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High-Performance Detection of Pulmonary Diseases in CT Images Using PFC-DenseNet121 and Binary Robust Independent Elementary Features

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Abstract—**A serious interstitial lung disease called pulmonary fibrosis (PF) causes the lung tissue to gradually scar, impairing respiratory function irreversibly and posing serious health risks. CT scans play a pivotal role in diagnosing lung diseases by providing detailed cross-sectional images with offering a more comprehensive view of lung structures compared to conventional imaging methods. This study introduces an enhanced DenseNet architecture combined with BRIEF (Binary Robust Independent Elementary Features) for effectively detecting pulmonary fibrosis in CT scan images. The model identifies critical regions of interest by integrating BRIEF for keypoint detection and local feature extraction while maintaining computational efficiency. The modified DenseNet, named PFC-DenseNet, incorporates additional layers and attention mechanisms to improve feature extraction, mitigate the vanishing gradient problem, and ensure robust performance. Preprocessing techniques, including resizing and normalization and further enhance the network reliability by reducing overfitting. A pulmonary fibrosis dataset with tagged CT images is used to train and assess the model. It demonstrates improved performance in terms of accuracy, sensitivity, specificity, F1 score, and precision. Additionally, it effectively identifies affected areas in CT images associated with pulmonary fibrosis.**

Keywords: ***Binary Robust Independent Elementary Features (BRIEF), Classification, Convolutional Neural Network, CT images, Deep Learning, PFC_DenseNet, Pulmonary disease.***

I. INTRODUCTION

The second stage of lung diseases is pulmonary fibrosis, which mainly affects in olden age people at the age of above 50 in the United States. Pulmonary fibrosis refers that lungs scars tissue formation and it mainly occurs in lungs, which impairs the ability to deliver oxygen to the bloodstream. This disease causes the abnormality in the lungs and which disturbs normal breathing. Computed tomography (CT) plays a vital role in identifying and diagnosing lung diseases more accurately with the help of high-resolution imaging. Pulmonary fibrosis has a variety of causes. Pulmonary fibrosis may be classified as idiopathic arising without a clearly identifiable cause or it may result from factors such as chronic infections, autoimmune conditions, environmental pollutants, or adverse reactions to certain medications. Pulmonary fibrosis (PF) is a chronic and progressive lung disorder marked by the scarring of the pulmonary interstitium, which diminishes the effective surface area for gas exchange and can eventually lead to respiratory failure. This is an implication of timely identification leading to earlier crippled health-pitting for the stronger patients in minimizing ineffective intercession. Traditional diagnostic procedures such as CT scans and lung biopsies are time-consuming, invasive, and expensive. To combat these challenges, machine learning techniques, especially deep learning, offer huge the potential to increase the diagnostic accuracy and helping clinicians to refrain from invasive procedures.

This work presents a modified DenseNet-based architecture for pulmonary fibrosis detection using Binary Robust Independent Elementary Features (BRIEF). DenseNet [2] is based on a deep convolutional neural network (CNN) architecture that is noted for its efficient parameter use and strong feature extraction capabilities. To enhance the sensitivity and accuracy of PF detection, the Binary Robust Independent Elementary Features (BRIEF) with a feature detection algorithm would be integrated for this purpose. In this research work will be improving the computer vision method for the detection of PF by modifying the DenseNet (a convolutional neural network (CNN) architecture).

CT scan performs an accurate identification for pulmonary fibrosis disease diagnoses compared to the x-ray imaging modality. A convolutional neural network gives better efficiency for the recent development in deep learning medical diagnosis.

II. RELATED WORK

Pulmonary fibrosis has spurred significant advancements in lung disease detection research. Numerous approaches have been presented in the research literature and various research studies have been done.

Medical imaging systems like CT and X-ray are vital for non-invasive disease diagnosis but can suffer from noise, artifacts, and low resolution leading to classification errors in CNN models. To address this Al-Sheikh et. al [3] proposed an image enhancement method to utilize non-

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linear functions like Lerch transcendent functions (LTFs) to manage noise and lighting variations while preserving edges and fractional calculus is applied to enhance contrast by adjusting pixel intensities. By incorporating the k-fractional symbol in LTFs the model improves image clarity with 98.80% & 98.60% accuracy of disease classification for CT and X-ray images.

