Modelling Deep Learning Neural Networks For Pneumonia Detection

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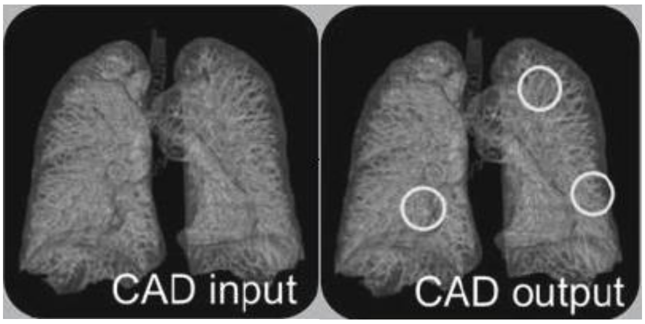
Abstract
A Contagious Disease Called Pneumonia Is The Single Largest Infectious Respiratory Disease That Is As Common As Cold. Pneumonia Is A Form Of An Acute Respiratory Infection That Affects The Lungs. The Lungs Of The Victim Are Filled With Pus And Fluid, Which Results In Painful Breathing And Also Reduces The Intake Of Oxygen. According To The World Health Organisation (Who), Pneumonia Accounts For 15% Of All Deaths Of Children Under 5 Years Old, Killing 808,694 Children In 2017. The Success Of The Deep Neural Networks In The Field Of Image Classification Has Aided Medical Professionals By Improving Their Decision Making. Convolutional Neural Networks, A Branch Of Deep Neural Networks Came Into The Spotlight Due To The Ability To Classify Diseases Based On Medical Images. In This Work, We Study The Application Of Cnn's In The Context Of Pneumonia Detection. We Tactically Determine The Optimal Architecture For Classifying The X-Ray Images To Indicate The Presence Of Pneumonia.

Keywords: Convolutional Neural Networks, Feature Extraction, Image Classification, Medical Image Analysis.

1. Introduction

The Disease Pneumonia Is A Descriptor Of An Acute Respiratory Infection That Affects A Great Deal To The Lungs. The Source Of The Disease Can Be Microorganisms Such As Viruses, Bacteria, Fungi, And Also Parasites. It Is A Virulent Disease That Has A Pernicious Effect On The Human Body Often Leading To Death. Pneumonia Prevails Mainly In South Asia And Sub-Saharan Africa. It Is Quite Difficult To Diagnose Pneumonia As Its Clinical Symptoms Overlap With Many Other Diseases Such As Asthma, Bronchitis, And The Common Cold. Medical Tests Such As Chest X-Ray, Blood Tests, Pleural Fluid Culture, Ct Scan, Sputum Test And Pulse Oximetry Test Are Recommended By A Doctor To Detect Pneumonia. In The Deprived Regions Of Asia And Africa, People Often Die Due To A Lack Of Knowledge And Facilities. The Finest Way To Increase The Swiftness Of Decision Making And Improving The Efficiency In It Is To Implement A Model To First Aid The X-Rays Or Radiographs Obtained In The Process Of Diagnosis. A Brief Solution To The Problem Was Given In The Late 1990s Called Computer-Aided Diagnosis [1] (Cad). Computer-Aided Diagnosis Is An Interdisciplinary Technology Combining Elements Of Artificial Intelligence And Computer Vision With Radiological Image Processing And Also Pathology. It Is Capable Of Recognizing Highly Complex Patterns In Images. The Limitation Was, It Had A Long Pre-Processing Stage And Was Time-Consuming. Figure.1 Shows The Identified Lumps On The Lungs To Detect Lung Cancer.

Fig 1. An example of Computer Aided Diagnosis to detect lumps formed in lungs to detect Lung Cancer.



To Overcome The Limitations Of Cad, Deep Learning Leaped. Artificial Intelligence Has Proved In The Past Its Efficiently Solving The Problem Of Image Classification Using A Dominant Technology Of Deep Learning.

