Pneumonia Detection and Classification using Neural Network

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at BRAC University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Abstract

Medical image classification is of vital importance when it comes to clinical treatment. Numerous imaging techniques exist in diagnosis of various diseases, but X-rays remain one of the most popular techniques. Given that, X-rays are inexpensive and the easiest to perform, it is one of the most frequently used radiology examinations for diagnosis. X-rays are performed in different parts of the body. In this paper, we will focus on chest X-rays which give us images of the lungs, heart, airways and the bones which are present in the chest and spine. Chest X-rays can also display fluid inside the lungs or the area surrounding the lungs. The image produced by chest X-rays can help doctors determine many lung-diseases. However, examining chest X-rays clinically can be tedious and complex. Therefore, computer aided detection can help to achieve more accurate and simpler ways of acquiring correct diagnosis. Computer aided detection techniques include the use of machine learning algorithms and deep learning methods.

Keywords: X-ray, Chest X-ray, Diagnosis, Computer aided detection, Machine learning, Deep learning, Thoracic diseases, Pneumonia, Threat, Pollution, Insufficient, Medical, Resources, Neural Network.

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Chapter 1

Introduction

In this chapter we explain our topic and motive of working with this particular topic.

1.1 Background

Thoracic diseases are major concern among all people especially children. These diseases cause many deaths and lifelong health issues. Pneumonia is one of the thoracic diseases which infects one or both of the lungs. Pneumonia can be a major threat for children living in low to middle-income countries due to extreme pollution. According to the World Health Organization (WHO), being exposed to polluted air, the source being both indoor and outdoor, increases the rate of acquiring pneumonia to nearly double[22]. In developing countries, there are insufficient medical resources and medical professionals compared to the vast population which prevents most of the people from receiving prompt treatment and thus further aggravating their health.

1.1.1 Classification of Pneumonia

The two types of pneumonia are Community-acquired pneumonia and hospital-acquired pneumonia. Community-acquired pneumonia occurs when a patient becomes infected outside of any healthcare facilities and hospital-acquired pneumonia is caused during a patient's hospital admission. Causative agents of pneumonia are microorganisms which include various types of virus, bacteria and fungi[4]. Both types of pneumonia cause morbidity worldwide. Identification of the microorganism causing pneumonia is significant as it ensures the accurate treatment needed for a patient. It is a challenging task to distinguish between the type of pneumonia caused by virus and bacteria. Viral pneumonia occurs because of some viruses such as Influenza and SARS-COV-2 and several types of bacteria for example, Streptococcus pneumoniae is the leading cause of bacterial pneumonia[11]. Treatment differs for both bacterial pneumonia and viral pneumonia. Antibiotics are required for treating bacterial pneumonia whereas viral pneumonia is treated by keeping the patient on observation [9] or using antiviral medication.

1.1.2 Diagnosis of Pneumonia

Pneumonia can be diagnosed using numerous medical examinations, one of them being X-rays imaging which is one of the most affordable procedures. X-rays are cost effective, and have no after effects as radiation does not stay in the body after the procedure[18]. X-rays are extensively available everywhere even in countries where the medical facilities are not top notch. Since X-ray imaging is considerably quick and simple technique to perform, it can be helpful in case of medical emergencies. Pneumonia can be detected by careful observation of X-ray images by a radiologist or by a doctor. X-ray allows the medical professional to detect spots in the lungs, which is an indication of a lung infection. Furthermore, X-rays enable the doctor or radiologist to perceive the severity of disease and additionally look for other lung complications which can be a result of pneumonia such as abscesses or pleural effusions[24].

1.2 Motivation

To detect pneumonia as well as to distinguish between bacterial and viral pneumonia is extremely important for ensuring the correct treatment. Some X-rays are difficult to interpret that even skilled radiologists can overlook certain problems. Effective and less time-consuming methods are required for analyzing X-ray images and providing proper treatment. Automated diagnosis can ensure faster and more effective treatment. In this paper, we have decided to work using deep learning methods to provide reliable results for detecting the presence of pneumonia. By properly implementing deep learning methods in medical X-ray images we can diagnose a patient with pneumonia and whether the patient has bacterial or viral pneumonia which will allow the doctor to treat the patient accordingly.

1.3 Objective

Deep learning has shown some remarkable outcomes using image classification over the years with lowest error rate. Medical facilities can adopt deep learning-based detection to assist them in diagnosing patients faster[12]. Our main goal is to make a reliable system based on deep learning methods to detect pneumonia and classify the type of pneumonia that is viral or bacterial therefore patients can avail early treatment which will result in less lifelong health issues and reduction in mortality rate due to the disease. Moreover, it will also help doctors to determine the severity of pneumonia and decide which patients require immediate medical care.

1.4 Document Outline

In this section we have provided information about complications that arise due to pneumonia, some related work and our aim to use deep learning methods to successfully implement a system. In the following section, we will be discussing the related work in more depth and the literature review. The literature review consists of the parts mentioned below:

- Image Classification

- Previous Researches

Chapter 2

Literature Review

In this chapter we explain the methodologies of image classification and related work.

2.1 Image Classification

Image classification is an intricate process in which information is extracted from multiple images. Pixels are assigned to classes of interest in the sample images during image classification. The classification involves multiple steps therefore to make the task less complex, an image classification toolbar has been developed to perform the classification in a suitable integrated environment[19]. Classification of images can be of two types:

- Supervised classification: The training process takes place under supervision where mapping is formed between data variables and information classes variables[1]. The image classification toolbar assists in generating trained samples to depict the desired classes[19].

