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Chest Disease Classification Based on Deep Convolution Neural Network (DCNN)

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Abstract

In this paper, a robust method for diagnosing chest illness from chest X-ray images is designed and implemented utilizing deep learning networks. The goals of the suggested system are to ensure that patients receive the appropriate treatment at the appropriate time, enable prompt and accurate diagnosis, and stop a patient's health from declining. We developed a neural network approach that fine-tunes convolutional layers and hyper parameters to categorize chest diseases into 14 groups. Using a U-net model for lung separation and a Res-Net50 for chest diagnosis, our approach can distinguish between 14 categories of chest illnesses and normal patients. The proposed method showed exceptional diagnostic efficiency with a 92.71% classification model accuracy and a 97% segmentation model accuracy across all classes.

Keywords*— *Convolutional Neural Networks, Chest Diagnosis, U-Net, ResNet-50, Gamma Correction.

I. Introduction

Because they can immediately impact the breathing system, chest injuries are frequently fatal. Pneumonia is one of the most serious and common chest-related illnesses, killing around 1.9 million children under five every year [1]. Because they are affordable and expose patients to comparatively low radiation doses, chest X-rays (CXR) are a commonly serve as a diagnostic technique for chest illnesses [2][3]. Healthcare practitioners can confirm diagnoses thanks to the vital diagnostic information that X-rays valued knowledge must be extracted from vast aggregates of medical imaging data provide. Additionally, this diagnostic tool is accessible to anyone with little to no medical training, which expands its potential uses, including by patients themselves [4]. To prevent a patient's condition from worsening, early diagnosis is essential. Early detection of diseases and rapid intervention by technical specialists can significantly speed up treatment, especially for those living in rural or isolated areas with limited healthcare access [5]. One of the most promising recent developments is deep learning (DL) techniques to assist doctors in their diagnosis. Deep learning approaches have shown impressive results for various uses, particularly in the medical field, including computer-aided diagnosis, prediction, and classification of diabetic macular edema (DME) and detection of diabetic retinopathy (DR) in fundus images [6]. Deep learning has shown promising results for segmentation tasks in fields such as lung disorders, neuroimaging, and cell division [7]. Convolutional neural networks (CNNs), one of the most popular deep learning architectures, are capable of removing hierarchical features from images. Because CNNs can recognize complex patterns and features in images, they have been used to classify various medical images, including chest X-rays. [8]. This paper exploits the ResNet-50 architecture to improve the accuracy of chest disease diagnosis from X-ray images. The proposed system objectives to reach high accuracy in patients' diagnosing situations, which would meaningfully assist doctors in making timely and informed decisions. The system is designed to classify chest X-ray images into two classes normal or abnormal. In abnormal case , the system can additional classify the images into one of fourteen types of chest diseases. Chest X-rays are a key diagnostic tool for lung disorders and provide clear images of numerous infections and conditions. To build an effective and consistent diagnostic model, Researchers must extract valued knowledge from vast aggregates of medical imaging data, which needs the use of advanced **artificial intelligence (AI)** and **big data** methods [9]. The main objective of this paper is to advance an intelligent system skillful of diagnosing a variability of chest diseases using deep learning algorithms. In specific, ResNet-50, a transfer learning model with multiple layers, is employed. The ResNet-50 model is used to solve the vanishing gradient problem, which is a frequent difficulty while training deep neural networks. The network's performance plateaus and eventually deteriorates as a result of this issue, which makes the gradients extremely tiny during training and results in the loss of crucial information. Both the ResNet-50 and U-Net models incorporate batch normalization, which further stabilizes the training process by standardizing layer activations. This reduces errors and raises the system's overall accuracy. This article aims to develop and evaluate a deep learning-based diagnostic system that combines U-Net and ResNet-50 architectures for accurate classification and segmentation of chest diseases from X-ray images. Given the rising incidence of chest diseases and the demand for accurate, automated diagnostic tools in underserved regions, this study contributes to the ongoing effort to integrate deep learning into clinical radiology to improve diagnostic turnaround and reduce misdiagnoses