Krishnan et al. [4] introduced an image enhancement technique for medical images based on sunflower optimization. To improve visual quality, the technique first uses a modified median filter to denoize input images, then increases pixel intensity. The method's overall performance and effectiveness may be impacted by difficulties with parameter tuning, such as modifying population size, maximum iterations, and other algorithm-specific factors. Ibrahim et al. [5] described a fractional calculus-based method featuring a novel fractional partial differential class to enhance low-contrast images of the brain and lungs. However, this approach is primarily tailored to address the challenges of low-resolution images.

Mahapackialakshmi K and Jaffino [6] described an innovative method for lung disease detection by integrating U-Net for accurate lung segmentation with Scale-Invariant Feature Transform (SIFT) for feature extraction. U-Net effectively segments lung regions from chest X-rays, while SIFT extracts critical image features that highlight potential lung abnormalities. Ramalho et. al [7] presented an innovative lung disease detection approach that extracts features from ACACM-segmented images within the cooccurrence statistics framework. It employs the Spatial Interdependence Matrix (SIM) to analyze lung structural details, which are subsequently classified using an Extreme Learning Machine Neural Network (ELMNN). This method achieves a 96% accuracy rate in differentiating between normal lungs, COPD, and fibrosis.

Rashid et. al [8] proposed a Feature-Extracted Graph Convolutional Network (FGCN) for diagnosing COVID-19 using CT scans. Unlike traditional CNNs that utilize filters and pooling layers, FGCN incorporates Graph Convolutional Networks (GCNs) to capture spatial connectivity features. A U-Net model is employed for segmentation and feature extraction, converting the deep features into a graph-based adjacency matrix for classification while enhancing the classification accuracy of 99.19%

Shamrat et. al [9] described a fine-tuned MobileLungNetV2 model to diagnose multiple lung diseases. The preprocessing pipeline includes CLAHE for enhancing image contrast, Gaussian filtering for noise reduction, and data augmentation to improve model robustness. Among various transfer learning techniques, MobileNetV2 stood out with the highest initial accuracy of 91.6%, which was further enhanced to 96.97%. Grad-CAM was utilized for heatmap visualization effectively demonstrating the model's remarkable ability to classify pulmonary fibrosis with a striking accuracy of 99.62%, surpassing its performance in other lung disease classifications.

Goyal et. al [10] presented a framework for predicting COVID-19 and pneumonia from chest X-ray images. It employs median filtering and histogram equalization for image quality enhancement, followed by a modified region growing method for ROI extraction. Key features such as visual, shape, texture, and intensity are extracted and normalized for classification. Among various classifiers tested, the proposed RNN-LSTM model outperforms others, demonstrating high accuracy and robustness in experimental results. The research introduced a distance-based method aimed at enhancing similarity-based matching. It also utilized the contourlet transform to propose an edge detection approach specifically for forensic dentistry, as outlined by Jaffino et al. [11]

Deep learning techniques have significantly advanced medical image analysis by enhancing diagnostic precision and minimizing manual intervention. Wan.Z et. Al [12] introduces an innovative model for metastatic cancer classification, employing DenseNet, Rectified Adam (RAdam), and focal loss. DenseNet excels in extracting intricate features, while RAdam contributes to stable and efficient training processes. Zahid et al.[13] Proposed the Densely Attention Mechanism-based Network (DAM-Net) for automated COVID-19 detection in chest X-ray (CXR) images. In order to guarantee precise COVID-19 case identification, the model effectively collected key visual features. The model's overall performance was further improved by the addition of the DenseNet architecture, which improved the model's feature extraction capabilities.

III. Proposed Methodology

The proposed approach detects pulmonary fibrosis with excellent accuracy by combining the resilience of BRIEF with the feature extraction power of DenseNet. Figure 1 shows the suggested flow diagram for the detection of pulmonary fibrosis (PF).

