Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 2, February : 2025

MULTI-CLASS LUNG DISEASE CLASSIFICATION WITH INCEPTION-V3

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Abstract— Lung diseases continue to pose a major global health issue, necessitating prompt and precise diagnosis to enhance patient outcomes. This project introduces a deep learning approach for the automated detection and classification of lung diseases, utilizing the Inception-v3 and ResNet50 architectures. A model uses convolutional neural networks (CNNs) to analyse chest X-rays and identify lung conditions like COVID-19, Tuberculosis, Pneumonia, and healthy cases. The dataset is subjected to comprehensive preprocessing and augmentation to ensure its robustness, and the transfer learning capabilities of both architectures improve performance even with limited data. The model is trained and optimized using categorical cross-entropy loss along with the Adam optimizer, achieving an accuracy of 94.92% with Inception-v3 and 92.99% with ResNet50 on the testing dataset. This research underscores the promise of deep learning in enhancing medical imaging diagnostics, providing a scalable, efficient, and dependable solution for predicting lung diseases.
Keywords—Lung disease detection, Deep learning, Inception-v3, Convolutional Neural Networks (CNN), Transfer learning, Chest X-ray classification, Automated diagnosis.

I. INTRODUCTION

Respiratory diseases continue to be a major global health concern, impacting millions of lives each year and contributing to high mortality rates. The World Health Organization emphasizes that access to healthcare is a fundamental human right, yet conditions such as Pneumonia, Tuberculosis, and COVID-19 remain prevalent and pose serious health risks. Environmental factors like air pollution, smoking, poor living conditions, and weakened immune systems significantly increase the likelihood of developing these diseases. Many healthcare systems worldwide struggle to manage the rising number of respiratory illness cases, leading to increased medical costs, extended hospital stays, and a growing demand for efficient diagnostic techniques. The Global COVID crisis made it even clearer that we urgently need quick and accurate ways to detect lung diseases, since early diagnosis is essential for effective treatment and reducing the strain on healthcare systems.

To enhance diagnostic accuracy, deep learning-based models have been increasingly utilized for lung disease detection through chest X-ray (CXR) analysis. This study explores the use of InceptionV3 and ResNet50, two powerful convolutional neural network (CNN) architectures, to classify lung diseases into four categories: COVID-19, Pneumonia, Tuberculosis, and Normal cases. These models apply transfer learning techniques to enhance their performance, especially when dealing with limited datasets. The dataset undergoes rigorous preprocessing steps, including image resizing, normalization, contrast enhancement, and data augmentation, to ensure robustness and prevent overfitting.

The methodology involves training and optimizing the models using categorical cross-entropy loss and the Adam optimizer, which aids in improving learning efficiency. The CNNs process input chest X-ray images, extracting relevant features to differentiate between diseased and healthy lungs**.** Figure 1 represents a COVID-19-infected lung X-ray, Figure 2 illustrates a Pneumonia-affected lung, Figure 3 displays Tuberculosis infection, and Figure 4 shows a normal lung X-ray. These visual representations demonstrate key differences in lung structures across different conditions. Experimental results indicate that InceptionV3 achieved an accuracy of 94.92%, while ResNet50 reached 92.99%, proving the effectiveness of deep learning models in detecting lung diseases.

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Fig-1: Covid-19

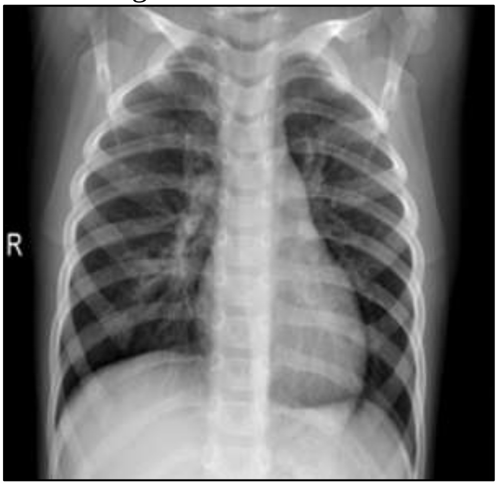

Fig-2: Pneumonia

Fig-3:Tuberclosis

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 2, February : 2025

Fig-4:Normal

Given the increasing prevalence of respiratory illnesses, the integration of AI-driven diagnostic tools into clinical practice offers a promising approach for early and accurate lung disease detection. By improving diagnostic precision and reducing the time required for analysis, these deep learning models provide a scalable, cost-effective, and reliable solution for enhancing healthcare accessibility and assisting medical professionals in making timely decisions.

