Milestone 1 - Detection of Pneumonia

Team

Name	Macid	Role	Role Breakdown
Akash Santhanakrishnan	santhana	Model	- Implementing Residual Neural Network (Resnet) - Ensuring input, output and hidden layers mesh together - Compiling and training model
Rochan Muralitharan	muralr3	Evaluation	- Identifying and implementing evaluation strategy - Evaluating model on test set and validation set - Reporting and interpreting performance of the model
Dhruv Thakor	thakord	Data	- Identifying data sampling technique - Gathering data and preprocessing data - Applying required data augmentation

Context

Pneumonia is a possibly life-threatening respiratory infection for vulnerable populations like children, the elderly and people with weak immune systems. Pneumonia is the world's leading cause of death among children under the age of five accounting for 16% of all deaths of children under five, which was approximately 2,400 child deaths a day in 2015. The early and accurate diagnosis of this infection is vital for effective treatment, however we currently rely on traditional methods of radiologists interpreting chest X-rays. This makes detection of pneumonia challenging as this process can be time-consuming and relies on the expertise of the radiologist making the diagnosis. We are aiming to tackle this issue by creating quick and accurate methods of detecting pneumonia (bacterial and viral) through the inspection of chest X-rays. Machine learning can aid in the detection of this disease by utilizing Residual Neural Networks (ResNet), to automate and improve the detection of pneumonia from medical imaging data. By training a predictive model using labeled chest X-ray images, the model can help doctors by providing reliable, fast and scalable support for diagnosis, especially in settings where resources like expert radiologists are limited. An accurate model can aid in a quick treatment and possibly save countless lives who contract pneumonia but do not receive a quick diagnosis. The key to lowering this large number is through a quick diagnosis, and that is what we are trying to accomplish with our machine learning model. Pneumonia is a disease that affects many worldwide and by creating this model, our team can help in lowering the amount of serious cases that lead to countless child deaths around the world.

Dataset

The dataset we will be using is from Kaggle : Chest X-Ray Images (Pneumonia). The number of features will be based on the number of pixels in the grayscale images. Although the size for each image is constant, it is unclear what the actual size is, but the number of features will be the image width multiplied by the image height. In total, there are 5856 samples. The model will attempt to use the max number of samples that is computationally possible on our machines. The images will be resized to 224 by 224 pixels so that all images will be a standard size and will fit through the layers of the ResNet.

Proposed Solution

The proposed solution is predictive, as it aims to use labeled chest X-ray images to predict whether a patient has pneumonia and whether it is viral or bacterial. The pixel values of the images will serve as features, and the number of features depends on the image size, which may change if we resize the images. The target variables are {0: Normal, 1: Pneumonia (Viral), 2: Pneumonia (Bacterial)}. The machine learning technique will be Residual Neural Networks (ResNets), which are effective for image analysis and automatically learn features such as edges, textures, and shapes. Although the dataset already includes a training, test, and validation set, we will create randomized sets for unbiased evaluation. Since the dataset categorizes pneumonia types in file names rather than in separate folders, we will need to organize the data into distinguishable sets. We will resize the images to a standard size (224x224) and scale pixel values to [0, 1]. If there is class imbalance, we may employ oversampling to balance the classes. Performance metrics will include precision, recall, and F1-score, as accuracy may be misleading with imbalanced classes. After training, we will evaluate the model on a held-out test set. This task has been extensively explored in medical image analysis, and transfer learning from pre-trained models like ResNet or DenseNet is a common solution. Instead of using transfer learning, we will build a small ResNet model from scratch. Pytorch will also be used for pre-processing/resizing the images and Mathplotlib will be used for visualization. Evaluation metrics will be calculated using scikit-learn.

References

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https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