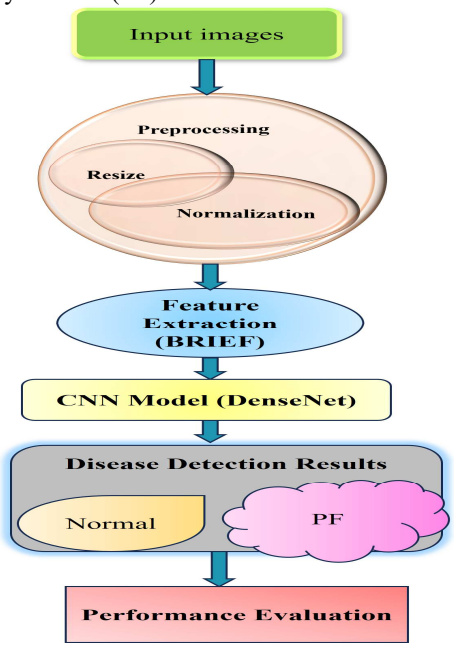

Fig. 1 Proposed Flow Diagram for Pulmonary Fibrosis (PF) Detection

The process of preprocessing is to improve the resilience of the model and reduce overfitting. Preprocessing methods like normalization and scaling are used before feeding CT scan data into the network. Additionally, BRIEF-based feature extraction is applied to effectively identify important areas of interest in the images. Keypoint detection and local feature extraction from CT scan images are part of the

BRIEF (Binary Robust Independent Elementary Features) integration process. High-level feature representations are then obtained by feeding these binary descriptors into the updated DenseNet model. The model efficiently focuses on important areas of the image, like those suggesting possible fibrosis, while maintaining computational efficiency due to the addition of BRIEF. In feature analysis, this method maximizes scale consistency while preserving relevance.

A. Data set Description

The publicly accessible dataset was used in this research. Pulmonary fibrosis Dataset gathered from Kaggle. The collection consists of 3,182 CT images, pulmonary CT scan images. The image dataset is partitioned into two classes: the abnormal class consisting of images displaying pulmonary fibrosis and the normal classes consisting of images without the condition. It is divided into three subsets. Training, validation, and testing with (1,178 pulmonary fibrosis and 1,050 normal images) 2,228 images in the training set. Validation and testing parts are separated equally (252 with pulmonary fibrosis and 225 normal). To achieve a pixel resolution of 224x224, the images were shrunk. The datasets were pre-processed, then randomly split into 80% training and 20% test data. The classification models were trained on lung classification using 80% of the training data. To assess the classification model, the remaining 20 percent of the data was employed.

B. Preprocessing

A DenseNet121-based classification model preparation stage involves transforming CT images to maximize feature extraction and improve model performance. Enhancing the input resolution to 224x224 ensures that DenseNet121 dependably learns features across the input space. Moreover, normalization scales the pixel intensity values to a range between 0 & 1, which improves training stability and promotes quicker convergence. DenseNet121 can differentiate between pulmonary fibrosis patients and normal individuals thanks to these preprocessing steps, ensuring accurate and reliable classification results.

C. Feature Extraction

A feature extraction technique called Binary Robust Independent Elementary Features (BRIEF) was created to identify important patterns in images before they are classified. It significantly lowers computational complexity by efficiently encoding important structural features in a small binary representation. Because of its effectiveness, BRIEF is especially well-suited for deep learning models such as DenseNet121. BRIEF improves the model's ability to distinguish between cases of pulmonary fibrosis and normal by extracting key features with little computational overhead which raises the classification accuracy.

D. CNN Model for Classification

Images are classified as either normal or pulmonary fibrosis (PF) using a Convolutional Neural Network (CNN). The CNN is given the features gathered during the BRIEF stage, which helps it recognize and pick up patterns efficiently. Lung disorders like pulmonary fibrosis can be detected with great success using deep learning approaches, particularly convolutional neural networks (CNNs) based on designs like VGGNet, ResNet, moblieNet, and DenseNet. Using its dense connectivity to improve feature propagation and maximize the utilization of lower-level features, DenseNet is notable among these for its outstanding performance in medical image categorization.