The Implementation Of Deep Learning Models Specifically Convolutional Neural Networks [2] (Cnn) Has Revealed Their True Potential By Extracting The True Features In Image Classification Tasks. The Availability Of Pre-Trained Cnn Models Like Alexnet, Vggnet, Xception, Resnet, And Densenet Highly Aid In The Procedure Of Significant Feature Extraction [3]. But Our Work Restricts Us To Build An Optimal Architecture That Yields Better Performance In Less Time. The Significant Contribution Of This Study Is As Follows: To Be Able To Build A Neural Network That Best Performs On The Data Without Overfitting. The Structure Of The Paper Is As Follows: Section 2 Contains The Description Of Research Done In A Similar Field. Section 3 Consists Of All The Details Relevant To The Data Used. Section 4 Contains A Description Of The Implemented Methodology. Section 5 Exposes The Scores And Accuracies Of The Model. Section 6 Concludes The Research Done By Far.

2. Related Works

Very Recently, It Has Been Found That There Is A Possibility To Detect The Presence Of Pneumonia By Analysing The Sounds From A Human Cough And Predict The Severity Of The Disease [4]. This Idea Was From The Answers Of A Doctor Who Checks The Breathing Through A Stethoscope And Asks The Patient To Cough. An Article Titled “Determination Of Pneumonia Symptoms Through Acoustic Analysis Of Cough Sound And Machine Learning”, Authored By Chung, Youngbeen; Jin, Jie; Kim, Sang-Heon; Lee, Hyun; Jeon, Jin Yong; Park, Junhong Explores And Discovers The Detection Of Pneumonia Through The Most Representative Signals Of The Sound And Vibration Generated By The Human Body With The Notion Of Machine Learning And Acoustic Analysis.

Detection Of Pneumonia Is Possible Efficiently With The Concept Of Transfer Learning [5]. The Reuse Of A Pre-Trained Model On A New Problem Is Known As Transfer Learning. A Machine Exploits The Knowledge Gained From A Previous Task To Improve Generalization About Another Problem. “Comparative Analysis Of Convolutional Neural Networks Applied In The Detection Of Pneumonia Through X-Ray Images Of Children”, Authored By Luan Silva, Victor Souza, Leandro Dos Santos Araujo, And Adam Santos Explores Many Pre-Trained Models To Detect Pneumonia In Children.

3. Data Description

The Dataset Used Is Labelled Optical Coherence Tomography (Oct) And Chest X-Ray Images For Classification Released By Mendeley Data And Also Available On The Kaggle Platform. Chest X-Ray Images (Anterior-Posterior) Were Selected From Retrospective Cohorts Of Pediatric Patients Of One To Five Years Old From Guangzhou Women And Children’s Medical Center, Guangzhou. The Images Of All Chest X-Ray Were Performed As Part Of Patients’ Routine Clinical Care. All The Images Of Low Quality Or Unreadable Scans Were Removed As A Part Of Quality Control. The Diagnoses For The Images Were Then Graded By Two Expert Physicians Before Being Cleared For Training The Ai System. To Account For Any Grading Errors, The Evaluation Set Was Also Checked By A Third Expert. There Are 5,863 X-Ray Images (Jpeg) And 2 Categories (Pneumonia/Normal). The Data Is Split Randomly Into 3 Folders Namely, Train, Test, And Validation. There Are No Duplicate Images In The Dataset. Every Folder Consists Of 2 Subfolders Namely Pneumonia And Normal.

4. Methodology Of Proposed Model

This Section Provides A Detailed View And Implementation Of The Applied Methodology. The Proposed Model For The Detection Of Pneumonia Is A Multiple Layered Convolutional Neural Network. The Architecture Of The Model Is Divided Into 5 Stages – The Pre-Processing Stage, The Augmentation Stage, Feature Extraction Stage, Model Optimisation Stage, And The Testing Stage.

4.1. Pre-Processing Stage

The Pre-Processing Stage Is A Combination Of Two Parts, Fetching The Data In A Way That Works For You And To Analyze The Data And Make Intuitions From It.

4.1.1. Process The Data:

The Data Is Already Split Into Two Subfolders In All Three Main Folders And The Images Are Segregated Into Them. The Images Are Unlabelled But Are Divide Into A Folder, So We Must Label The Data And Get Them All In A Single Folder. This Can Be Solved Using Libraries Like Numpy And Opencv. The Foremost Role Of Using A Convolutional Neural Network In Image Processing Is To Get Down The Computational Complexity Of The Model. The Original Images Were Varying In Size From 2090*1858*3 To 1024*756*3, Where 3 Represents The Number Of Channels. To Decrement The Heavy Computation, The Image Is Resized To 150*150*3. Further Implementation Has Been Applied To The Downsized Images.

