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Pneumonia Diagnosis Web Application using Deep Learning

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Abstract: *Pneumonia Is A Dangerous And Sometimes Fatal Disease That Primarily Affects Older People. Early Diagnosis Of Pneumonia Is Key To Saving Many Lives. This Study Attempted To Identify And Classify Patients With Pneumonia Based On Chest X-Rays. The Diagnostics Above Were Performed Using A Convolutional Neural Network, Which Was Built From The Ground Up And Produced Incredibly Accurate Results. When X-Raying A Patient, A Deep Learning Model Automates The Procedure And Ensures Fast, Competent And Efficient Results.ThisStudy Prioritizes A Convolutional Neural Network Model Trained On X-Ray Image Data To Distinguish And Diagnose Pneumonia. Convolutional Neural Network Models Were Used To Determine If A Person Had Pneumonia By Isolating Features From Specific X-Ray Chest Images, Compared To Previous Methods That Relied On Transfer Learning Techniques Or Traditional Manual Methods To Isolate Features Differently. They Overcome Liability And Reliability Issues When Creating Images.*

Keywords: Convolutional Neural Network, Pneumonia, Data Preprocessing, Data Augmentation, Rmsprop

I. INTRODUCTION

Recent Advances In Computing Technology Have A Wide Range Of Potential Applications In Medical Imaging. Convolutional Neural Networks (Cnns) Represent A Major Innovation. For Analysis Using Images. It Can Be Used To Successfully Classify Images. The Past Decade Has Seen Remarkable Advances In Medicine, Especially In Medical Diagnostics. SNA And Deep Learning Are Frequently Used In Medical Research, Especially Image-Based Research. They Are Used For Purposes Such As Lesion Segmentation [2], Tumor Segmentation And Classification [3], Image Enhancement, Abnormality And Disease Recognition, Nuclear Detection, Etc. With The Introduction Of Transfer Learning, Cnns Now Have More Advanced Capabilities. For Image Classification, You Can Use Training Models Trained OnImagenet Datasets Such As VGG16, Inceptionv3, Etc. To Build Models Faster And More Efficiently. Pneumonia Is One Of The Leading Causes Of Death From Infection Worldwide In Children Under 5 Years Of Age. .This Is Called An Infection That Occurs In The Air Sacs Of The Lungs. Among Other Things, It Can Be Caused By Various Viruses, Bacteria And Fungi. People Of All Ages Exposed To It Experience Mild To Severe Side Effects. Vaccines Are Intended To Treat Certain Types Of Pneumonia [4]. A Chest X-Ray Allows Doctors To Examine Internal Organs Or Look For Abnormalities And Diseases Of The Blood Vessels, Lungs, Heart, Airways, And Bones. A Chest X-Ray May Show Pneumonia Caused By A Lung Infection. In This Study, An Automatic Pneumonia Diagnosis Model Based On Radiographs Was Constructed Without Human Intervention. Deep Learning, Commonly Known As

Neural Networks, Has Gained Popularity In Recent Years And Is Now Widely Used In Various Industries. One Of The Most Popular Uses Is Image Classification Using Convolutional Neural Networks (Or "Cnns"). In The Field Of Medical Diagnosis, The Possibility Of Image Classification Is Also Being Explored. This Article Shows How To Create A Convolutional Neural Network To Diagnose Pneumonia Using Chest X-Rays.

II. RELATED WORK

In Their Research Article, Deniz Yagmur Urey Et Al. Discuss Early Diagnosis Of Pneumonia Using Deep Learning. The Authors Propose A New Strategy Centered On X-Ray Imaging. Convolutional Neural Networks (Cnn) And

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Residual Neural Networks Are The Classification Techniques Used. Comparative Studies Help Detect Pneumonia Early So That Effective Treatments Can Be Given To Treat The Disease.

This Study Inspired Us To Perform A Similar Analysis In Our Paper, But Using Larger Data, More Images, And A More Conservative Approach To Neural Network Layers To Improve Efficiency And Accuracy [10].