II. **Literature Survey**

Deep learning algorithms have flagged the mode for important advancements in the scope of computer vision applications, particularly medical image categorization [11]. Jain et al. [12] proposed six models of Convolution Neural Networks to decrease the number of youngsters who die due to phenomena. The proposed models achieved 85.6% and 92.31% validation accuracy respectively, which is improved accuracy. The deficiency of spatial invariance can be an aspect of the limitation of methods. In order to achieve reach perfect accuracy, this paper uses Transfer Learning. Anthimopoulos M. et al. [13] developed a CNN method to classify interstitial lung illness shapes. Their model consists of five convolutional layers, including a leaky ReLU stimulation purpose, average pooling layers, and three dense layers. There are seven classes in the dataset used to train it, as well as the dataset itself. This collection contains 14696 images. Their prototypical had a correctness of 85.5 %. They wish to add 3D classifying images to their model so that it can be utilized as a diagnostic aid. For the lung cancer classification, Bicakci et al. [14] was using a deep learning method, with the proposed technique able to classify into two types such as namely adenocarcinoma and squamous cell carcinoma, the authors use three models of CNN, like SqueezeNet, VGG16, and VGG19 with three types of images. The researchers found that a segmentation method is not necessary for the detection of lung cancer, and thoroughness of the peritumoral area and tissues both contribute to the success of techniques. Guo et al. [15] suggest a model deep convolutional network containing 50 layers is useful for the computerized discovery of numerous lesions in the stomach for endoscopy area. The sensitivity and specificity achieved about 90% and 92% respectively. The model uses only static images. The introduction of computer-aided solutions in the detection of cancer and other kinds of disease can be an evolution in gastrointestinal tract endoscopy. Yan, et al. [16] introduced a DL (FCN) outline to make a classification for chest diseases based on X-rays by using noisy multi-class disease labels. The heat maps were obtained to grow the representative influence of the network. The FCN model compared the results with google net, VggNet, and AlexNet. The quantitative and qualitative results showed superiority over the latest technology application. Chandra & Verma [17] employed five different models to categorize pneumonia illnesses, with the best accuracy of 95,631 percent. Only opinions on autonomously determined non-rigid deformable recording in lung region and feature segmented abstraction limited to "ROI" were included in the model.

TABLE (1) SUMMARIZES THE AUTHORS, MODELS, APPLICATIONS, AND KEY RESULTS.

Author(s)	Proposed Model	Application	Dataset	Accuracy	Additional Notes
Jain et al. [12]	6 CNN models	Medical Phenomena (Child mortality)	Not specified	85.6% - 92.31%	Improved accuracy, limited spatial invariance
Anthimopoulos M. et al. [13]	CNN (5 convolutional layers, leaky ReLU, pooling, dense layers)	Interstitial lung disease	14,696 images	85.5%	Plans to add 3D image classification for diagnostic aid
Bicakci et al. [14]	CNN models (SqueezeNet, VGG16, VGG19)	Lung Cancer (Adenocarcinoma, SCC)	3 types of images	Not specified	Segmentation not required for cancer detection
Guo et al. [15]	Deep CNN (50 layers)	Lesion detection (Stomach, Endoscopy)	Static images only	Sensitivity: 90%, Specificity: 92%	Computer-aided solutions for GI tract endoscopy
Yan et al. [16]	FCN model (compared with GoogleNet, VGGNet, AlexNet)	Chest diseases (X-rays)	Multi-class disease labels	Not specified	Heat maps to enhance network's performance
Chandra & Verma [17]	5 different models	Pneumonia classification	Not specified	95.631%	Non-rigid deformable recording and ROI-based feature segmentation

III. Methodology

A. Gamma Correction Model

In medical image processing, gamma correction is frequently employed to increase contrast and make important features more visible. It enhances the features in the darker or brighter areas of an image by adjusting its brightness using a non-linear transformation. The image's cumulative histogram is typically used to determine the gamma value. To compute the gamma value g, the following steps are performed:

1. Cumulative Histogram Calculation: To examine the distribution of pixel intensities, a cumulative histogram of the image is produced. The ongoing sum of the frequency of pixel values is shown by the cumulative histogram.

2. Calculate C5 and C95: The pixel intensity values C5 and C95, respectively, represent the 5% and 95% cumulative histogram thresholds. Extreme pixel values that are too bright or dark to be useful for the improvement process are eliminated using these criteria.