- Unsupervised classification: Intervention of a supervisor is not needed in this case, the toolbar helps by contributing the tools needed to make the clusters, to examine the quality of clusters and the tools required for classification[19].

2.1.1 Medical Image Analysis with Deep Neural Networks

In analysing and classifying medical images deep neural networks have crucial importance. Medical images such as X-ray are given as input and the resulting output verifies whether the disease exists or not in the given input images[8].

2.1.2 Image Classification Techniques

Classifying an image is a complicated procedure as it needs multiple types of components. Techniques such as Neural Network, Support Vector Machine(SVM),Fuzzy logic and Genetic algorithm are used for classification.[8]

2.2 Previous Researches

After doing some research, we have gathered some information that machine learning approaches were used previously to detect abnormalities in chest X-rays. Machine learning approaches like hand-crafted algorithms to support vector methods (SVM) were used to recognize the disease from X-ray image classification. These models provide results close to accurate. The weaknesses of these models are that the results are not close to the practical standard and development is not as fast in the last few years. Automated diagnosis of various lung diseases is successfully achieved using deep learning. Using algorithms to interpret diseases from medical images can lack reliability. Numerous researches have been conducted in clinical diagnosis using medical imaging. Deep neural networks can detect vast details in images. Using deep learning we can classify images in a simple manner rather than the previous image classification methods which require multiple steps. In a paper[5], "Identifying Medical Diagnoses and Treatable Diseases By Image-Based Deep Learning", we found that deep learning based diagnosis has been used for the screening process of patients. Using an AI platform, pneumonia was diagnosed and the two leading pathogens that are viruses and bacterias causing the pneumonia were distinguished. Transfer learning was employed on the image dataset which enabled impressive results without requiring a specialised deep learning machine and with a relatively small dataset[5]. Transfer learning is a reliable technique which is applied when the training dataset is small.Testing was done in the model with 234 normal images and 390 pneumonia images. Detection of pneumonia reached an accuracy level of 92.8%, 93.2% sensitivity and 90.1% specificity[5]. Bacterial and viral pneumonia binary comparison reached an accuracy of 90.7%, sensitivity of 88.6% and 90.9% specificity[5]. The accuracy of the model was extremely close to human specificities.

Chapter 3

Deep Learning Algorithms

In this chapter, we briefly explain how the algorithms we used works.

3.1 Convolution Neural Networks(ConvNet/CNN)

It is a deep learning algorithm which is remarkably crucial in the computer vision branch. It takes images as input and assigns learnable weights and biases to different objects in the image which allows it to disparate one image from another[7]. Compared to other classification methods the application of CNN takes less time for pre-processing the data. In comparison with primitive methods, CNN does not require hand engineered filters as it can learn these filters. CNN has the ability to capture Spatial and Temporal dependencies by applying relevant filters in an image[7]. The architecture of CNN is such that by reusing the weights and reducing the parameters in an image dataset it carries out a better fitting. Training and testing in a CNN model entails each image in a dataset to proceed through a sequence of convolution layers with filters(Kernels), Pooling, fully connected layers (FC) and finally activation function such as softmax and sigmoid is used to classify the images[13].

$$Gain[m,n] = (f * h)[m,n] = \sum_j \sum_k h[j,k]f[m-j,n-k] \tag{3.1}$$

In the above formula, f is the input image, h is the kernel, m and n are matrix row and column index respectively.

3.1.1 Convolution Layer

This is the initial layer in which features are extracted from an input image. By utilizing a small square matrix of the input data CNN stores the relationship between pixels of an image by determining image features[13]. By multiplying the filter matrix with the image matrix we achieve the feature map. Different operations can be attained for example, edge detection, blur and sharpen by applying divergent filter matrix.

- Strides: The number of pixel shifts required to over the input image is known as strides. For example, if the stride is 2 each time the pixel is shifted 2 times and so on.

- Padding: Padding is used when the filter matrix does not fit fully.Padding is used on our model automatically.
- Non Linearity (ReLU): Rectified Linear Unit(ReLU) is for non-linear operation. Here, the outcome is (x) = max(0,x).The task of ReLU is to establish non-linearity in CNN. Sigmoid and tanh is also applicable when it comes introducing non-linearity but ReLU outperforms both.

3.1.2 Pooling Layer

This layer reduces the number of parameters when the image size is substantial. It retains valuable information in an image when spatial pooling(subsampling and downsampling) is applied which decreases the dimensionality of each and every map[13]. The three types of spatial pooling are as follows:

- Maxpool
- Average Pooling
- Sum Pooling

3.1.3 Fully Connected Layer

This layer is also known as FC layer, the matrix is flattened and it is given as an input in the neural network. A vector is derived from the feature map matrix and a model is created by integrating all the features. An activation function,that is, a softmax function is obtained which is applied to categorize images.

3.2 Convolution Neural Network 4

Convolution Neural Network 4 consists of 4 convolution networks layers which have filters 8,16,32 and 64. The size of the kernel of the filter is 5x5 and the size of the max-pooling filter is 2x2. The initial layers draw out the low-level features whereas the inner layers extracts the high level features. After each convolution step, the ReLU layer gives out the non-linearity in the features extracted. Only the most dominant features remain after the image is passed through the last layers. The feature maps which are extracted are put together which translates into a vector and connected to a fully connected layer with 1024 neurons. The resulting outcome is the probability of each class[17].