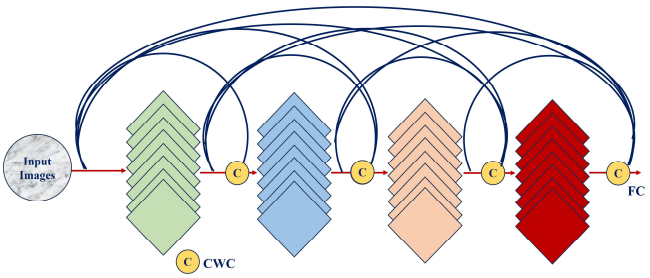

Fig: 2 DenseNet Connectivity architecture

DenseNet Connectivity architecture is shown in Figure 2. and it represents the connectivity in DenseNet where each layer not only receives input from all preceding layers but also passes its feature maps to subsequent layers through Channel-Wise Concatenation (CWC). This design promotes efficient feature reuse and ensures improved gradient flow. Feature Concatenation (FC) improves efficiency and feature utilization by combining the outputs of each layer with those of all preceding levels rather than replacing them. DenseNet efficiently reduces the amount of parameters, resolves vanishing gradient concerns, and improves overall accuracy in contrast to traditional CNNs that stack layers sequentially.

This study modifies DenseNet-121's design by adding numerous dense blocks, where each layer creates feed-forward connections with every other layer to improve the network's effectiveness in identifying pulmonary fibrosis. The vanishing gradient problem is lessened and effective feature reuse is encouraged by this extensive connection. Additionally, introduce refinements such as embedding attention mechanisms to refine feature representation by concentrating on significant lung regions effectively highlighting essential features and prioritizing critical areas for improved analysis and utilizing smaller convolution kernels (3x3 or 1x1 convolutions) to further optimize feature extraction and improve accuracy. These modifications are done in E-DenseNet121 with a detailed explanation shown in Figure 3.

In the DenseNet framework, dense connections can be expressed as follows:

$$X_l = H_l(X_0, X_1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots X_{l-1}) \qquad (1)$$

Where, $[X_0, X_1 \ldots\ldots]$ denotes the concatenation of the feature maps generated by the layers $[0,1,.. L_{th}]$ layers. The model is trained on an extensive dataset of CT scan images annotated with labels indicating the presence and absence of pulmonary fibrosis.

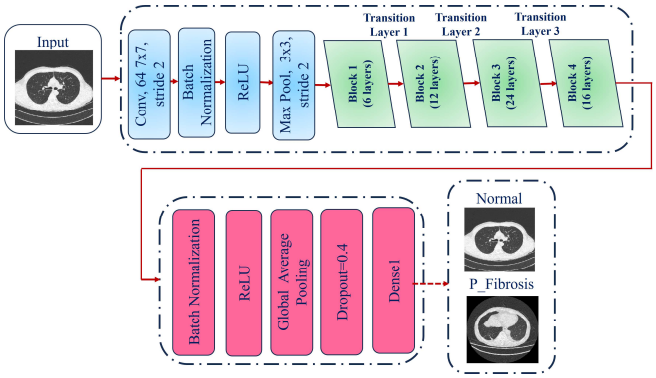

Fig: 3 Modified DenseNet-121 architecture

A Conv7×7 layer and MaxPooling are used at the start of the model to extract key features from the input CT image while decreasing its spatial resolution, as seen in Figure 3. This is followed by four Dense Blocks, each composed of multiple convolutional layers. Within these blocks, every layer is directly connected to all previous layers within the same block and promoting feature reuse and enhancing gradient flow to address the vanishing gradient problem. Transition Layers are positioned after each Dense Block (except the last), decreasing the spatial dimensions and the number of feature maps to ensure the model remains efficient and compact. After Batch Normalization, a Global Average Pooling layer is applied to the output then combining all of the spatial data into a single vector. The last Dense layer with a sigmoid activation produces a binary output: 0 for Normal and 1 for Pulmonary Fibrosis. A Dropout layer (set at 0.4) is used to minimize overfitting.