II. LITERTATURE SURVEY

Recent advancements in deep learning, along with the accessibility of large datasets, have facilitated the creation of models that frequently surpass medical professionals in specific tasks, such as analyzing medical images. As automated diagnostics become increasingly vital, significant research efforts have focused on the application of deep learning within the healthcare sector. This section outlines critical studies at the crossroads of technology and medical science, particularly in the detection of lung opacity and related conditions. G. Keerthi et al. (2023) [1] performed a comparative analysis of three deep learning models—VGG16, ResNet50, and DenseNet121—focusing on lung opacity detection in chest X-ray images. Utilizing datasets sourced from the COVID-19 radiography repository and Kaggle, they evaluated the models' efficacy in identifying lung opacity. The results indicated that DenseNet121 was the standout model, owing to its dense connectivity which improves gradient flow and feature reuse. While VGG16 yielded encouraging results due to its systematic design, ResNet50 struggled to detect finer patterns despite its deeper network architecture. These findings suggest that DenseNet121 is the optimal model for incorporation into diagnostic processes. Zeenat Tariq et al. (2019) [2] examined the use of deep learning for classifying lung diseases through annotated lung sound samples. They introduced a model named Lung Disease Classification (LDC) that utilized sophisticated data normalization and augmentation techniques. Their model illustrated the substantial influence of preprocessing on performance, emphasizing the crucial role of data augmentation and normalization in achieving superior outcomes in medical diagnostics. Sungyeup Kim et al. (2022) [3] investigated the efficacy of transfer learning for multi-class lung disease classification using chest X-ray images. Their method utilized EfficientNet v2-M for direct feature extraction from raw images, enabling an end-to-end learning process. The study highlighted the increasing potential of deep learning for enhancing diagnostic accuracy and efficiency concerning various lung diseases. Goram Mufarah M. Alshmrani et al. (2022) [4] researched the application of deep learning for classifying multiple lung diseases, including pneumonia, lung cancer, tuberculosis (TB), lung opacity, and COVID-19, based on chest X-ray (CXR) images. Their methodology involved a pre-trained VGG19 model combined with convolutional neural network (CNN) blocks for feature extraction and classification.

Marios Anthimopoulos et al. (2016) [5] proposed a deep learning approach designed to classify interstitial lung disease (ILD) patterns, using a convolutional neural network (CNN). This CNN was tailored to identify various lung patterns, such as healthy, ground glass opacity (GGO), micronodules, consolidation, reticulation, honeycombing, and GGO/reticulation combinations. The model's architecture comprises five convolutional layers with 2×2 kernels, succeeded by average pooling and three dense layers. Fethya Seid Yimer et al. (2021) [6] developed a deep learning framework employing Xception for the automated classification of several lung diseases from chest X-ray images. The system, trained with datasets from Jimma University Medical Center and NIH, achieved high accuracy, sensitivity, and specificity, showcasing its potential as a decision-support tool in resource-limited environments. Their research emphasizes the capability of deep learning to assist in precise lung disease diagnoses in areas with scarce medical expertise. Yaman Akbulut (2023) [7] introduced a tailored deep learning model (ACL) that integrates CNN, attention, and LSTM models to classify lung diseases—specifically healthy, COVID-19, and pneumonia—from chest X-ray images. The model utilized marker-controlled watershed segmentation to emphasize significant features and attained high accuracy, particularly with a 90–10% training-test ratio, surpassing existing methodologies. This strategy highlights the promise of deep learning in the early diagnosis and decision support for infectious lung diseases. Keerthi Guttikonda et al. (2024) [8] presented an innovative approach for predicting autism spectrum disorder (ASD) using a least absolute shrinkage and selection operator (LASSO)-regularized bat search optimization (LBSO) algorithm. This technique combines LASSO for feature selection and the BSO algorithm, inspired by bat echolocation, for optimal efficiency. The proposed method improves predictive performance by refining feature selection, minimizing redundancy, and enhancing model interpretability, making it a valuable resource for early ASD detection. Xiaoyi Liu et al. (2024) [9] studied various pre-trained models for classifying lung diseases based on X-ray images. After evaluating SqueezeNet, VGG11, ResNet18, DenseNet, and MobileNetV2, they determined that MobileNetV2 was the most effective model. Silvia Magrelli et al. (2021) [10] created a deep learning-based computer-aided diagnosis (CADx) system aimed at classifying pediatric lung diseases, focusing on bronchiolitis and bacterial pneumonia through lung ultrasound (LUS) images. This study explored the use of deep learning for lung disease diagnosis. Four models (VGG19, Inception-v3, Xception, and Inception-ResNet-v2) were trained, and the Inception-v3 model was most effective for identifying multiple lung disease categories (multi-class classification), while the Inception-ResNet-v2 model performed best for distinguishing between two classes (binary classification). The findings suggest that lung ultrasound (LUS) imaging, combined with deep learning, offers a promising and readily available method for diagnosing childhood lung diseases.