3.3 CNN Model Parameters

The performance of the model depends on hyperparameters. During the training process parameters are weights of the matrices. The predictability of the model highly depends on the parameters that are changed when the back-propagation occurs. Finding suitable parameters is essential to get the best results[3].

3.3.1 Activation Function

In the classification layer the activation function that was used is softmax. The following equation is used to find the activation function[15].

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{3.2}$$

Sum of the output values:

$$\sum_{j=1}^{K} e^{z_j} \tag{3.3}$$

Exponential function:

$$e^{z_i} \tag{3.4}$$

Input vector elements:

$$z_i \tag{3.5}$$

Input vector:

$$\vec{z} \tag{3.6}$$

Number of classes:

$$K \tag{3.7}$$

3.3.2 Optimizer Adam

Training in neural networks requires an optimizer. Adam is a learning rate optimization algorithm. This is a method of stochastic optimization which does not need high memory capacity to perform and requires first-order gradients [16].

3.4 Categorical Cross Entropy Loss

This is to calculate the loss on a neural network. This is also known as softmax loss. When we use this loss the CNN will be trained on the probability of all the image C classes[21].

$$CE = -\sum_{i}^{C} t_i \log(s_i) \tag{3.8}$$

Where t_i and s_i are the ground truth, C is the CNN score for each class i.

Chapter 4

Data Analysis and Processing

In this chapter, we explain the dataset we used and pre-processing methods.

4.1 Data Analysis

The dataset was taken from mendeley. The dataset consists of radiographs of children. It contains X-rays of the two types of pneumonia that is bacterial and viral and also the normal where pneumonia does not exist. The data is validated by medical professionals to ensure the highest accuracy rate. This dataset is split into test and training. It consists of 5,232 chest X-rays, 3,883 X-rays diagnosed with pneumonia with 2,538 bacterial and 1,345 viral and 1,349 normal[6]. In total 5,856 X-rays were used to train the neural network.

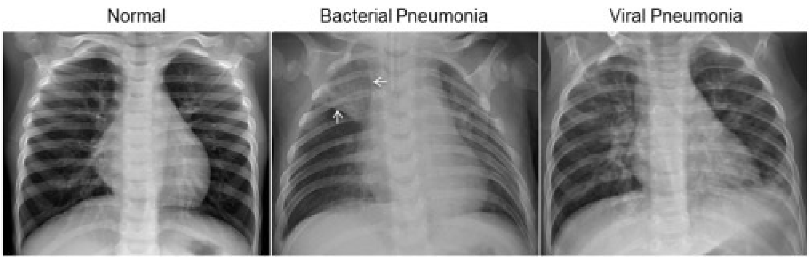

Figure 4.1: Normal, Bacterial and Viral Pneumonia

After observing the dataset The dynamic range of X-rays from the dataset varied from one X-ray to another. Dynamic range is the series of exposure values in X-rays. Some X-rays were overexposed and some were underexposed which resulted in several X-rays being too light or too dark. The underexposed radiographs looked grainy and the anatomy was not clearly represented. In the overexposed X-rays, the radiographs appeared burnt out which made the X-ray difficult to interpret[23].

Each X-ray had a different angle of rotation, which would be misleading for the neural network to predict precisely. Some X-rays were also more magnified than the other which also made the dataset tricky to classify in a neural network. Furthermore, the X-ray images were not of the same size which additionally contributed to difficulties in training.

Figure 4.2: Underexposed X-ray

Figure 4.3: Overexposed X-ray

To overcome the complications discussed above, we concluded that histogram equalization is necessary prior to training the dataset in a neural network.

Figure 4.4: Rotated X-ray

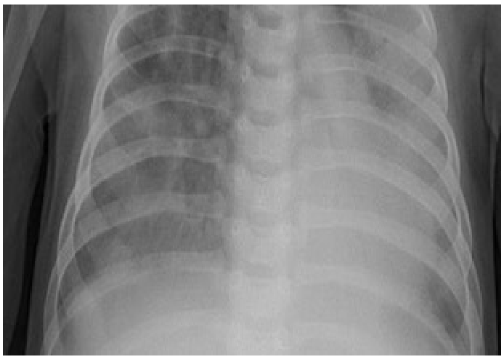

Figure 4.5: Magnified X-ray

4.2 Data Processing

Raw image data are required to be preprocessed to extract features. Each image has a fixed number of pixels and each pixel has intensity values representing the intensity of the color or their respective positions. We have used TensorFlow 2.0 library to read and store all images. This library also helps us to transform all the images at once. The images are then converted to grayscale images to perform histogram equalization.

4.2.1 Histogram Equalization

Histogram equalization is a method used to enhance contrast of an image by distributing the pixel intensity values uniformly which mean stretching out the intensity range of the image [3].
In histogram equalization, the pixel intensity of an input image x is transformed to a new intensity value, x' by T where T is the product of a cumulative histogram and a scale factor[2].

$$x' = T(x) = \frac{max.intensity}{N} \sum_{i=0}^{x} n_i \tag{4.1}$$

where n_i is the number of pixels at intensity i, N is the total number of pixels in the image.