DimpyVarshniEt Al Describe The Creation Of An Automated System To Detect Pneumonia Using Different Deep Learning Models. The Authors Created A Convolutional Neural Network For Data Scaling And Disease Classification Using Medical Image Analysis. For Feature Extraction, The Design Uses TheDensenet-169 Layer Architecture. For Binary Classification, The Scheme Is Linked To The SvmModel.

Visualization Curves Make It Possible To Analyze The Results Of The Model And To Give A Synthesis [11].

A Research Paper, Garima Verma Et Al. Analysis And Classification Of Pneumonia From X-Ray Images Using Convolutional Neural Networks. Six Convolutional Layers Are Used In The Design, Each Followed By A Maximum Pooling Layer. This Allows Us To Understand How To Integrate A Smaller Number Of Convolutional Layers To Speed Up The Computation And Classification Of Deep Learning Models.

The Study Used Chest X-Rays To Identify Pneumonia. [12]

A Similar Idea Was Made ByOkeke Stephen Et Al. In Their Study, Convolutional Neural Networks Were Used To Classify Large Numbers Of X-Rays And Identify Pneumonia. Based On The Loss And Accuracy Of The Neural Network, We Can Compare Our Model With Theirs And Evaluate Its Performance. To Reduce Calculations, Their Network Receives An Input Form Of Dimensions (200x200x3), While The Images Are Focused And Use Dimensions (64x64x3).

III. LITERATURE REVIEW

Chest X-Rays Are Difficult To Interpret Without A Qualified Radiologist. Many Scientists Are Working To Automate X-Ray Analysis. In February 2018, A Team Of Academics Created A System Using A Deep Learning Framework To Classify Photos Of Macular Degeneration And Diabetic Retinopathy. Additionally, It Can Identify Typical Chest X-Rays And Pneumonia [5]. The Model Was Trained On 5,232 Pediatric Chest X-Ray Images, Of Which 3,883 Were Pneumonia-Related And 1,349 Were Normal.

They Achieved An Accuracy Of 92.8%, A Sensitivity Of 93.2% And A Specificity Of 90.1%. The Winning Submission To The Rsna Pneumonia Challenge 2018 On Kaggle Focused On Diagnosing Pneumonia And Locating Chest X-Rays Using A Fully Convolutional Network Integrated With Object Detection [6].

Stanford University Researchers Built Chex Net, A 121-Layer Convolutional Neural Network Trained Using TheChestx-Ray14 Dataset. Their Deep Learning Algorithm Was More Accurate Than Typical Radiologists When Identifying Pneumonia And Other Lung Diseases From Chest X-Rays [7].

Recently, A Detection Strategy For Pediatric Pneumonia Using Transfer Learning And A Deep Residual Network Approach Has Been Proposed. It Ranks Patients Using Chest X-Rays With A Recall Of 96.7% And An F1 Score Of 92. 7%[8]. Moreover, Other Researchers Have Only Used Cnns Without Transfer Learning And Managed To Classify Pneumonia Pictures With A Validation Accuracy Of 93.73% [9].

IV. DATASET

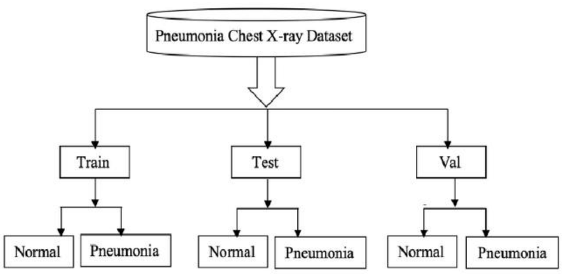

Fig 2.1: Outline Of X-Ray Image Dataset

Fig 2.2: Example Of Dataset

The Datasets Used For Each Diagnosis Were Based On Chest X-Ray Datasets Provided By Radiology Departments/Societies On The Kaggle Platform. All Images Are X-Rays InRGB Format. Convolutional Neural Networks Are Built And Trained Using The Open Source KerasDeep Learning Framework And TensorflowBackend. The Training, Test, And Validation Images Were Split Into Chest And Normal X-Rays To Create The Dataset. In Total, There Are Around 6000 Before And After Photos.