Algorithm: CT Image Classification

Input: CT Scan images
Preprocessing:
Images should be resized to 224x224 pixels (normal size).
Adjust pixel values to a standard range between 0 and 1.
Training:
Divide the dataset into two parts: 20% for validation and 80% for training.
Feature Extraction:
Utilize a DenseNet CNN model with BRIEF to extract relevant features from the CT scan images.
Classification:
Utilize a fully connected neural network to categorize the extracted features into distinct classes, determining the presence or absence of specific abnormalities within the dataset.
Output: classification of normal and pulmonary fibrosis & affected area of pulmonary fibrosis
Affected area =Contour Area/Image Area

E. Evaluation Metrics

Clinical dependability and diagnostic accuracy must be given top priority in evaluation measures for pulmonary fibrosis classification using CT images. Reducing false positives and false negatives is essential to addressing the grave consequences of misdiagnosis. Metrics including sensitivity, specificity, F1 Score, precision, and accuracy are essential for assessing the model's effectiveness in real-world clinical contexts. The equations are provided below. Accuracy (ACC) is used to measure the proportion of correct predictions. Recall measures how many actual positives are correctly identified. Precision measures the percentage of correctly predicted positives. When working with unbalanced classes, the F1 score is very helpful because it strikes a compromise between recall and precision. The model's ability to prevent erroneous positives is measured by its specificity (Spec).

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$RECALL = \frac{TP}{TP + FN} \quad (3)$$

$$PREC = \frac{TP}{TP + FP} \quad (4)$$

$$F1 = \frac{2 * (PREC * RECALL)}{(PREC + RECALL)} \quad (5)$$

$$SPEC = \frac{TN}{TN + FP} \quad (6)$$

$$\text{Affected area} = \frac{\text{Contour Area}}{\text{Image Area}} \quad (7)$$

IV. RESULTS AND DISCUSSION

High-resolution chest CT scans were gathered from Kaggle specifically to help with the diagnosis and evaluation of pulmonary fibrosis, and they make up the dataset used in this work. The dataset's 3,182 images are divided into sets for testing, validation, and training. In order to enhance the process and streamline workflow, the research started with the integration of necessary software tools and modules using well-known packages like TensorFlow. The model accuracy and loss plots, which illustrate the evolution of training and validation accuracy over 37 epochs, are shown in Figures 3 and 4. Despite the initial aim for 50 epochs of training, early halting caused the process to end at 37 epochs. This choice was used because prior to finishing all 50 epochs, the validation accuracy had stabilized and had stopped improving, suggesting that the model had attained its peak performance. Using a customized DenseNet121-based model with modified layers and parameters, the classification of CT images into Normal and Pulmonary Fibrosis was achieved with an improved accuracy of 98.74% as shown in the Figure 4.

The classification results are displayed in Figure 5. The picture shows a step-by-step process for locating and emphasizing pulmonary fibrosis in a CT scan. The first frame displays the original grayscale CT scan, which displays the whole anatomy, including the lungs, bones, and surrounding tissues.

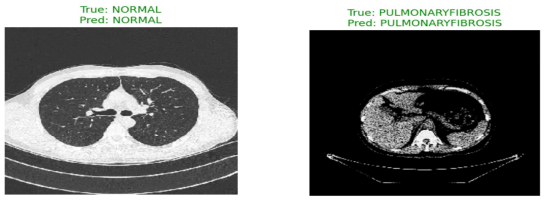

Fig: 4 Classification results

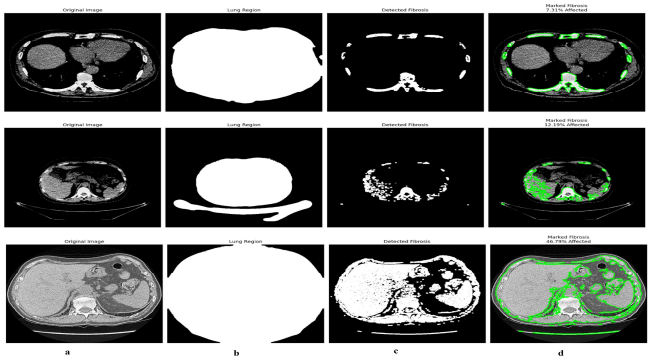

Fig: 5 Classification Results with affected Region
(a) Original CT image, (b) Lung Region Image (c) Detected Fibrosis Images (d) Region of the affected area