Milestone 2 - Detection of Pneumonia

Preprocessing

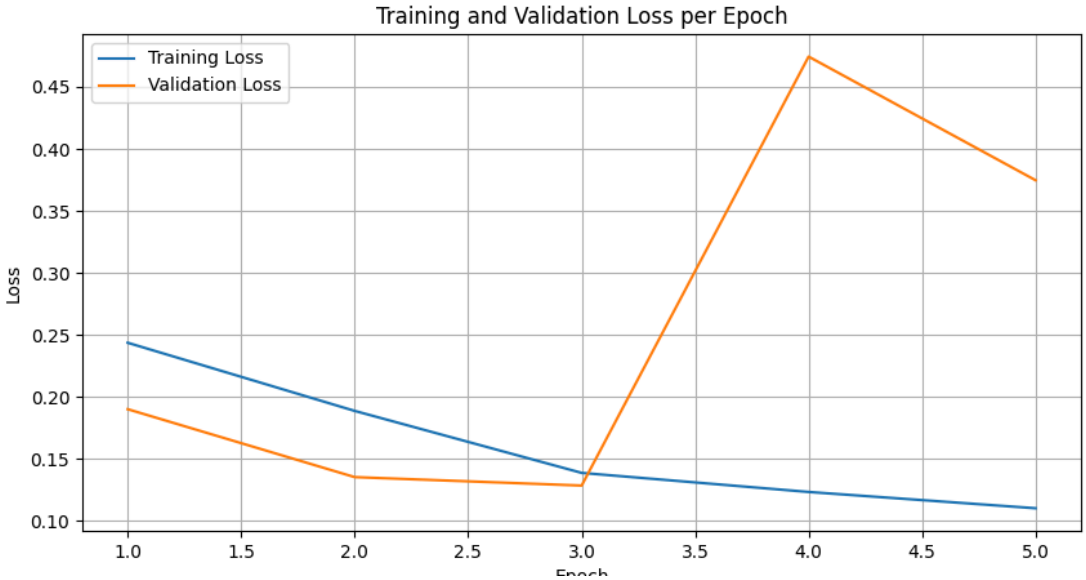
To preprocess the data, the images were loaded into the model and then converted into tensors. The tensors were then normalized using the ImageNet mean ([0.485, 0.456, 0.406]) and standard deviation ([0.229, 0.224, 0.225]). Finally, tensors were wrapped as in DataLoaders, one each for the train, test and validation set. The train set consists of 5000 images, the validation set has 232 images and the test set has 624 images. The train and validation set were split from the train images in the dataset. No other preprocessing of the data was performed as there once the images were converted to tensors and normalized, our ResNets could process the data. No specific feature selection strategies were implemented, our CNN model learns the features automatically from the pixel data. No explicit feature correlation removal was done, as the CNN will be able to distinguish the pixel-level features. No explicit data augmentation was applied, only resizing and normalization was performed. One-hot encoding was not hard coded into our model, however the data loader and PyTorch cross-entropy loss are able to handle the integer labelling internally. No pretrained models were used to train our model as a custom ResNet model is used and no pretrained weights are used.

Model Specifications

The model we chose for our project is a Supervised Deep Neural Network which was based on the ResNet architectures. The model configuration consists of the residual block and the ResNet50 architecture. The residual block consists of 3 convolutional layers with skip connections to learn residual mappings. The block expands channels by a factor of 4 by using the final convolutional layer in each block. A batch normalization and ReLU activation function are used after each convolutional layer. The ResNet50 architecture is composed of an initial convolutional layer followed by 4 stages of residual layers with varying numbers of blocks. There are 3, 4, 6 and 3 blocks in each of the 4 layers respectively, creating a total of 50 layers. The initial convolutional layer has a kernel size of 7x7 with a stride of 2. The residual blocks have kernel sizes of 1x1, 3x3, and 1x1 in its 3 convolutional layers respectively. The model implements down-sampling using a stride of 2 for specific layers. An adaptive average pooling function reduces the output of the network to a single value per feature map before the final fully connected layer. The output layer is a fully connected layer with 2 neurons to perform binary classification(Normal vs. Pneumonia). The model's hyperparameters include a learning rate of 0.001, a batch size of 32, and 5 epochs. The Adam optimizer and CrossEntropyLoss function were used for the network as well. We also implemented a progress tracking strategy, which tracked the training loss by computing the cross-entropy loss at every batch interval, and the training and validation loss is recorded after each epoch.

Evaluation

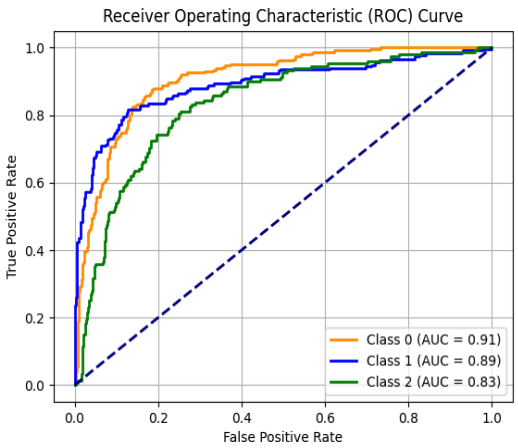
During training, validation loss(CrossEntropyLoss) and accuracy are computed after each epoch to evaluate the training progress. During testing, the average test loss is computed across all batches and the accuracy of the model is also computed.