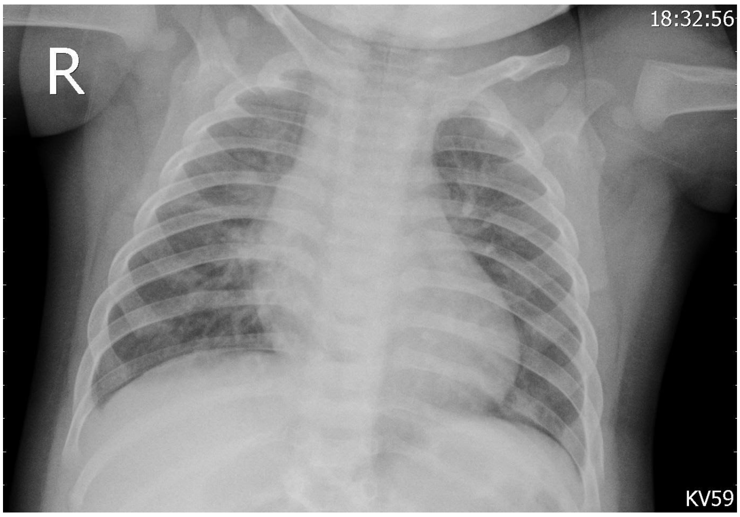

Figure 4.6: Image before Histogram Equalization

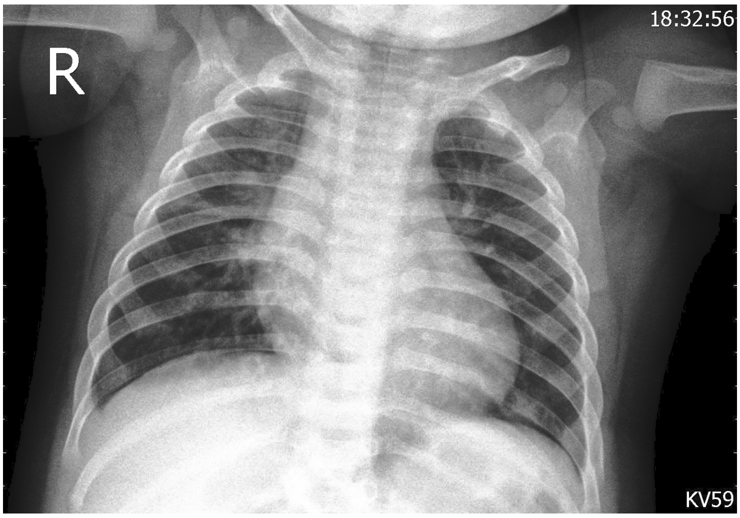

Figure 4.7: Image after Histogram Equalization

4.2.2 Data Augmentation

The goal of a model is to generalize patterns from the training dataset so that it can predict new data that has not been shown to the model before.Dealing with small amounts of data will lead to the adjustment of the model to the training dataset to a great extent but as a result will fail to predict new data, this is a problem of overfitting[14]. To avoid the problem of having a small dataset, we can expand our image dataset by creating synthetic images from the existing image dataset[10]. Using the ImageDataGenerator class we can generate batches of tensor image data while the model is still training [25].
Some of the augmentation techniques we used are shown below[20]:

- rescale: Rescaling factor. Multiplied with the data before any other processing. As the values of the original image are in RGB coefficient in the 0-255 range, it is too high for the model to process so we scale it by 1/255 so that the target values remain between 0 and 1.

- horizontal_flip: Flips out the input image horizontally.

- width_shift: Is for randomly shifting images horizontally.
- height_shift: Is for randomly shifting images vertically
- shear_range: Is for randomly applying shearing transformation.
- zoom_range: Is for randomly zooming in the pictures.

```
train_datagen = ImageDataGenerator(rescale=1./255,
                                   horizontal_flip = True,
                                    width_shift_range = 0.2,
                                    height_shift_range = 0.2,
                                    shear_range = 0.2,
                                    zoom_range = 0.2)

test_datagen = ImageDataGenerator(rescale=1./255)
```

Figure 4.8: Generating Synthetic Image Data

The dataset was split into 90% training and 10% test for validation.

Chapter 5

Proposed System

In this chapter we give a detailed explanation of our model.

5.1 Proposed CNN models

Our proposed model consists of two different sequential models to test out how histogram equalisation affects the accuracy of the model's classification of pneumonia. There would be two versions of each convolution neural network architecture, one for raw x-rays passed as input and another for preprocessed x-rays which has been converted to grayscale and histogram equalised then passed as input. There would be two and four layers CNN architecture with max pooling to down-sample input representation which reduces its dimensionality and allows for assumption to be made about features contained in the sub-regions binned. Then this two dimensional data would be passed through a flatten layer to transform to one dimension to be able to connect to a fully connected dense layer. Finally this dense layer connected to a dense layer with 3 neurons for classification purposes. Each neuron represents one of the three classification normal, bacterial pneumonia and viral pneumonia.

5.1.1 Two Layered CNN

The image was resized to 64x64 for input. For raw RGB images it was entered into as three channels making it 64x64x3 .For histogram equalized Grayscale images it was passed as one channel 64x64x1. Batch size was set to default of 32. CNN Kernel size is set to 3x3. Both max pooling layers used a mask of 2x2. Activation function used in all the layers is the Rectified Linear Unit except the last layer. Before connecting to the last layer the input is flattened and connected to a dense layer with 128 fully connected neurons. The last classification layer uses the activation function of softmax. For learning optimization Adam was used. And finally for loss function categorical cross-entropy was used.