- The intensity value at which the cumulative distribution approaches 5% of the total is denoted by C5.
- The intensity value at which the cumulative distribution reaches 95% of the total is denoted by C95 Determine the Average, Supreme, and Smallest Values: From the equation (1) :

$$g = \frac{\log\left(\frac{C95}{C5}\right)}{\log\left(\frac{C_{\max}}{C_{\min}}\right)} \quad \text{……..(1)}$$

Where:

- C95 is the pixel intensity corresponding to 95% of the cumulative histogram.
- C5 is the pixel intensity corresponding to 5% of the cumulative histogram.
- C_{max} and C_{min} represent the maximum and minimum pixel intensities in the image.

By adjusting the image contrast and enhancing the visual quality of medical images, this gamma value helps medical practitioners identify and analyze problems more easily. The following formula can be used to normalize the gamma value g between 0.9 and 1.1. By keeping the gamma value within a predetermined range, normalizing helps to prevent it from deviating too far from the usual gamma values for image enhancement. The normalization equation illustrative in equation (2):

$$g_{\text{normalized}} = 0.9 + \left(\frac{g - \min(g)}{\max(g) - \min(g)}\right) \times (1.1 - 0.9) \tag{2}$$

Where: g : The normalized gamma value between 0.9 and 1.1.

The gamma alteration technique, which makes use of the normalized g value, increases the image's difference. In the improved picture G, which is produced by equation (3) [19]:

$$\boldsymbol{G}(\boldsymbol{x}, \boldsymbol{y}) = (\boldsymbol{f}(\boldsymbol{x}, \boldsymbol{y}))\ g_{1} \tag{3}$$

Where f(x ,y) :contribution concentration x-ray image

B. U-net Model for Division Images

To extract the crucial regions (the lungs region) from the chest X-ray, a division or segmentation model is used [20]. As seen in figure 1, the U-net model, which was suggested for lung segmentation, has good segmentation. Convolution, pooling, and up sampling layers are among its components. When it came to accurately segmenting the entire lung area in chest x-ray images, the original U-net was superior. The U-net has been deepened with batch normalization layers and a failure prior to the production layer. The intended network consists of an encoder and a decoder, with feature maps generated by each encoder unit being replicated to a decoder unit. Even in healthy individuals, the borders of lung regions in X-ray pictures can vary significantly in size, shape, and contrast. A more profound network and batch [21]. The U-net follows two principles:

- The U-Net architecture is fully symmetric.
- Instead of using a full administrator, The skip connections between the upsampling and downsampling paths and the down sampling path use a concatenation manager [22].

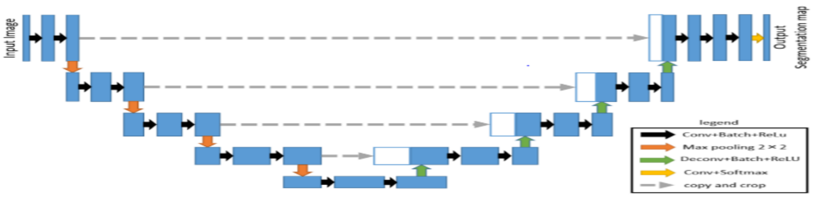

Fig. 1. U-Net Model

C. ResNet-50 Model

Increasing the number of layers in deep learning networks typically aids in capturing more intricate characteristics. But eventually, just adding more layers results in diminishing benefits. The accuracy saturates and finally starts to deteriorate as the network gets deeper. This problem happens as a result of overfitting and increasing mistakes in the model during training. In essence, additional layers may hinder the network's ability to generalize effectively to unknown data, which could result in subpar performance.

- ✓ The Degradation Problem:
- ✓ The degradation problem in deep networks happens when additional layers don't lead to greater performance. Instead, the increasing complexity makes the network harder to train, resulting in vanishing gradients, overfitting, and greater mistakes. This limits the potential to improve the performance of the network as the number of layers grows.

Microsoft launched the Residual Learning Framework—more especially, the ResNet architecture—to solve this problem. One of the most often used Convolutional Neural Network (CNN) variations is ResNet-50. ResNet-50's main concept is the use of skip connections, also known as residual connections, which let the network learn residual mappings instead of the unreferenced mapping directly, so avoiding the degradation issue.