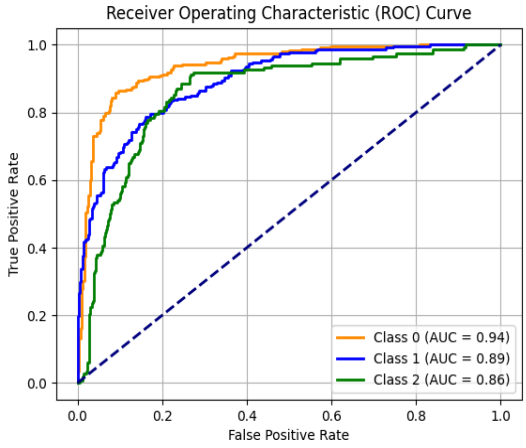


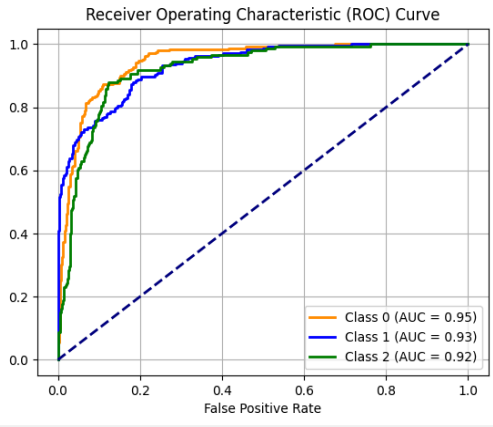
Test Loss: 0.353 Test Accuracy: 84.94% Test F1-Score: 0.85 Test Recall: 0.85

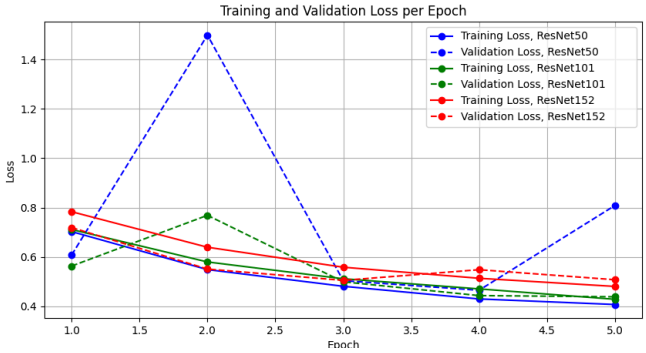
Milestone 3 Evaluation

The first experiment determines the optimal learning rate for our model. We have the following Receiver Operating Characteristic (ROC) curves respectively for 1e-3, 1e-4, and 1e-5. The accuracy for each one was 63.46%, 72.76%, and 57.69%. These metrics tell us that 1e-4 is the most optimal as it is not so large that overshoots and leads to poor generalization, but it's also not so large that it significantly overfits the data.