The second frame shows a binary lung mask that isolates the lung region (white) from the rest of the anatomy (black) to guarantee that additional evaluation is restricted to the lungs. Using intensity-based thresholding in conjunction with morphological filters, the third frame identifies possible fibrotic regions within the lung mask. Suspected fibrotic regions are indicated by white spots on a black backdrop. The fourth frame, which overlays the detected fibrosis onto the original CT image, shows the proportion of the lung area that is impacted, such as 7.3%, 12.19%, and 46.79% affected, and uses green contours to highlight fibrotic spots within the lungs. A thorough and therapeutically useful representation is provided by this visualization, which successfully highlights the exact location and degree of fibrosis while omitting unnecessary areas like the ribs and chest wall.

A. Analysis of Classification Report

The table presents a comparison between two models, Densenet121-basemodel and the Proposed model PFC_Densenet121 evaluated using metrics such as Accuracy, Recall, Precision, F1-score, and Specificity. The accuracy of 97.48%, recall of 98.01%, precision of 97.24%, F1-score of 97.58%, and specificity of 96.88% are all impressive results of the base Densenet121 model. This is in contrast to the suggested PFC_Densenet121 model, which achieves 98.74% accuracy, 99.20% recall, 98.42% precision, 98.83% F1-score, and 98.22% specificity, outperforming the others on all parameters. These modifications improved the PFC model ability to distinguish between normal instances and pulmonary fibrosis. The classification performance of the PFC model is more reliable and robust since it reduces false positives and false negatives. Table 1 shows a comparison of the proposed work with existing results. The proposed results are enhanced compared with the state-of-the-art work approach.

TABLE I. : EVALUATION & COMPARISON RESULTS

PULMONARY FIBROSIS CLASSIFICATION					
Model	***Accuracy***	***Recall***	***Precision***	***F1-score***	***Specificity***
Shamrat et. al [9]	88.9	91.31	91.57	91.43	92.87
Gayathri et.al [14]	0.98	0.975	0.965	0.965	-
Densenet 121-basemodel	0.9748	0.9801	0.9724	97.58	0.9688
PFC_ Densenet121 (Proposed)	0.9874	0.9920	0.9842	0.9883	0.9822

B. Training and validation Accuracy

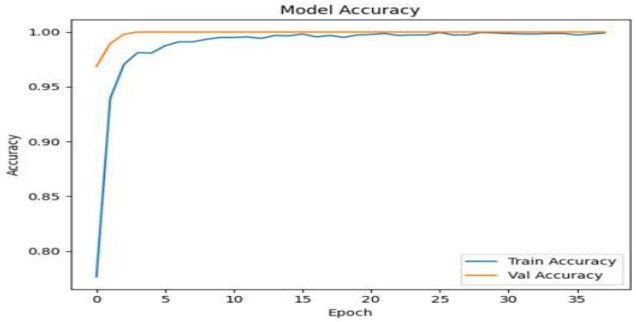

Fig: 6 Accuracy for Pulmonary Fibrosis Detection

Figure 6 shows the model accuracy for pulmonary fibrosis detection across 37 training epochs. The training accuracy which is specifies the blue line starts from relatively modest level and rapidly increase in the further epochs finally its archives 100%. In the meantime, the orange line representing the validation accuracy begins higher and rapidly stabilizes with staying near 100% over the training phase. This shows that the model maintains good generalization to unseen validation data while simultaneously learning from the training data. The model appears to be well-optimized with no indications of overfitting or underfitting as indicated by the near alignment of both curves and their low variation. All things considered, the figure demonstrates a very successful model with outstanding classification abilities on both training and validation datasets.