4.1.2. Analysis Of Data:

Now Human Intuitions Are Made By Viewing The Images Of Both Cases. There Are No Areas Of Abnormal Opacification In Normal Chest X-Ray Image (Left Panel). The Image Of Chest X-Ray Affected With Pneumonia (Right Panel) Typically Exhibits A Focal Lobar Consolidation, Specifically In The Right Upper Lobe.

We Can Conclude That There Is Lesser Air Capacity In Either Of The Lungs Of A Patient Affected With Pneumonia Compared To The Normal Patients As Shown In Figure.2.

Fig 2. A Picture Of Normal (Left) And Pneumonia Affected (Right) Lung Radiograph From The Dataset.

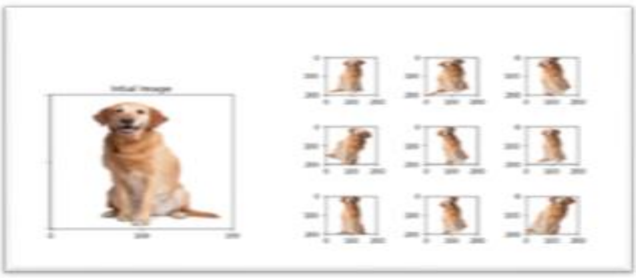
-On Further Statistical Analysis And Data Visualizations [6] Using Libraries Such As Matplotlib And Seaborn, Based On The Count Of The Number Of Pneumonia Cases And Normal Cases, It Is Revealed That The Train Folder Consists Of 3875 And 1341 Images In Pneumonia And Normal Folders Respectively. This Implies That Any Model That Trains On This Data Would Probably Extract More Detailed And Complex Features Of Pneumonia Cases Comparatively With The Normal Images As There Is A Scope Of Better And Enhanced Learning From More Data And Thus Resulting In A Biased Model. This Problem Must Be Solved Before We Train Our Model Either By Collecting More Data On Lungs Unaffected By Pneumonia Or To Make Editions To The Existing Dataset.

4.2. Augmentation Stage

The Above-Mentioned Problem Of The Model Being Biased Due To The Inclination Of Data On Pneumonia Images Can Best Be Solved Using The Concept Of Data Augmentation. The Model Gradually Over Fits The Pneumonia Images As There Is A Greater Count. Data Augmentation Is An Efficient Way To Achieve This [7]. This Is Done Under The Assumption That Through Augmentations More Features Can Be Extracted From The Original Dataset. It Implements Functions Such As Rotating The Images In Degrees, Zooming In And Out By A Defined Factor, Horizontally Flipping The Image, Cropping The Image, Etc. Training The Data In Various Ways Deters Overfitting. Overfitting [8] Can Also Be Avoided Using Methods Such As Dropout, Batch Normalization, Transfer Learning, Pre-Training, And Many More.

Augmentation Can Be Carried Out Along With These Methods To Restrict Overfitting. Figure.3 Shows The Simultaneous Decrease In Training And Validation Error By Using Augmentation Technique.

Fig 3. A Pictorial Representation Of Data Augmentation On An Input Image.

