speed can lead to quicker decisions and treatment initiation.

Accuracy Improvement: The model has the ability to learn complex patterns and features in images that might not be easily discernible by human experts. This could lead to more accurate diagnoses.

Reduction of Human Error: By automating the diagnosis process, the model can help reduce the likelihood of human errors that occur in the manual interpretation of medical images.

Scalability: The model can be used to analyze a large number of images quickly and consistently, making it suitable for high-throughput scenarios.

Thank You