To Improve The System And Increase Efficiency, Data Is Modified And Added To Training And Validation Sets. To Improve Overall Accuracy, The Training Set Contains Approximately 5216 Images, Of Which 3875 Are Pneumonia Images And 1341 Are Normal Images, While The Validation Set Contains Approximately 624 Images, Of Which 234 Are Normal Pneumonia Images And 390 Images Are Pneumonia Images. Pneumonia.

V. DATA AUGMENTATION

Data Augmentation Techniques Are Widely Used To Improve The Performance Of Deep Learning Algorithms. The Main Purpose Of Data Augmentation Is To Improve The Classification Of Chest Radiographs By A Convolutional Neural Network Model. To Improve And Improve The Quality, Power And Size Of The Data, Data Augmentation Is Applied To The Training Data, In This Case Photos. The Amount Of Data Is Expanded Through Various Processes To Help Deep Learning Models Capture The Many Nuances Of Training Images. In Order To Avoid Data Overfitting And Improve Model Performance, A Large Amount Of Data Is Fed Into The Convolutional Neural Network.

A Machine Learning Or Deep Learning Model That Performs Well On The Training Set But Produces Unfavorable Results On The Test And Validation Sets Is Called Overfitting. Therefore, Overfitting A Model Is Undesirable And Should Not Occur During Implementation. [14] Deep Learning And Computer Vision Algorithms Can Fit Models More Efficiently And Competently By Expanding The Training Data Set. The Model Is Trained Using Various Data Augmentation Strategies. It Essentially Preserves The Original Dataset, As It Is Only Implemented At Runtime, With No Additional Disk Space To Store Improved And Updated Photos. [15]

The Data Augmentation Technique Implemented To Improve The Accuracy Of Our Deep Learning Models Is –

1. **Rescaling Normalization** – This Method Is Used To Reduce The Amount Of Calculations And Processing Required When Processing Of Image Data Types And Has Been Applied To Improve The Accuracy Of Our Deep Learning Models. In Any Image, Pixel Values Can Range From 0 To 255. Each Result Is Multiplied By A Scaling Factor Of 1.0/255. 0 Normalizes This Wide Range And Produces Numbers Between 0 And 1. Therefore, Much Less Computational And Processing Power Is Required. When Using TheTensorflowLibrary Image Data Generator Functions In Python, It Is Called When Images Are Loaded And Processed In The Training And Validation Sets.
2. Geometric Transformation - Used To Modify The Geometric Characteristics Of An Image, Allowing The Model To Collect Training Images Transformed According To These Characteristics. This Helps The Model Recognize And Analyze The SameImages As The First Training Set, But With Changes In Subtle Physical Characteristics. To Illustrate This, Consider That A Model Trained On Scaled Training Images May Not Clearly Capture The Scaled Images. Therefore, New Training Images Are Created By Modifying The Geometric Parameters Of Height, Width And Scaling. These New Training Images Can Help The Model To Accurately Recognize The Test Images. It Includes Many Functions And Settings Such As "Width Offset Range", "Height Offset Range" And "Zoom Range" Described In Image Data Generator Functions.
3. Flipping: During The Testing Phase, The Model May Not Be Able To Correctly Identify And Judge The Mirror Image Of The Training Image. Flipping Is Used To Augment The Data And Present Inverted Copies Of The Training Data, Rather Than Actually Storing Mirrored Versions Of Each Training Sample In Disk

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Storage, To Ensure Proper And Optimal Model Performance On These Mirror Images. Therefore, A Dynamically Efficient Flip Augmentation Procedure Can Improve The Performance Of Deep Learning Models On Chest X-Ray Datasets.