Skip Connections: These are additional connections that skip one or more layers during the learning process, directly passing information from one layer to the next. This helps to alleviate the vanishing gradient problem and enables the training of much deeper networks. In a residual block, the output from a previous layer is added to the output of a subsequent layer, allowing the model to focus on learning the residuals (differences) rather than directly mapping the features.

Batch Normalization: This technique normalizes the input of each layer by adjusting and scaling the activations, which helps in speeding up training and improving model performance, especially in deeper networks.

The construction of the ResNet-50 DL model is exposed in Figure (2). The residual connections include two types:

1. The first type, if the dimensions of the productions and inputs are the same, then identity shortcuts (x) used directly.

$$y = \mathscr{F}(x,\{Wi\})+ x \qquad (4)$$

Where Wi is the weight of the convolutional layer .

2. The second category, after the dimensions are dissimilar, in adding to the shortcut, zero amplified resolve to be additional, thus the dimensions will increase, where a linear projection Ws a shortcut will be utilized to brand the dimensions corresponding, as showed in the calculation (5).

$$y = \mathscr{F}(x,\{Wi\})+ Wsx \qquad (5)$$

where Ws is the square matrix.

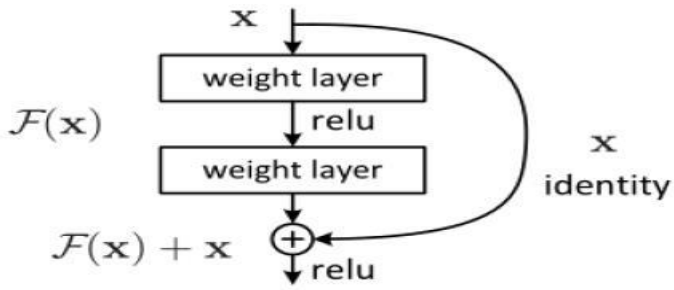

Fig.2. The residual identity mapping

IV. Proposed System

The proposed system consists of **two main stages**: **Image Preparation** and **Deep Learning (DL) Models**. Figure (3) illustrates the general medical image preparation process and the steps involved in using deep learning models for segmentation, cropping, and classification. Here's a detailed breakdown of each stage:

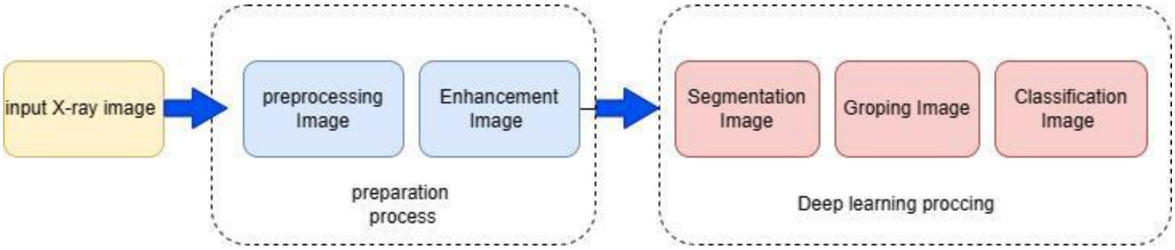

Fig.3. General Proposed System Block Diagram

A. Chest X-ray Images Dataset

The proposed method makes use of the "Chest X-ray 14" dataset, which was initially provided by Wang et al. [25]. With 3,180 chest X-ray images, this dataset is a great tool for developing and evaluating deep learning models for medical image processing.

• Size: 3,180 X-ray images; dataset: Chest X-ray 14 by Wang et al.
• Labels: Fifteen ailments, including effusion and pneumonia.
• Data Split: 15% is used for validation, 15% is used for testing, and 70% is used for training.

Fig.4. Simple of Chest X-ray 14 Dataset

This dataset is needed for training deep learning models for accurate image segmentation and classification. The Medical Image Preparation Phase, which includes pre-processing and image enhancement, optimizes X-ray images to improve segmentation, enable efficient cropping, and raise diagnostic accuracy.

B. Image Preparation Process

At this point, the medical image is optimized through a number of processes before being fed into the deep learning model:

• Size and Dimension modifications: The input image was modified to ensure that its dimensions are appropriate for the neural network. This step ensures that the image meets the required input size for the DL model, whether it be a fixed size or a standard aspect ratio.