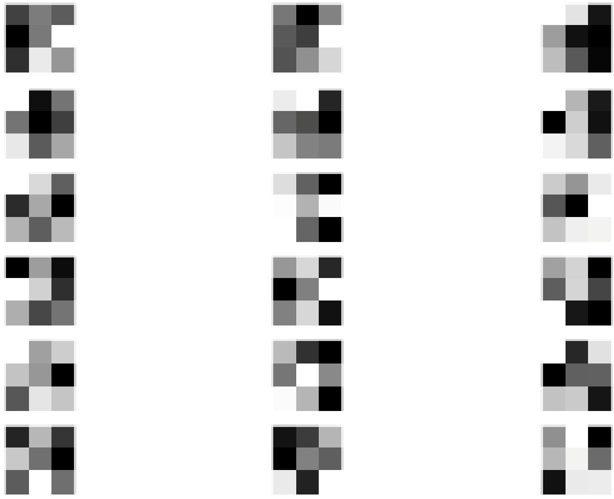


4.3. Feature Extraction Stage

Convolution Neural Networks (Cnns) Have Become Efficient Frameworks In The Domain Of Image Processing, Object Detection, And Recognition. It Is One Of The Robust Techniques Consisting Of Many Linear And Non-Linear Layers. Extending The Neural Network With Multiple Hidden Layers Allows Our Model To Extract Complex Features From The Input Data. The Model Mainly Consists Of Convolutional Layers, Pooling Layers, And Dropout Layers. We Do Convolutions So That We Can Transform The Original Function Into A Form To Get More Information. It Can Be Said That A Convolutional Operation Is Same As A Matrix Multiplication, Where One Of The Matrices Is An Image While The Other Is A Filter That Makes Changes To The Image. The Output Of This Is A Final Convoluted Image.

The Convolution Layers Generate A Set Of Linear Activations, Which Is Followed By Non-Linear Functions, And Also Applies Multiple Numbers Of Filters To Decrement Complexity Of The Data. These Filters Detect Features Of Images. The Filters Of Initial Layers Detect Basic Features Such As Horizontal And Vertical Edges And While The Number Of Layers' Increases, The Filters Extract More Complex Features Such As Blobs. The Matrix Form Of A Filter Can Be Represented In A Matrix Of Colours. These Filters Also Blur And Sharpen Images And Train The Network Even If The Resolutions Of Input Images Are Uneven. The Filters Used In The Second Hidden Layer Is Shown In Figure.4.

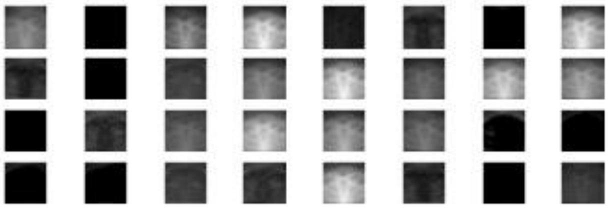
Fig 4. Eighteen Of 64 Filters Used In The Second Hidden Layer Of The Neural Network.



The Pooling Layers Are Used To Down-Sample The Results Received From The Convolutional Layers. The Functionality Of Pooling Layers Is To Reduce The Size Of The Activation Maps Into A Smaller Matrix By Transferring Them. This Is Done Using By Applying The Concept Of Striding And Padding The Input. The Activation Function Used For Convolution Layers In This Model Is Rectified Linear Units(Relu).

While Convoluting And Pooling The Images To Extract Features And Process Them The Size Of The Image Decreases As We Apply Filters By Sliding Them All Over The Image, In This Process A Minute Part Of The Image Vanishes. Gradually This Gives Rise To Problem When There Is Loss Of Information. This Can Be Solved By Implementing The Concepts Of Padding And Striding. Padding Refers To The Number Of Pixels Added To An Image When It Is Being Processed By The Filter Of A Neural Network. If The Padding Is Set To 2, Then There Will Be Two-Pixel Borders Added To An Image With A Pixel Value Of Zero. It Works By Extending The Area Of Which A Neural Network Process. To Assist The Kernel With Processing The Image, Padding Will Be Added To The Frame Of The Image To Allow For More Space For The Kernel To Cover The Image. Striding Is A Component Of A Neural Network That Is Tuned To Compress To Image Data. It Has Control Over The Movement Of The Filter Across The Image. If A Neural Network's Stride Is Set To 2, The Filter Will Move Two Pixels, Or Units, At A Time. Striding Value Was Set To 1 And 2 For Convolutional And Pooling Layers Respectively. With The Help Of The Filters In Each Layer, The Model Extracts Feature From The Image Data. The Filters Of Initial Layers Adjust The Contrast And Scale The Images. The Features Extracted From The Second Layer The Model Is Shown In Figure.5.

Fig 5. Results Obtained After Convolving Filters Of Second Hidden Layer To The Input Image.