4. Shearing: Clipping Can Be Introduced In Training Images To Help Generate Clipped Images And Enable Deep Learning Models To Display Images With Clipped Orientations. Some Test Images May Share A Tear Direction With Some Training Images. Therefore, The Cropping Directions Of Some Training Set Images Allow Us To Better Understand How To Properly Process These Test Images.
5. Rotation: To Modify The Training Images And Improve The Content Of The Training Dataset, The Training Images Can Be Rotated By A Specific Value**.** This Is Achieved By Initializing The Image Data Generator Function While Adjusting The "Rotation Range" Variable To An Acceptable Value. For Data Augmentation, Photos Rotated From Different Angles Are Used.

Convolutional Neural Network

A Deep Neural Network Technique Called Convolutional Neural Network (CNN) Is Used To Evaluate Visual Data. In Addition To Many Hidden Layers, It Has An Input Layer And An Output Layer. The Input Is A Tensor Of The Form (Number Of Images)*(Image Height)*(Image Width)*(Image Depth). After The Image Passes Through The Convolutional Layer, It Is Summarized Into A Feature Map With The Following Dimensions: (Number Of Images)*(Feature Map Height)*(Map Weight Of Features)*(Channel Number Of The Feature Map). The Main Advantage OfCNN Over Other Neural Networks Is That It Can Detect Key Features Accurately And Efficiently Without Human Intervention.

The Main Feature Is That Cnns Work Almost Flawlessly On Image Databases. TheConvolutional Neural Network Can Extract Useful Information From Images, Eliminating The Ongoing Need For Manual Image Processing Techniques. Cnns Are Incredibly Effective In Areas That Involve Large Amounts Of Unstructured Data. CNNs Are More Efficient And Computationally Powerful Than Machine Learning Methods. Sigmoid Function, Tanh Function And Widely Used ReluFunction Are Just Some Of The Activation Functions Used In CNNs.

VI. DEEP LEARNING(DL) MODEL ARCHITECTURE

Determination Of The Presence Or Absence Of Pneumonia In Specific Chest X-Ray Images Using A Deep Learning Approach. Convolutional Neural Networks Are Implemented For This, Consisting Of Several 2D Convolutional Layers, 2D Max Pooling Layers, And Finally The Output Of The Last Convolutional And Max Pooling Layer Is Flattened And Fed To A Network With 128 Dense Layers Of Neurons. Finally, It Is Introduced Into The Layer Activated By The Sigmoid Function. Since Our Classification Is Binary And We Used A Sigmoid Activation Function In The Last Layer Of The Deep Learning Network, The Result Is Either Normal Or Pneumonia. [17]

Applies The Sequential Convolutional Layers Specified By The KerasModel To Images.

This Convolutional Layer Has 32 Filters And A (3x3) (3x3x32) Structure. At This Point, The Image Takes On A New Dimension. The Resulting Image Now Has The Shape (29x29x32). The Most Important Is The Second Layer Of MaxpoolMolding (2x2). Again, This Changes The Shape Of The Image.

Also, As Shown In The Second Blue Box In The Figure. 4. The Transformed Image Passes Through Another Convolutional Layer Of The Same Size. This Convolutional Layer Has The Same Structure As The Previous One (3x3x32). Convolutional Layers Are Used To Reprocess The Image To Capture The Finer Details Of The Radiographic Image. The Image Takes On A Shape Other Than (12x12x32).

The Image Is Now Passed Through AMaxpoolingLayer Of Size (2x2). [18]

The ReluFunction Activates All The Previously Mentioned Convolutional Layers. Directed Or Relu Linear Unit Is A Commonly Used Term In Classification [19].

The Output Is Passed To The Neural Network (DNN) Layer At The Final Convolutional Layer And The Input Is Flattened. This Is Then Fed Into The Next Layer, Which Has 128 Neurons, To Analyze The Important Elements Of The Image And Allow The Neural Network To Classify Itself Based On What The Neurons Are Seeing And Calculating.

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This Layer Also Uses AReluActivation Function To Analyze The Input And Determine The Output For That Particular Layer.