• Image enhancement techniques: include contrast modification, de-noising, or gamma correction are used to make important features (such the rib cage or lung areas) more evident in medical imaging. This is a crucial step to make sure the image has clear and identifiable elements for better analysis. Using gamma correction enhances contrast and detail visibility. We use the image's cumulative histogram (e.g., C5 to C95 range), the gamma value is dynamically adjusted to highlight critical regions, such as the lungs or lesions, without over- or under-exposing them.

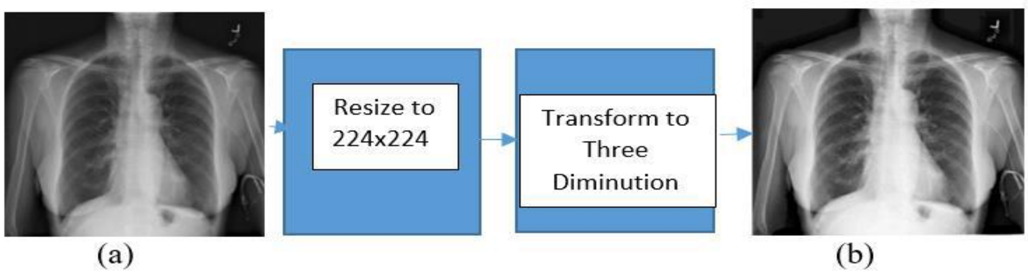

Fig.5The process of preparing a chest X-ray image Prior to Enhancement b) After Enhancement

C. Deep Learning (DL) Models

After preprocessing, the system uses deep learning models to segment, crop, and classify images for diagnostic purposes: The system processes medical images in three steps: categorization, cropping, and segmentation. A deep learning network, such as U-Net, initially segments the image to identify key regions, such as the rib cage or lungs. The segmented area is then trimmed to highlight the needed area in order to reduce the computational effort. Finally, the segmented image is classified to identify lung illnesses, pneumonia, and cancer.

1) U-Net Lung Segmentation phase

In the Segmentation Phase, the region of interest (ROI), such as the lungs, was located and isolated using the U-Net model. This makes it possible to precisely crop the pertinent area for better classification, as shown in Figure 7

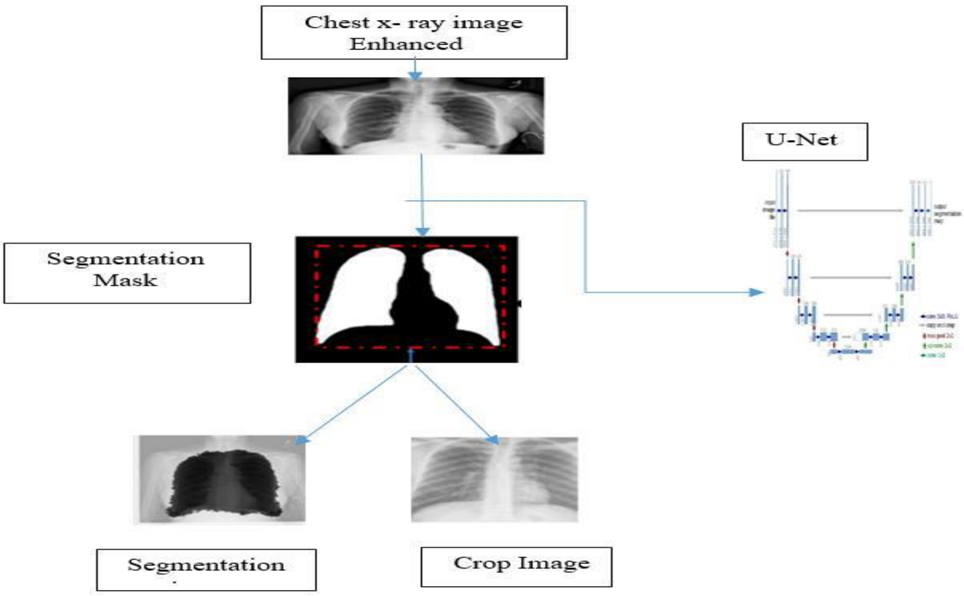

Fig.6. U-Net Lung Segmentation

2) ResNet-50 Phase

For an appropriate diagnosis, this classification phase makes sure the model concentrates on the most pertinent image regions. Because of its high performance in medical imaging and deep learning efficiency, ResNet-50 was used. It employs Softmax activation and feature extraction to accurately forecast conditions like edema, as shown in Figure 8.