To Avoid The Overfitting Problem Dropout Layers Are Used. They Are Used To Regularise Neural Networks [9]. The Dropout Layers Randomly Drop Out Both Hidden And Visible Units Of The Layer Preceding It. The Percentage Of Ignorance In Dropout Layers Have To Be Specified Explicitly. Dropping A Unit In This Way Is Quite Reasonable Since — Qualitatively — It Promotes The Redundancy In The Weight Matrices As Sub-Networks Can Robustly Perform The Desired Operation. The Use Of Dropout In Neural Networks Has To Carefully Monitored As It Can Make The Model Flimsy By Dropping Out A Greater Number Of Units In The

Neural Networks. Therefore, Pooling And Dropout Solve The Over-Fitting Problem And Regularises The Neural Network By Decreasing The Complexity Of The Model. The Later Part Of The Model Consists Of A Flattening Layer And A Dense Layer That Uses Sigmoid Activation. The Output Of A Convolutional Layer Gives An Output In A Two-Dimensional Format, The Flattening Layer Compresses This Into A Single Dimensional Array There By Aiding The Dense Layer To Make Sure That The Output Of The Model Is In The Desired Form. The Model Architecture Is Shown In Figure.6.

Fig 6. Overall Architecture Of The Proposed Model

Model: "sequential"

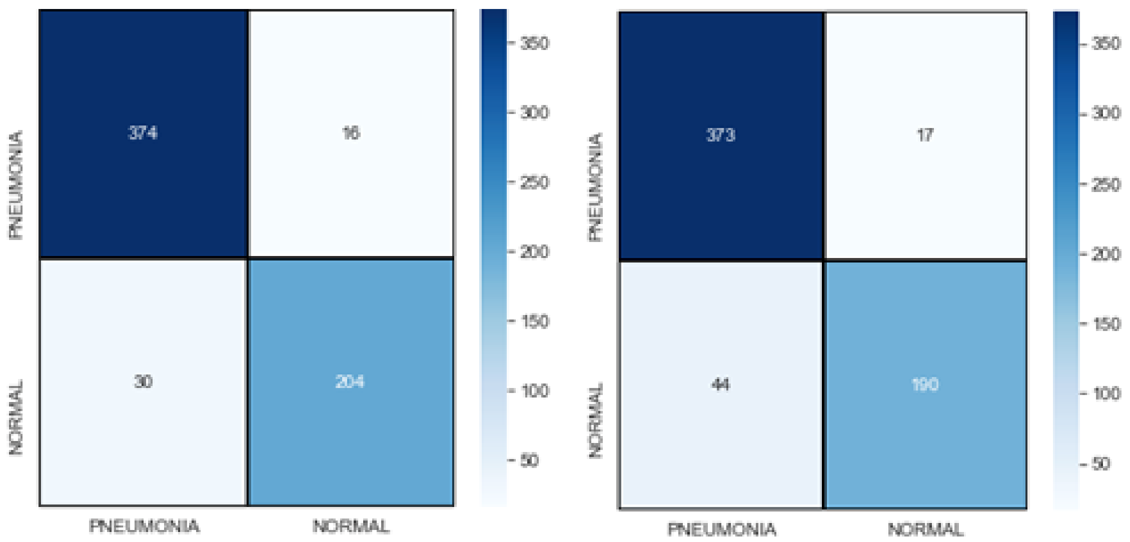
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 150, 150, 32)	320
batch_normalization (BatchNo	(None, 150, 150, 32)	128
max_pooling2d (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_1 (Conv2D)	(None, 75, 75, 64)	18496
dropout (Dropout)	(None, 75, 75, 64)	0
batch_normalization_1 (Batch	(None, 75, 75, 64)	256
max_pooling2d_1 (MaxPooling2	(None, 38, 38, 64)	0
conv2d_2 (Conv2D)	(None, 38, 38, 64)	36928
batch_normalization_2 (Batch	(None, 38, 38, 64)	256
max_pooling2d_2 (MaxPooling2	(None, 19, 19, 64)	0
conv2d_3 (Conv2D)	(None, 19, 19, 128)	73856
dropout_1 (Dropout)	(None, 19, 19, 128)	0
batch_normalization_3 (Batch	(None, 19, 19, 128)	512
max_pooling2d_3 (MaxPooling2	(None, 10, 10, 128)	0
conv2d_4 (Conv2D)	(None, 10, 10, 256)	295168
dropout_2 (Dropout)	(None, 10, 10, 256)	0
batch_normalization_4 (Batch	(None, 10, 10, 256)	1024
max_pooling2d_4 (MaxPooling2	(None, 5, 5, 256)	0
flatten (Flatten)	(None, 6400)	0
dense (Dense)	(None, 128)	819328
dropout_3 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Total params: 1,246,401
Trainable params: 1,245,313
Non-trainable params: 1,088