To Determine If Pneumonia Is Identified In A Given Chest X-Ray, The Data From This DnnDense Layer Is Passed To A Final Dense Layer With A Single Output Neuron.

The Sigmoid Activation Function Is Often Used When It Comes To Binary Type Output That Needs To Be Split Into Two Main Classes. Therefore, The Deep Learning Algorithm Combining Deep Neural Network And Convolutional Neural Network Is Summarized Above. [20]

VII. SYSTEM ARCHITECTURE

The System Architecture Above Shows That When Building Our System, We Took The Above Mentioned Dataset Of Chest X-Ray Images As Input To Our Developed System And Then After Following These Steps On The Data Preprocessing, The Dataset Will Follow The Data Preprocessing And Data Augmentation Procedures

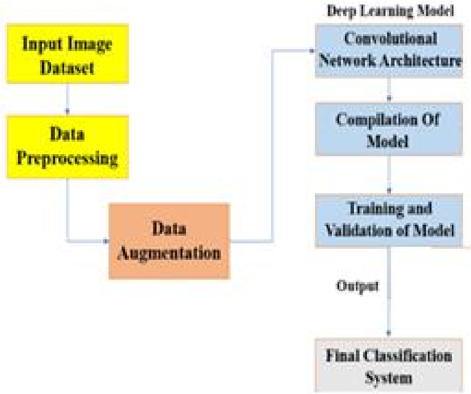

Fig 6.1: System Architecture

Arrive At The Deep Learning Model Stage. At This Point, The Data Is Also Reconstructed, Which Gives Better And More Efficient Results For Different Deep Learning Models. The Data Augmentation Step Takes Into Account A Wide Range Of Parameters, Including Scaling Factors, Shear Extents, And Rotation Extents. This Data Is Then Fed Into A Convolutional Network In A Deep Learning Model, Where It Goes Through Several Processes. To Improve The Results Of The Compilation Phase, Accuracy And Loss Are Quantified As Binary Cross-Entropy Using An Optimizer Called Rmsprop.

Additionally, Convolutional Network Architectures Are Used To Train And Evaluate Models. The Final Classification System For Determining If A Patient Has Pneumonia Is The Result Of All Processes.

VIII. MODEL IMPLEMENTATION

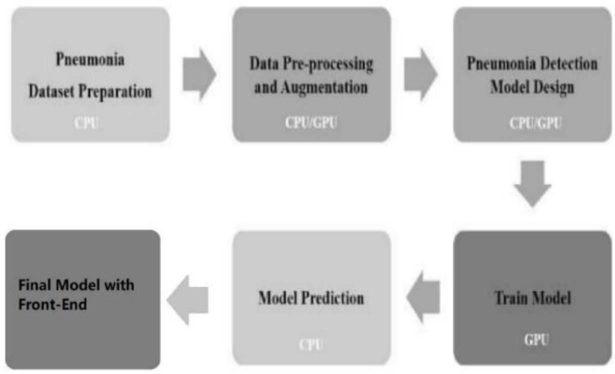

Fig 9.1: Uml Diagram Representing Model Implementation

Users Import Images Into Our System By Accessing The File System. Using The Web UI, Pass The Selected Image As Input To The CNN Model. The Output Of The Additional Preprocessing Of The Images Is The Prediction Of

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Pneumonia Or Normal According To The Stored CNN Model. The Front-End Uses TheAPI Interface To Send Pneumonia Or Regular X-Rays To The Model. Users Will Then See The Results Through The Web UI.