5.1.2 Four Layerd CNN

This mode has two more CNN layers then the first one. The image was resized to 64x64 for input. For raw RGB images it was entered into as three channels making it 64x64x3 .For histogram equalized Grayscale images it was passed as one channel 64x64x1. Batch size was set to default of 32. CNN Kernel size is set to

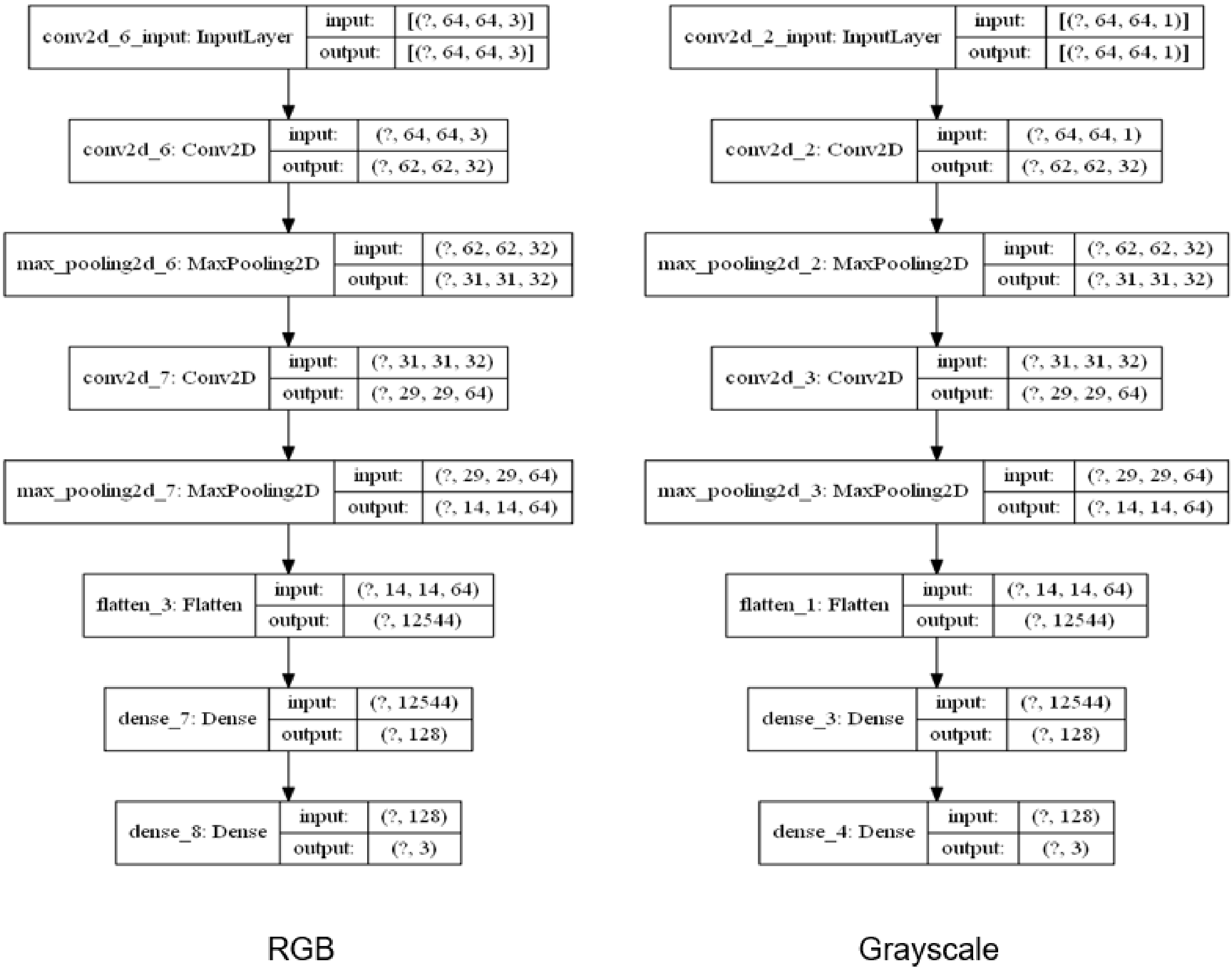

Figure 5.1: Two Layerd CNN RGB vs Grayscale

3x3. Both max pooling layers used a mask of 2x2. Activation function used in all the layers is the Rectified Linear Unit except the last layer. Before connecting to the last layer the input is flattened and connected to a dense layer with 1024 fully connected neurons.The last classification layer uses the activation function of softmax. For learning optimization Adam was used. And finally for loss function categorical cross-entropy was used.