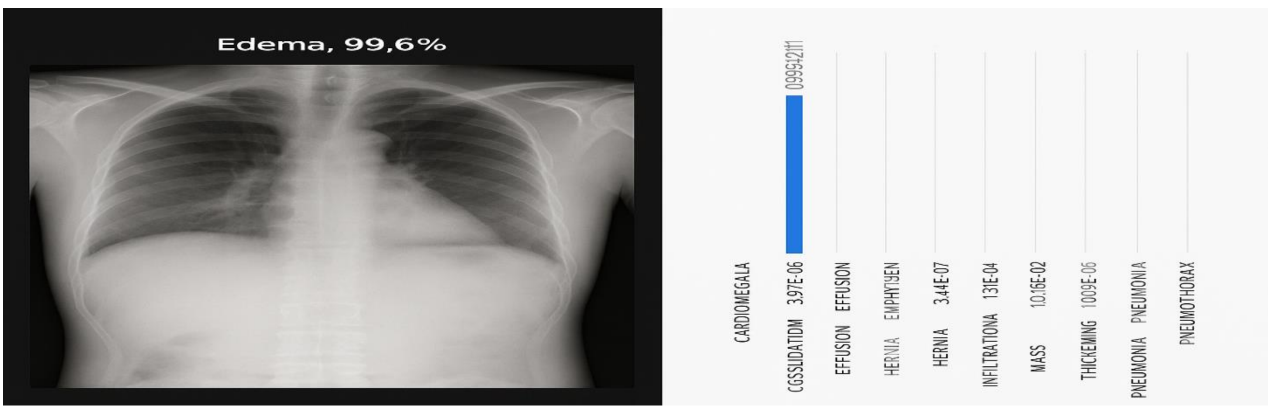

Fig 7. diagnosis the chest x-ray and probabilities of classes

V. Result And Discussion

After the pre-processed image was obtained from the image preparation phase, it was segmented, which entailed locating and trimming the Region of Interest (ROI). The U-Net deep learning model, which is renowned for its effectiveness in medical picture segmentation tasks, especially for lung X-rays, was used to carry out the segmentation.

Three primary evaluation measures were employed to asses

s, the segmentation results:

1) Global Accuracy:

The ratio of correctly categorized pixels to all pixels in the image is known as global accuracy. An overall assessment of segmentation performance is provided by this metric.

$$\text{Global Accuracy} = \frac{\text{Correctly Classified Pixels}}{\text{Total Number of Pixels}} \tag{6}$$

2) Accuracy Score:

The percentage of correctly categorized pixels (T) relative to all relevant pixels (T + F) is known as the accuracy

score, where:

$$\text{Accuracy Score} = \frac{T}{T+F} \tag{7}$$

- T = True Positives (pixels that correctly classified)
- F stands for false positives, or pixels that were erroneously classified.

3) Mean Accuracy:

Mean accuracy provides the average accuracy across all classes. It helps evaluate the performance for multi-class segmentation, accounting for the accuracy per class.

$$\text{Mean Accuracy} = \frac{\sum_{i=1}^{n} \text{Accuracy of Class i}}{\text{Number of Classes}} \tag{8}$$

Where **n** is the total number of classes.

4) Jaccard Index (Intersection over Union, IoU):

One popular statistic for image segmentation tasks is the Jaccard Index, sometimes referred to as Intersection over Union (IoU). It calculates the ratio of the intersection area (the overlapping region between the predicted and ground truth masks) to the union area (the entire area covered by both the predicted and ground truth masks). When assessing how well the segmentation model represents the real area of interest (in this case, the lungs), the Jaccard Index is especially helpful.

$$\text{Jaccard Index (IoU)} = \frac{\text{Intersection Area}}{\text{Union Area}} \tag{9}$$

The overlap between the expected and actual lung areas is measured by this metric. An improved segmentation performance is indicated by a greater IoU.