III. METHODOLOGY

The proposed technique includes a profound learning-based approach for the robotized classification of lung maladies utilizing chest X-ray (CXR) pictures. The method starts with contributing a lung X-ray picture into a prepared convolutional neural arrange (CNN) demonstrate, which at that point examinations and classifies it into one of four categories: covid, Tuberculosis, Pneumonia , Normal

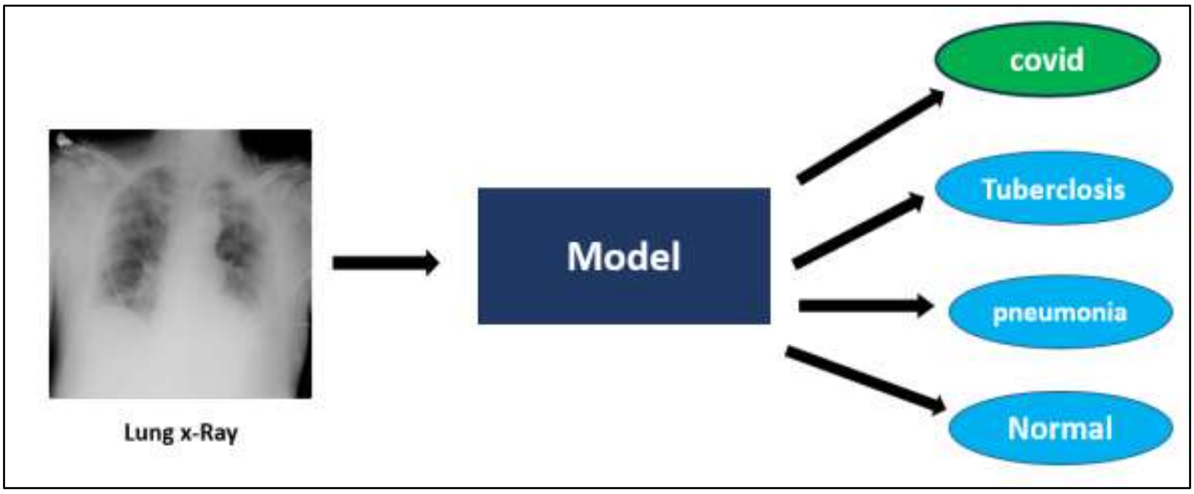

Fig-5: Methodology

IV. IMPLEMENTATION

The methodology for lung disease classification follows a structured pipeline, beginning with data collection, where chest X-ray images are gathered from reliable sources. Next, data augmentation and preprocessing techniques, such as normalization and contrast enhancement, are applied to improve model robustness. The dataset is then divided into training and testing subsets, followed by model selection, where InceptionV3 and ResNet50 are chosen for classification. The selected model is trained and optimized using categorical cross-entropy loss and the Adam optimizer. Finally, the trained model undergoes performance analysis, and based on its accuracy and precision, it is deployed for automated lung disease classification.