To Prepare A Chest X-Ray Dataset For CNN Model Training, Process It First. We Then Split The Dataset Into A 43:7 Ratio And Used 86% Of The Chest X-Ray Labels (Such As Pneumonia Or Normal) To Train The CNN Model And The Remaining 14% For Testing. The Model Used Is Kept After Validation To Wait For User Input. Once The Template Is Developed, It Will Provide A Visual Interface Where Users Can Insert Their Chest X-Ray Images And Determine If They Have Pneumonia.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 150, 150, 32)      320

 batch_normalization (BatchN  (None, 150, 150, 32)     128
 ormalization)

 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 (Batc  (None, 75, 75, 64)       256
 hNormalization)

 max_pooling2d_1 (MaxPooling  (None, 38, 38, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 38, 38, 64)        36928

 batch_normalization_2 (Batc  (None, 38, 38, 64)       256
 hNormalization)

 max_pooling2d_2 (MaxPooling  (None, 19, 19, 64)       0
 2D)

 conv2d_3 (Conv2D)           (None, 19, 19, 128)       73856

 dropout_1 (Dropout)         (None, 19, 19, 128)       0

 batch_normalization_3 (Batc  (None, 19, 19, 128)      512
 hNormalization)

 max_pooling2d_3 (MaxPooling  (None, 10, 10, 128)      0
 2D)

 conv2d_4 (Conv2D)           (None, 10, 10, 256)       295168

 dropout_2 (Dropout)         (None, 10, 10, 256)       0

 batch_normalization_4 (Batc  (None, 10, 10, 256)      1024
 hNormalization)

 max_pooling2d_4 (MaxPooling  (None, 5, 5, 256)        0
 2D)

 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
_________________________________________________________________
```

Fig 9.1.1:Model Summary

9.1 Model Summary

The Output Shapes Of Each Layer Of The Deep Neural Network And The Amount Of Parameters Included Are Shown In The Model Summary In The Figure Below. The Layers In Our CNN Model, Along With The Size Of The Output Shape And Number Of Parameters For Each Layer, Are Listed In TheOrder They Appear

In The Network. After A Flat Layer With Zero Parameters And A Thick Layer With About 81,000 Parameters, There Are Four Convolutional Layers And The Same Number Of Maximum Clustering Layers. So There Are 1,245,313 Trainable Factors In The Entire Network. This Model Summary Provides Quick Background Details On The Deep Neural Network Used.. [21]

IX. RESULTS AND DISCUSSION

Evaluation Metrics Showing Loss And Accuracy Of Our Model Is Given By