5) Mean BF Score:

The model's ability to segment the boundaries of objects—in this case, the lung regions—is measured by the Mean BF Score, also known as the Boundary F1 Score. It provides a balanced metric for border segmentation accuracy by accounting for both precision and recall.

$$\text{Mean BF Score} = \frac{1}{N}\sum_{i=1}^{N} \text{BF i} \quad (10)$$

where

- N = Number of objects, images, or regions evaluated.
- BF Score = BF Score for image or object number

A. *Classification Result*

The ResNet-50 deep learning model was utilized for chest X-ray classification because of its capacity to manage deep architectures and address vanishing gradient issues. An overview of the training parameters and classification results is provided below:

Training Parameters:

During training, the network is optimized using a learning rate of 0.0001.

• Optimization Algorithm: Mini-batch Stochastic Gradient Descent (SGD) was used to update the model weights.

• Batch Size: 10, which indicates that the model was trained using ten images at a time.

• Maximum Iterations: 13,320, which is the total number of training iterations the model underwent.

The model performed well in classifying chest X-ray images for illness diagnosis when these parameters were used.

1) *Performance of the Model:*

• Area Under Curve (AUC): With an AUC of 0.9261, the ResNet-50 model showed exceptional classification performance across all classes. The AUC of the model indicates its ability to distinguish between distinct disease categories; a higher AUC value indicates superior overall performance.

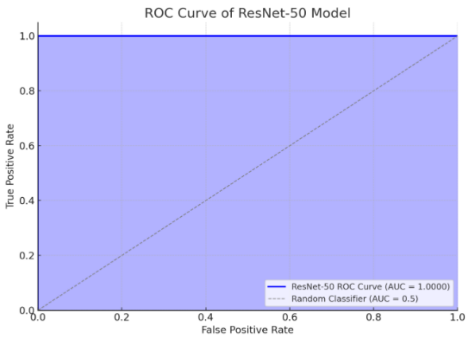

Fig 8. ResNet50 Classification

• Accuracy: The categorization model showed outstanding accuracy for a variety of chest situations.

- ✓ Top Accuracy: The Edema illness category, which contained 88 photos, had the highest classification accuracy, at 97.77%.

✓ Lowest Accuracy: The Hernia disease category had the lowest accuracy (87.56%) out of 88 photos.

These findings demonstrate how well the ResNet-50 model can identify chest conditions from X-ray images.

Classification Accuracy:

The proposed method produced impressive categorization results for chest X-ray images. The diagnostic's total accuracy was 92.71%. An overview of the model's performance across many datasets (training, validation, and testing) is shown below:

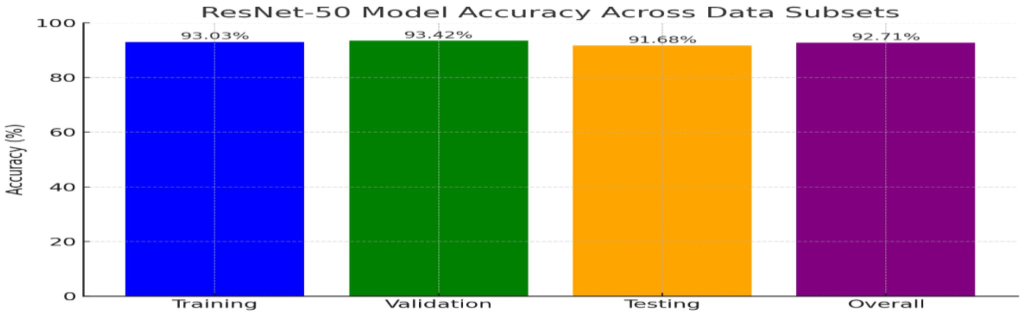

Fig 8. ResNet50 Model Accuracy

These outcomes demonstrate the ResNet-50 model's strong performance and ability to generalize across various data subsets.

2. *Training Time and Performance Result*

A total of roughly 17 hours of training were needed for the proposed system. The effective training method, which included freezing the early layers and tweaking hyperparameters like the learning rate and batch size, allowed for this comparatively short training time. In order to minimize health deterioration and guarantee prompt treatment, the Chest Disease Diagnosis System was created to enable medical practitioners reliably diagnose illnesses related to the chest. Using chest X-ray pictures, this system uses deep learning (DL) algorithms to give accurate and effective diagnosis. Table 2 illustrates this.