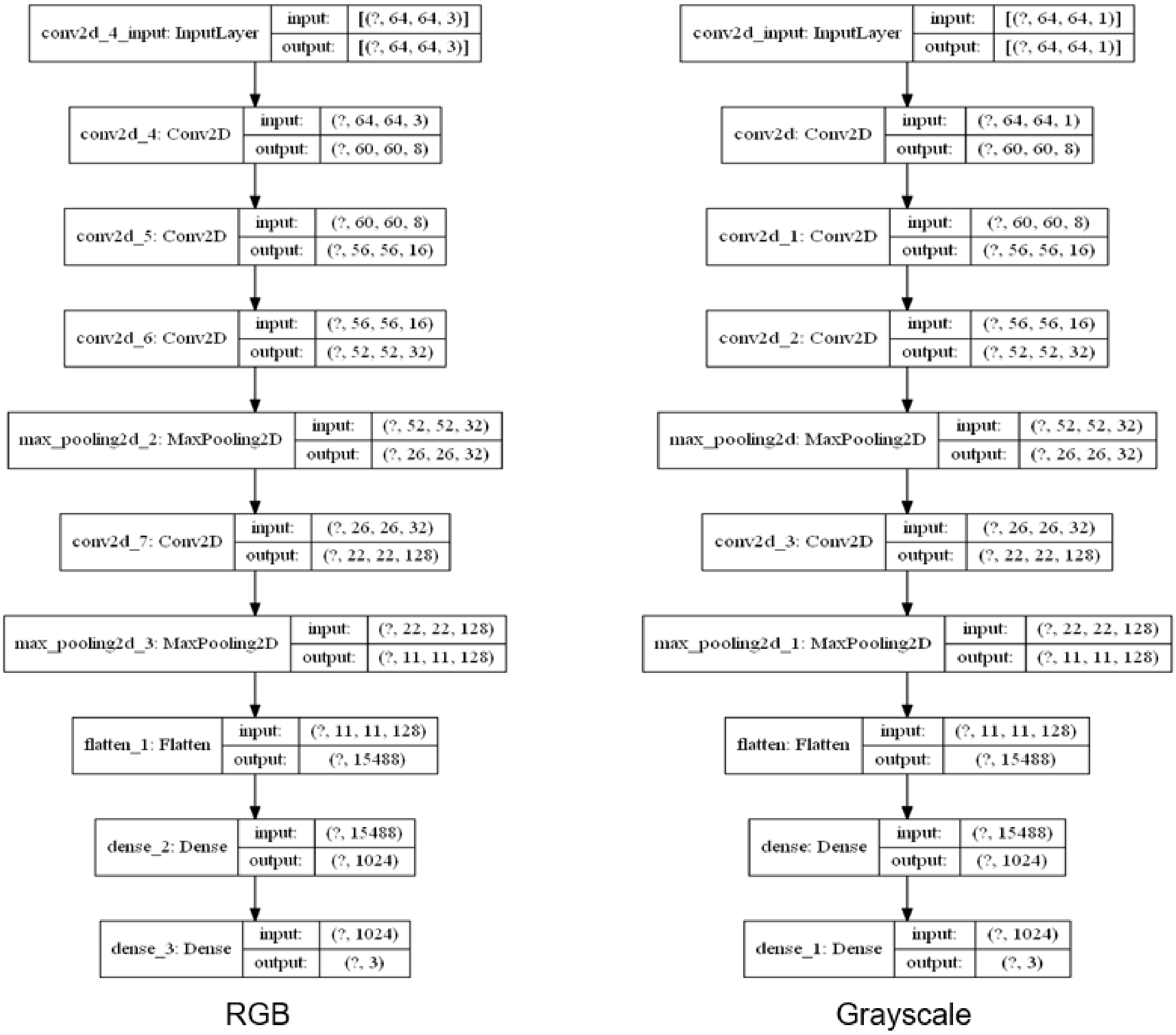

Figure 5.2: Four Layerd CNN RGB vs Grayscale

Chapter 6

Results

6.1 Experimental Setup

Python 3.8 was chosen to code this experiment. Anaconda development environment was set up in a local machine to execute the code. With the help of Anaconda, Jupyter Notebook was hosted in localhost. The specification of the local machine consisted of Intel i5-6500 CPU , H170 motherboard, 32 gigabytes of RAM, AMD RX5700 GPU and finally 650 watt power supply. Using Python enabled us to use a huge number of machine learning libraries. Libraries such as Numpy, CV2, Tensorflow, Keras were used to build the model.

6.2 Results

Model	CNN RGB	CNN Grayscale	CNN4 RGB	CNN4 Grayscale
Accuracy	80%	82%	80%	83%

Table 6.1: Results

6.3 Analysis

The histogram equalised grayscale images produced better accuracy when comparing the neural networks in respect to RGB vs Grayscale for each model. For the two layered CNN an improvement of 2 percent was achieved and for the four layered CNN an improvement of 3 percent was achieved. When testing the neural networks in the test dataset Grayscale image trained neural networks also produced better accuracy than RGB image trained neural networks. Therefore, grayscale images with histogram equalisation are superior for training neural networks.