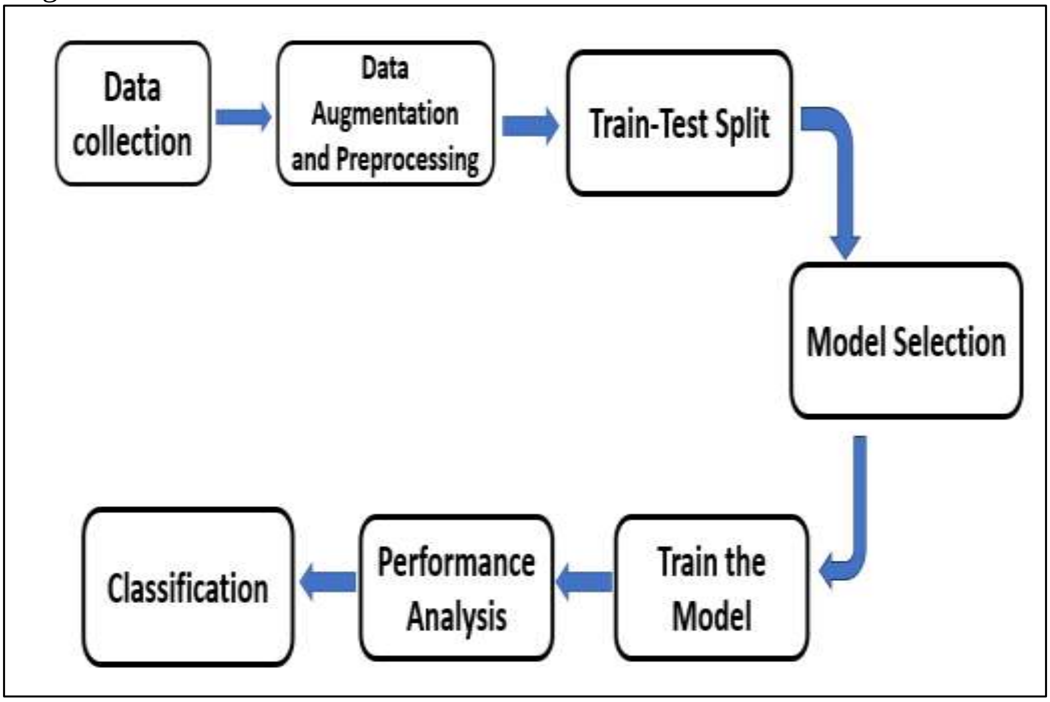

Fig-6: Implementation Pipe Line

Data Collection

The dataset used for lung disease classification is sourced from Kaggle, comprising chest X-ray (CXR) images for multiple lung conditions, including Pneumonia, COVID-19, Tuberculosis, and Normal cases. The first dataset, obtained from Kaggle (https://www.kaggle.com/datasets/fatemehmehrparvar/lung-disease), contains labelled images for Pneumonia, COVID-19, and Normal lungs. Additionally, the Tuberculosis (TB) dataset is sourced from Kaggle (https://www.kaggle.com/datasets/tawsifurrahman/tuberculosis-tb-chest-xray-dataset), ensuring a comprehensive dataset for multi-class classification. The complete dataset consists of 3,600 chest X-ray images, ensuring a diverse distribution across the four categories. The collected images undergo preprocessing and augmentation to enhance model robustness, ensuring improved accuracy and generalizability for deep learning-based lung disease prediction. The dataset used for lung disease classification consists of 3,600 chest X-ray (CXR) images, categorized into four classes: COVID-19, Normal, Tuberculosis, and Viral Pneumonia. The dataset used for this study consists of four distinct categories of chest X-ray images, each representing different medical conditions. The COVID-19 category comprises 1,089 images, capturing radiographic evidence of lung infections caused by the coronavirus. The Normal category includes 1,000 images of healthy lungs, serving as a control group for comparison. Additionally, the dataset contains 730 images of Tuberculosis, a bacterial infection affecting the lungs, and 800 images classified under Viral Pneumonia, which represents lung infections caused by various viruses other than COVID-19. This diverse dataset provides a comprehensive foundation for training and evaluating machine learning models in medical image classification.