4.4. Optimization Stage

Though We Have Prevented Overfitting By Building A Wise Architecture, Training The Model Has Key Importance As Training The Model To A Greater Extent Can Also Over Fit The Data. This Problem Is Solved In A Two-Fold Strategy. First, The Learning Rate Must Be Variable As Per The Need, Secondly, The Number Of Iteration/Epochs Must Be Carefully Found Out. Variation Of Learning Rate Can Be Achieved By Implementing A Learning Rate Reduction Function That Monitors On A Specified Evaluation Metric. The Optimal Number Of Epochs Can Be Found By Analysing The Graph Plotted Between Training Error And Testing Error. Compiling The Model With A Suitable Optimizer And A Classifier. The Adam Optimizer [10] Has Served The Best Purpose In Our Case. There Is A Significant Difference In Performance Of The Model Based On The Optimiser We Use. This Can Be Shown By Showing The Confusion Matrices Of Two Same Networks With Rms And Adam Optimiser As In Figure.7.

Fig 7. Confusion Matrices Of The Model On Using Rms Optimiser (Left) And Adam Optimiser (Right).

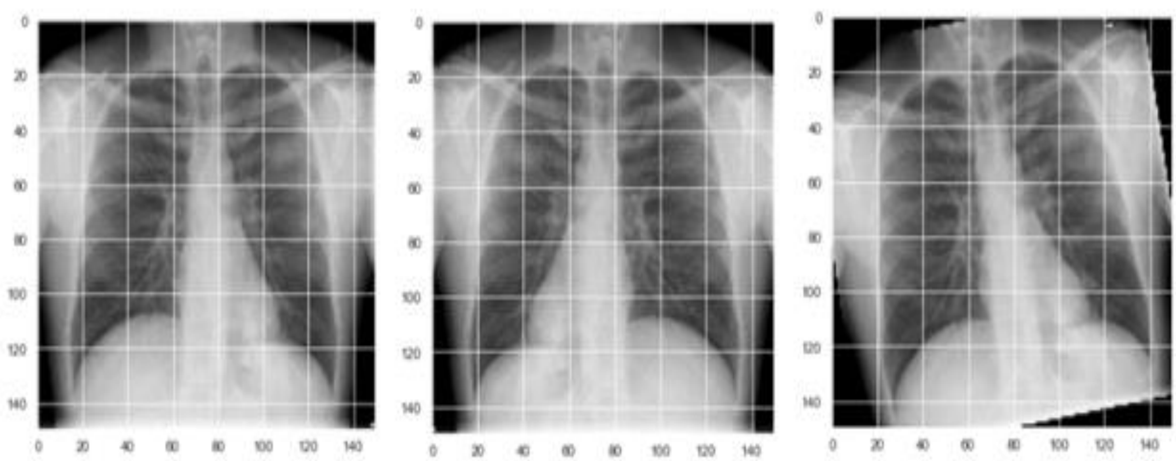


The Left And Right Images Represent The Confusion Matrices Of The Model For Rms And Adam Optimisers Respectively. It Can Be Inferred That Adam Optimiser Show Better Performance In Detecting Normal Cases Effectively Than The Rms Optimiser.

4.4. Testing Stage

Before We Finalise On A Model, It Is An Important Task To Check How The Model Performs On Real Data. To Test The Model, Chest X-Ray Images Were Collected From The Internet And Fed To The Network To Test Its Performance. The Model Successfully Detected The Pneumonia Affected Images. Further To Check The Robustness Of The Network We Feed The Network With Corrupted Images Such As Rotated Images And Flipped Images. The Performance Of The Model Was As Good As Normal As We Made Use Of Augmentation Techniques Beforehand. The Model Was Test As Shown Below. The First Image Is An Image Of Normal Lung, The Second Images Is Acquired By Flipping The First Image Horizontally And The Third Image Is Acquired By Rotating The First Image By 10 Degrees. Although The Images Were Corrupted, The Model Gave Out Correct Results.