TABLE 2. PERFORMANCE RESULT

Dataset	Accuracy
Training Dataset	93.03%
Validation Dataset	93.42%
Testing Dataset	91.68%
Overall Accuracy	92.71%

All things considered, the Chest Disease Diagnosis System has a great deal of promise for the medical imaging industry. This study's deep learning algorithms are a great tool for medical professionals since they can accurately diagnose common chest ailments from X-ray images. With 97% segmentation accuracy and 92.71% classification accuracy, the system's performance demonstrates how well it may support the identification of chest illnesses, potentially improving the diagnostic procedure in clinical settings.

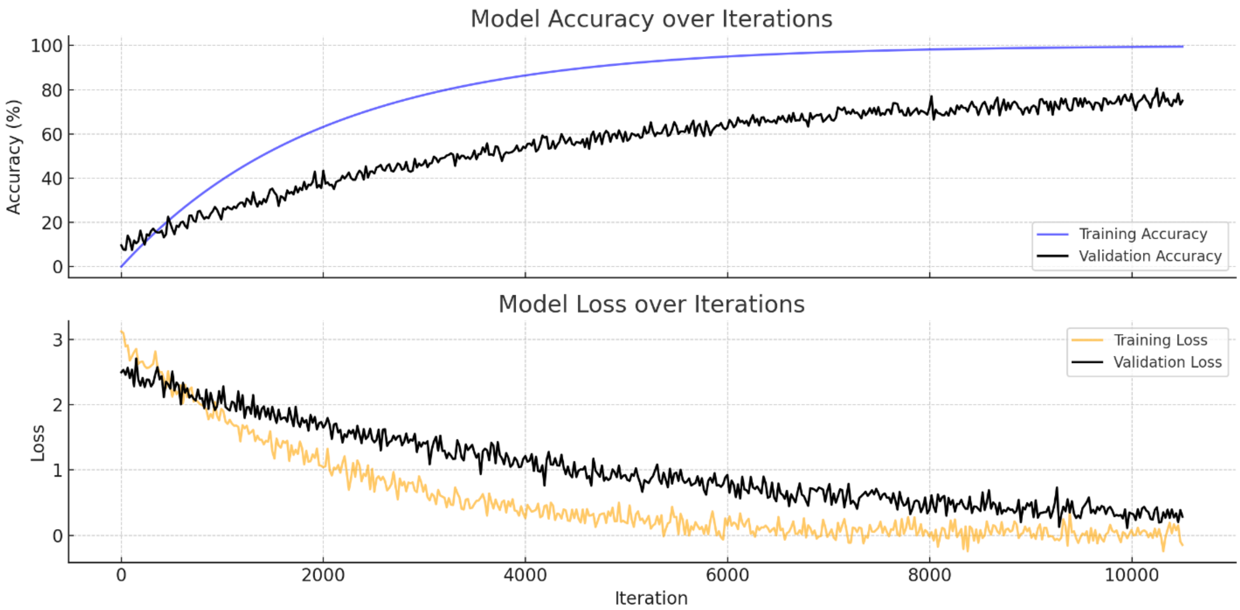

Fig 9. Validation and Training performance in classifying chest X-rays

VI. Conclutions

The Chest Disease Diagnosis planned system was created to help doctors diagnose the patient's condition and avoid the deterioration of the patient's health and thus get the right treatment at the right time; it has been drawing on the power of deep learning networks: Reliable diagnosing chest diseases has been designed and implemented on chest X-ray medical images. The planned system investigates an intelligent technique such as DL algorithms to diagnose and distinguish the most common types of chest diseases depending on the chest X-ray images. The proposed system consists of a number of phases. We begin with a preprocessing phase that uses gamma connectors to enhance the row x-ray images and increase accuracy, then subdivide the ROI area from images based on U-Net architecture. We used tiny patches derived from the original images to train the U-Net architecture. Small cropped patches were added to the U-Net architecture. The proposed system successfully combines U-Net and ResNet-50 deep learning architectures to classify chest diseases from X-ray images, achieving 97% segmentation accuracy and 92.71% classification accuracy. By applying gamma correction and advanced feature extraction, the system enhances diagnostic precision, supporting timely interventions in clinical settings. This demonstrates the potential for integrating deep learning frameworks into radiological diagnostics to augment medical decision-making.

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