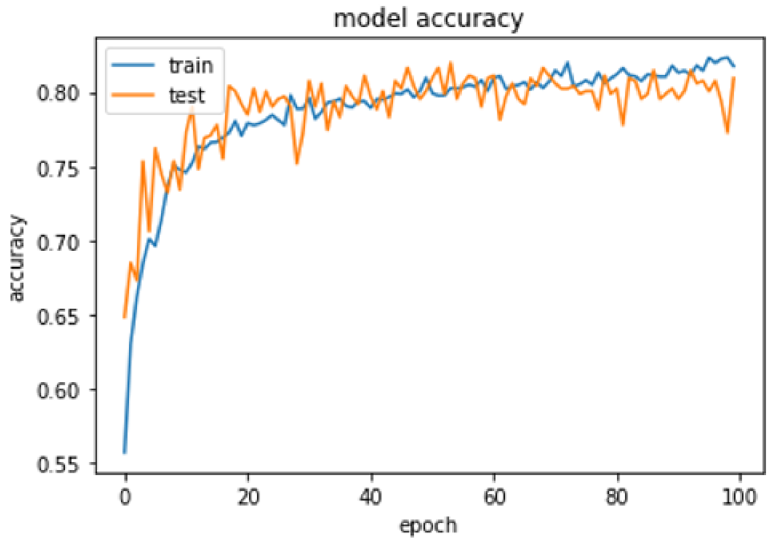

Figure 6.1: CNN4 Grayscale Model Accuracy

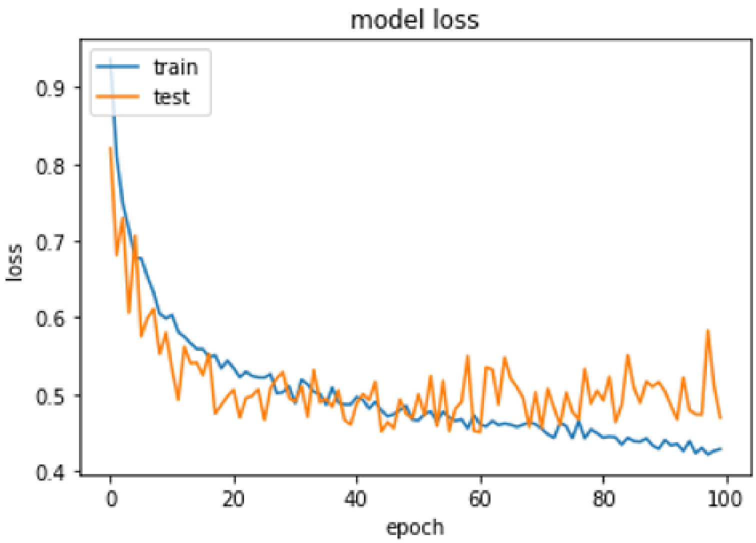

Figure 6.2: CNN4 Grayscale Model Loss

6.4 Result Comparison

In the paper "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning" a model was made for bacterial and pneumonia classification accuracy of 90.7%. This was achieved using an InceptionV3 model pre-trained on the ImageNet dataset, which was partially restrained on the raw x-ray images[5]. Whereas our model reached an accuracy of 83% for classification of normal, viral pneumonia and bacterial pneumonia using 4 layer CNN model with image augmenta-

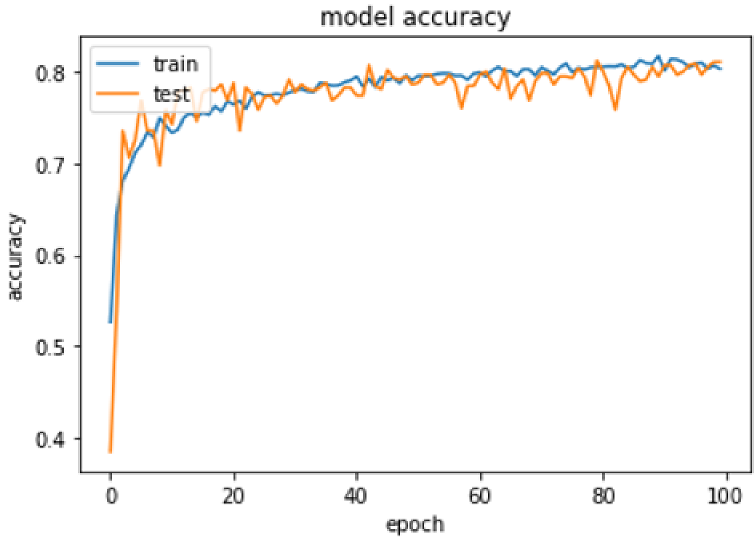

Figure 6.3: CNN4 RGB Model Accuracy

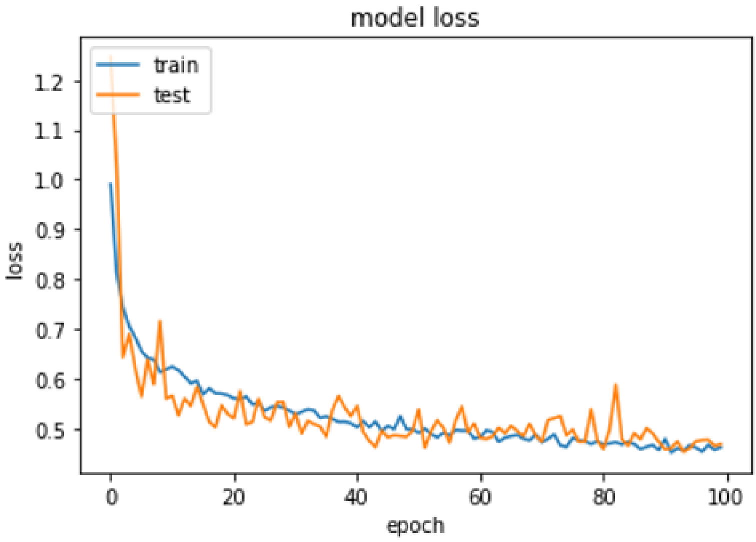

Figure 6.4: CNN4 RGB Model Loss

tion and histogram equalization. Our model does categorical classification between three classes but their model does binary classification between bacteria and virus. This makes our model versatile in teams of detecting pneumonia and classifying it in one go. Furthermore it proves image augmentation and histogram equalization can be added to improve their model as well.

Chapter 7

Future Work

In this chapter we discuss our future plans.