```
20/20 [==============================] - 7s 345ms/step - loss: 0.3027 -
accuracy: 0.9183
Loss of the model is -  0.302651047706604
20/20 [==============================] - 6s 305ms/step - loss: 0.3027 -
accuracy: 0.9183
Accuracy of the model is -  91.82692170143127 %
```

Fig 10.1: Evaluation Metrics

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10.1 Graphical Representation

Validation Accuracy Vs. Training Accuracy Use A Trend Chart To Show How Training And Validation Accuracy Vary With The Number Of Epochs. As Shown In The Figure, The Training Accuracy Increases Dramatically While The Validation Accuracy Increases And Gradually Decreases As The Number Of Epochs Increases. The Training Accuracy At The End Of Epoch 10 Is About 97%, While The Validation Curve Is 87% Accurate. Since We Set Each Epoch To Approximately 163 Steps In The Validation Accuracy Curve Instead Of 39 Steps Per Epoch To Achieve The Best Efficient Results, The Training Accuracy Curve Continues To Increase After Each Epoch.

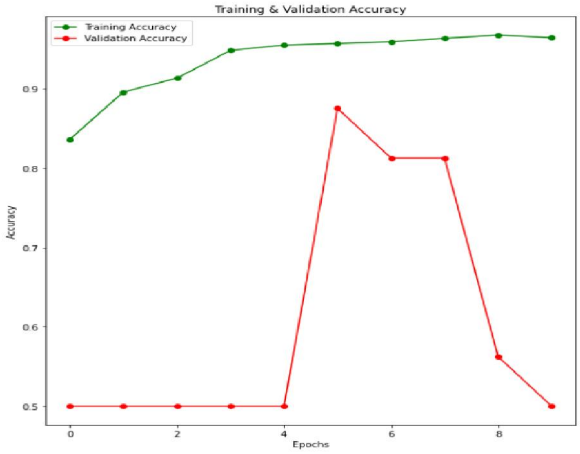

Fig 10.1.1: Training &Validation Accuracy Graph

The Network Loss Changes With Increasing Or Decreasing Number Of Cycles As Shown In Figure 10.1.2 Below. Looking Closer, We See That The Training Loss Decreases Significantly When The Number Of Epochs Reaches 10. With The Loss Greatly Reduced, The Network Becomes More Accurate And Efficient.

At The End Of All Epochs, The Training Loss Is Equal To 0.1026. Since The Number Of Steps Per Epoch Is Less Than The Number Of Steps On The Learning Curve, On The Other Hand, The Validation Loss Increases And Decreases Gradually With The Number Of Epochs. At The End Of All Periods, The Validation Loss Amounts To 0.2841.

Therefore, These Visualizations Support These Findings And Enable Our Network To Efficiently And Accurately Diagnose Pneumonia.

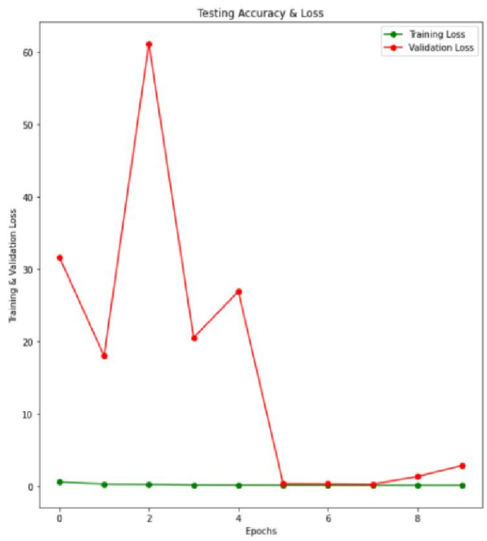

Fig:10.1.2: Training And Validation Loss Graph

10.2 Classification Report Using Confusion Matrix

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.94	0.93	0.93	390
Normal (Class 1)	0.89	0.89	0.89	234
accuracy			0.92	624
macro avg	0.91	0.91	0.91	624
weighted avg	0.92	0.92	0.92	624

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

Fig 10.2.1 Classification Report

XI. CONCLUSION

As A Result, It Can Be Said That The Deep Learning Model Mentioned Above Can Accurately Identify Chest X-Rays Used To Diagnose Pneumonia. In Order To Provide Clear Results For The Classification Of Pneumonia-Infected And Non-Infected Individuals, Model Loss Is Minimized During Training And Accuracy Is Simultaneously Improved At Each Epoch. Convolutional Neural Networks And Deep Neural Networks Work Best When Augmenting And Preparing Data, Avoiding Overfitting And Ensuring Results Are Always Clear. The Proposed Model Accurately Predicts Whether A Specific Chest X-Ray Specimen Has Pneumonia Or Is Normal With Fewer Convolutional Layers. It Is Very Useful In The Medical Industry To Provide Patients With Early And Accurate Diagnosis Of Pneumonia.

If A Person Is Diagnosed Early, Their Life Can Be Saved With Prompt And Effective Care.

Future Scope: Algorithms Could Be Improved To Provide Stepwise Diagnosis Of Pneumonia. The Search Could Be Expanded To Help Doctors Identify Patients With The Pandemic Coronavirus 2020 (Covid-19), Which Has Sickened Many Around The World. The X-Ray-Based Coronavirus Detection Method Will Ensure A Faster And More Accurate Testing Procedure, While Also Reducing The Risk Of Exposure To Medical Personnel Performing The Test. Deep Learning Models For Covid-19 Diagnosis Can Also Be Extended Using Transfer Learning If Enough Data Is Available.

Deep Learning Algorithms Can Also Be Used In Other Medical Diagnostics And Procedures, Such As Chest Bone Pressure For Respiratory Diseases Such As Lung Cancer. As Such, This Work Has Broad Applications In The Healthcare Industry And Could Continue For More Insightful Innovations.

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