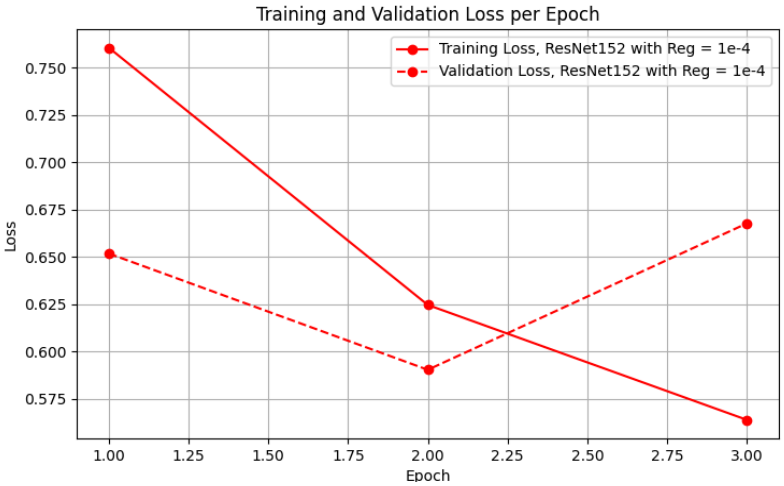


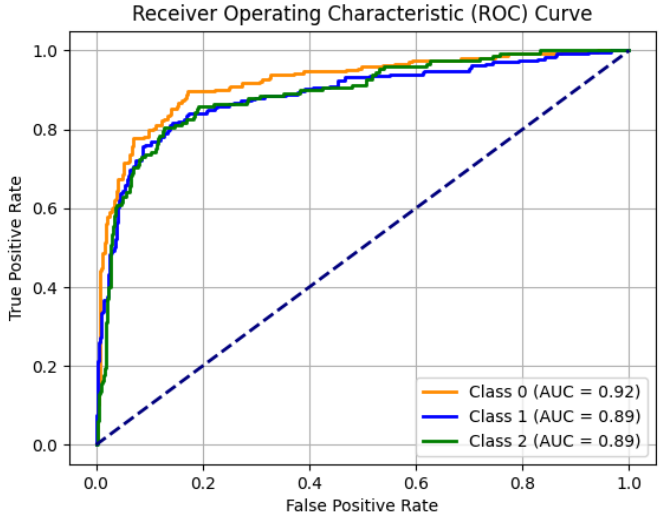




The 2nd experiment involves trying different ResNet architectures, namely, ResNet50, Resnet101, and ResNet152 with respective accuracies: 70.29%, 65.06%, 76.85%. What this tells us is on average the deeper models perform better but they are more prone to overfitting and obviously take a lot more time to train.

The final experiment determines the optimal regularization parameter with early stopping for ResNet152 among 1e-2, 1e-3, and 1e-4 with the following accuracies 72.1%, 74.4%, 78.21%. 1e-4 is the most optimal as it imposes a weaker penalty which allows the model to fit the training data more closely but still encourages smaller weights while the other values stop the training too early. Also, the general training error did increase, but the ROC curve is the most balanced from all the configurations.





Milestone 3 - Detection of Pneumonia

Preprocessing Improvements

To implement the multi-class classification of the images between normal X-rays, X-rays with bacterial pneumonia and X-rays with viral pneumonia, we needed to alter our preprocessing steps. For our model to distinguish between bacterial and viral pneumonia, we need to split the pneumonia image folder into two folders. The image filenames can be distinguished as cases of bacterial pneumonia have “bacteria” in their filename and cases of viral pneumonia have “virus” in their filename. Thus, we created a function that would parse through the pneumonia images filenames and place them in the corresponding folder. The datasets were loaded into the model and each image is labelled with one of three classes for the three cases we have. Another change

we made to the preprocessing is converting all images to grayscale because we are dealing with X-ray images. The reason for this change is not for model performance but to accelerate training as the network only has to work with one channel rather than three channels that would be needed for RGB images. However this does result in a loss in general accuracy as observed in the next section.

Model Specifications Improvements

For our final model we utilized the ResNet152 architecture. The residual block is the same as the ResNet50 architecture we implemented for milestone 2, however the number of layers in architecture varies. The ResNet152 architecture is composed of an initial convolutional layer followed by 4 stages of residual layers with varying numbers of blocks. There are 3, 8, 36 and 3 blocks in each of the 4 layers respectively, creating a total of 152 layers. The initial convolutional layer and the convolutional layers in the blocks have the same parameters as the ResNet50 architecture. Also, the layers and functions after the 152 layers are the same as the ResNet50 architecture. The increased number of layers in this architecture makes for a more accurate model when predicting the class of each X-ray. The only hyperparameter that changed was the learning rate of the model which was changed to 1e-4 as determined by our experiments. We added an L2 regularization of a factor of 1e-4 as well to penalize widely regular solutions and outliers, preventing the model from memorizing the dataset. Finally, we implemented early stopping into our model as the training of the model is very strenuous due to the many layers of the residual blocks. Our early stopping detection has a minimum threshold of 0.01 and a patience of 1, which stops the training if the change in loss between epochs is lower than the threshold.

Limitations

The general accuracy of the model did decrease after becoming a multi classification model and changing the images to grayscale. This is due to the fact that the pneumonia image class was split into two separate classes. Thus, the number of images in these split classes is much less than what we had originally with our pneumonia class, leading to a worse accuracy. It's important to recognize that this may not be the most optimal configuration as the combinations there were attempted may not reflect the accuracy and balance behind all possible configurations. With more computational resources and time it is entirely possible to find a better configuration.

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