C. Training and validation loss

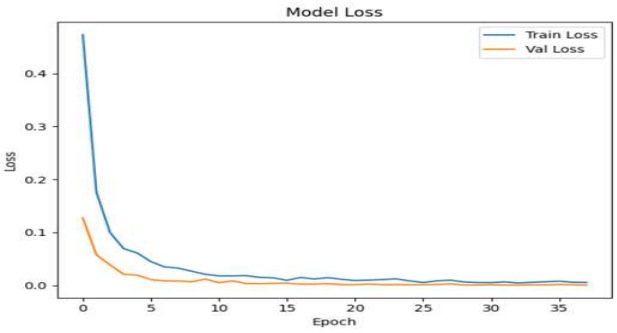

Fig: 7 Loss for Pulmonary Fibrosis Detection

The model loss curve is shown in Figure 7 spanning 37 epochs with both training loss (shown by the blue line) and

validation loss (shown by the orange line) consistently trending decreasing as the epochs go by. This decrease suggests high generalization to the validation data and efficient learning. At first, the training loss is very significant, but it rapidly drops over the first few epochs until stabilizing near zero. Similarly, overfitting is not clear as the validation loss steadily decreases and remains near the training loss throughout the process. These loss curves show smooth convergence towards a minimum indicates that the model is well-trained, performing well, and has a respectable capacity for generalization.

D. *Confusion Matrix Analysis*

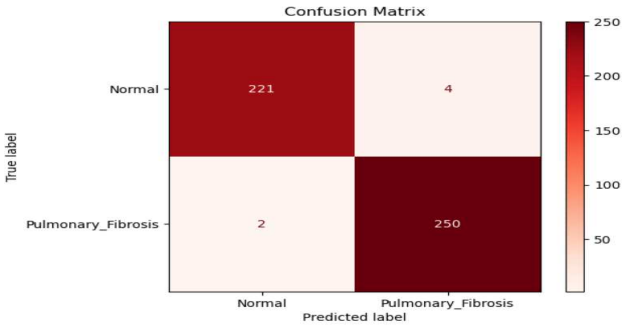

Fig: 8 Confusion Matrix of Pulmonary Fibrosis Detection

The confusion matrix is shown in Figure 8. It provides a more thorough explanation of the DenseNet121 model's forecast. The proposed model achieved 98.74% accuracy in detecting pulmonary fibrosis, indicating strong performance. It correctly identified 250 pulmonary fibrosis cases (true positives) and 221 normal cases (true negatives). However, there were two instances where fibrosis cases were incorrectly classified as normal (false negatives) and four cases where normal images were misclassified as fibrosis (false positives). With a precision of 98.42% and a recall of 99.20%, it consistently detects positive instances, guaranteeing real positives among anticipated positives. Its balanced precision and recall are highlighted by its F1 score of 97.58%, while its ability to correctly categorize negative situations is highlighted by its 98.22% specificity.

V. CONCLUSION AND FUTURE SCOPE

In this study, pulmonary fibrosis was classified and detected using a deep learning model based on DenseNet121, which achieved an amazing overall accuracy of 98.74%. The study highlights how well BRIEF (Binary Robust Independent Elementary Features) and the modified DenseNet architecture work together to reliably identify pulmonary fibrosis. The model exhibits a notable increase in identifying fibrosis in CT scan images by fusing cutting-edge deep learning techniques with conventional feature extraction approaches providing high levels of sensitivity and accuracy. The baseline DenseNet121 was surpassed by the suggested PFC_DenseNet121 model in every metric. With enhanced 98.74% accuracy, 99.20% recall, and 98.42% precision, it proved to be more capable of identifying pulmonary fibrosis. Improved metric balance and fewer erroneous findings are further highlighted by the F1-score of 98.83% and specificity of 98.22%. Early halting ensured optimum model generalization, with training ending at the 37th epoch. There were hardly any misclassifications found in the confusion matrix. In conclusion, it was found that the PFC-enhanced model was more accurate and successful in detecting pulmonary fibrosis. In order to better refine the model architecture and grow the dataset by adding more varied and representative pulmonary fibrosis cases, future research could investigate hybrid approaches. Severity classification would improve the model generalizability.

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