7.1 Future Work

Our plans include adding more data to increase the dataset. X-ray images of pneumonia caused by fungi would be a valuable addition to the dataset and also help further classification. Contrast Limited Adaptive Histogram Equalization is another image preprocessing technique that might increase accuracy of the neural network. We would like to test this out and then decide which method works better Contrast Limited Adaptive Histogram Equalization or Histogram Equalization. Then this knowledge could be used to retrain various pre trained neural networks to increase accuracy.

Chapter 8

Conclusion

We believe that our work has great potential to improve in the future. It is very evident that our accuracy could reach higher if we did not face limitations. We faced a great extent of limitations due to our dataset being low in number and low-computational power which resulted in low-accuracy.

Our target was to develop a system and examine the soundness of the method we used. By implementing our model further research can be done which can be helpful in detecting other lung-related diseases. Our main goal is to make our work public to avail other researchers to further improve our model. By improving our model in the future it will help the people in areas with inadequate medical facilities. With further research, we hope this model will be applied with real life setting which is beneficial for the medical sector.

Bibliography

[1] A. Bhattacharya, *Introduction to image classification*, University Lecture, 2000.

[2] R. Dorothy, R. Joany, R. J. Rathish, S. S. Prabha, and S. Rajendran, “Image enhancement by histogram equalization”, *International Journal Nano Corrosion Science and Engineering*, pp. 21–30, 2015.

[3] S. Sudhakar, *Histogram equalization*, Aug. 2017. [Online]. Available: https://towardsdatascience.com/histogram-equalization-5d1013626e64.

[4] S. Chow, *Pneumonia classification*, Aug. 2018. [Online]. Available: https://www.news-medical.net/health/Pneumonia-Classification.aspx.

[5] D. S. Kermany, M. Goldbaum, W. Cai, C. C. Valentim, H. Liang, S. L. Baxter, A. McKeown, G. Yang, X. Wu, F. Yan, *et al.*, “Identifying medical diagnoses and treatable diseases by image-based deep learning”, *Cell*, vol. 172, no. 5, pp. 1122–1131, 2018.

[6] D. Kermany, K. Zhang, and M. Goldbaum, “Large dataset of labeled optical coherence tomography (oct) and chest x-ray images”, *Mendeley Data, v3 http://dx. doi. org/10.17632/rscbjbr9sj*, vol. 3, 2018.

[7] S. Saha, *A comprehensive guide to convolutional neural networks-the eli5 way*, Dec. 2018. [Online]. Available: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53.

[8] K. Balaji and K. Lavanya, “Medical image analysis with deep neural networks”, in *Deep Learning and Parallel Computing Environment for Bioengineering Systems*, Elsevier, 2019, pp. 75–97.

[9] S. Johnson, *Viral pneumonia: Causes, symptoms, and diagnosis*, Apr. 2019. [Online]. Available: https://www.healthline.com/health/viral-pneumonia.

[10] J. P. Maheswari, *Breaking the curse of small datasets in machine learning: Part 1*, Apr. 2019. [Online]. Available: https://towardsdatascience.com/breaking-the-curse-of-small-datasets-in-machine-learning-part-1-36f28b0c044d.

[11] K. Ostermeyer, *Bacterial vs viral pneumonia*, Feb. 2019. [Online]. Available: https://www.elitecme.com/resource-center/nursing/bacterial-vs-viral-pneumonia.

[12] F. Pasa, V. Golkov, F. Pfeiffer, D. Cremers, and D. Pfeiffer, “Efficient deep network architectures for fast chest x-ray tuberculosis screening and visualization”, *Scientific reports*, vol. 9, no. 1, pp. 1–9, 2019.

[13] R. Prabhu, *Understanding of convolutional neural network (cnn) - deep learning*, Nov. 2019. [Online]. Available: https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148.

[14] Rafjaa, *Dealing with very small datasets*, Mar. 2019. [Online]. Available: https://www.kaggle.com/rafjaa/dealing-with-very-small-datasets.

[15] T. Wood, *Softmax function*, May 2019. [Online]. Available: https://deepai.org/machine-learning-glossary-and-terms/softmax-layer.

[16] L. Alabdullatef, *Complete guide to adam optimization*, Sep. 2020. [Online]. Available: https://towardsdatascience.com/complete-guide-to-adam-optimization-1e5f29532c3d.

[17] A. Chattopadhyay, P. Hassanzadeh, and S. Pasha, "Predicting clustered weather patterns: A test case for applications of convolutional neural networks to spatio-temporal climate data", *Scientific Reports*, vol. 10, no. 1, pp. 1–13, 2020.

[18] [Online]. Available: https://www.radiologyinfo.org/en/info.cfm?pg=chestrad.

[19] [Online]. Available: https://desktop.arcgis.com/en/arcmap/latest/extensions/spatial-analyst/image-classification/what-is-image-classification-.htm.

[20] F. Chollet, *The keras blog*. [Online]. Available: https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html.

[21] R. Gombru. [Online]. Available: https://gombru.github.io/2018/05/23/cross_entropy_loss/.

[22] *Household air pollution and health*. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health.

[23] A. Murphy, *Optimal exposure in digital radiography: Radiology reference article*. [Online]. Available: https://radiopaedia.org/articles/optimal-exposure-in-digital-radiography.

[24] *Pneumonia*. [Online]. Available: https://www.radiologyinfo.org/en/info.cfm?pg=pneumonia.

[25] K. Team, *Keras documentation: Image data preprocessing*. [Online]. Available: https://keras.io/api/preprocessing/image/.