Fig 8. Testing The Model With Original Image (Left), Horizontally Flipped Image (Middle), And Rotated Image (Right).



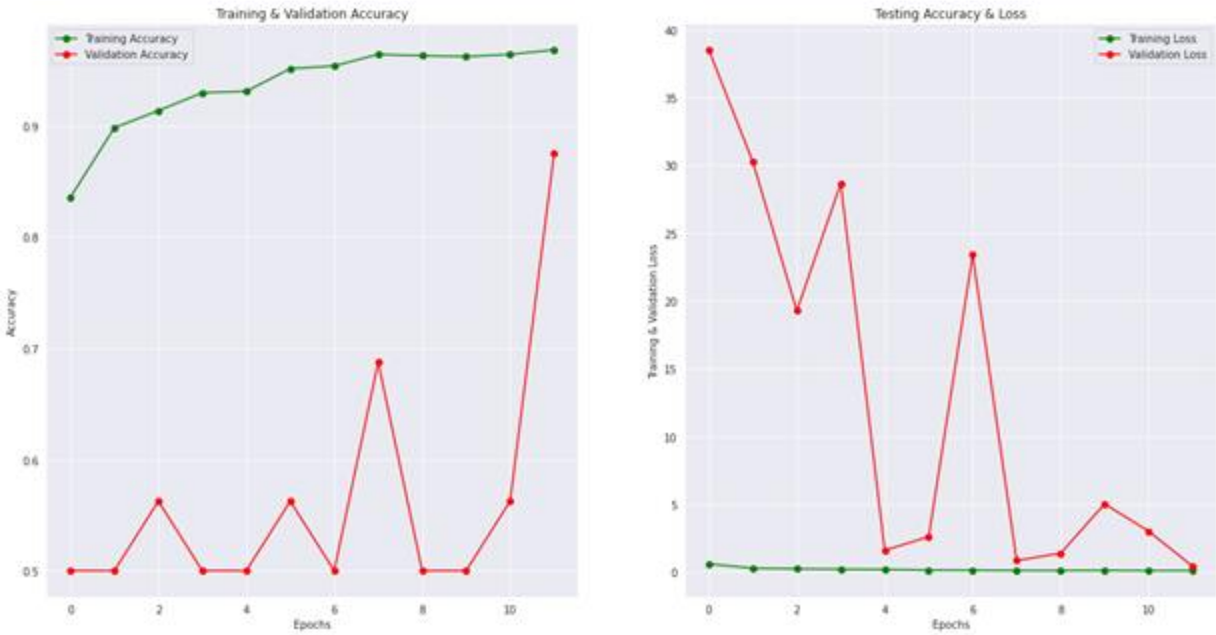
5. Results

The Customized Convolutional Neural Network That Was Built Has Achieved An Accuracy Of 93%, Recall Of 92%, And F1-Score Of 93% As Shown In Figure.9, Fig 9. Results Obtained By The Proposed Model.

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.93	0.96	0.94	390
Normal (Class 1)	0.92	0.88	0.90	234
accuracy			0.93	624
macro avg	0.93	0.92	0.92	624
weighted avg	0.93	0.93	0.93	624

The Line Graph Between Training And Testing Accuracy And Testing Accuracy And Loss Concerning The Number Of Epochs Is Shown Below In Figure.10.

Fig 10. Plots Between Training And Validation Accuracy (Left) And Testing Accuracy And Loss (Right).



This Shows That The Training And Validation Loss Is Minimal At The 12th Epoch, Hence We Have Trained Our Model To 12 Epochs.

6. Conclusion

There Are Several Underprivileged Regions Where Pneumonia Prevails Like Southern Africa And East Asia Where There Is A Shortage Of Both Resources And Also Expert Radiologists Who Can Diagnose The Disease. There Have Been Models That Have Used Pre-Defined Architectural Neural Networks Such As Alexnet, Vggnet, Xception, Resnet, And Densenet. But In This Research We Have Built A Fully Customised Neural Network Architecture To Solve The Problem Of Pneumonia Detection. The Proposed Work Can Help People Detect The Presence Of Pneumonia Through X-Rays And To Prevent Pernicious Consequences In Remote Areas. Our Study Will Likely Lead To The Development Of Better Algorithms For Detecting Pneumonia In The Foreseeable Future.

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