Data Augmentation and Preprocessing

To improve the model's performance and minimize overfitting, data augmentation techniques are implemented using ImageDataGenerator. These techniques introduce variations in the dataset, helping the model generalize better. The images undergo rescaling to normalize pixel values, ensuring consistent input ranges. Random rotations up to 30 degrees adjust image orientation, while horizontal and vertical shifts of up to 20% simulate variations in positioning. Shear transformations modify image perspective, and zooming within a 20% range mimics different distances from the imaging source. Horizontal flipping further increases diversity in the dataset. Additionally, 20% of the dataset is allocated for validation, allowing the model to be tested on unseen data. By incorporating these augmentations, the model becomes more adaptable to diverse chest X-ray images, enhancing its ability to identify lung diseases accurately.

Train-Test Split

In a lung disease classification project, the dataset is efficiently partitioned into training and validation sets using the validation_split parameter of the ImageDataGenerator. This automated split, performed during preprocessing, allocates 80% of the data for training, enabling the model to learn from chest X-ray images. The remaining 20% is designated for validation, allowing for model evaluation during training, crucial for preventing overfitting and hyperparameter optimization. By setting validation_split=0.2 within the ImageDataGenerator, the data split is handled dynamically upon loading, ensuring a balanced distribution of lung disease cases across both training and validation subsets.

Model Selection

In this lung disease classification project, we utilized two advanced deep learning architectures derived from Convolutional Neural Networks (CNNs) to improve diagnostic accuracy:

ResNet50:

ResNet50 is a deep convolutional neural network designed to address the challenges of training very deep models, particularly the vanishing gradient problem. It introduces residual learning, where shortcut connections allow the network to bypass certain layers, ensuring smoother gradient flow and improved convergence. The architecture consists of four main stages, each containing multiple residual blocks, which are made up of convolutional layers, batch normalization, and ReLU activation functions. Unlike traditional deep networks that struggle with degradation issues, ResNet50 efficiently learns complex patterns by stacking 48 convolutional layers, one max-pooling layer, and a fully connected layer. These shortcut connections enable the network to retain essential information across

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 2, February : 2025
layers, allowing it to extract deep hierarchical features, making it highly effective for medical image classification.
ResNet50's architecture centers around residual blocks, designed to learn the *residual*—the difference between input and output—rather than a direct input-output mapping. Each block comprises two or three convolutional layers, each followed by batch normalization and ReLU

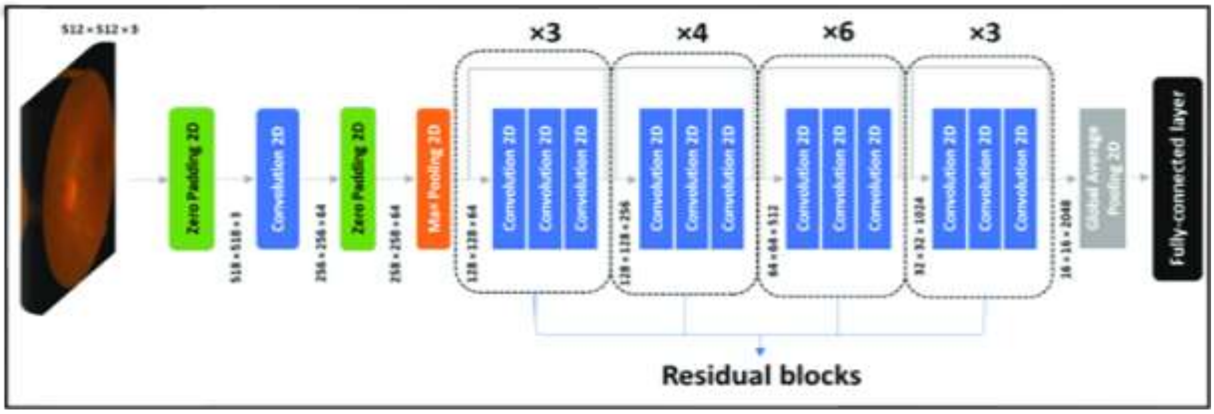

Fig - 7 : ResNet50 Architecture
activation. A key feature is the "shortcut connection," which directly adds the input to the block's output. This technique mitigates the vanishing gradient problem, stabilizing training and preventing performance degradation in deeper networks. Early layers learn fundamental features like edges and textures, while subsequent layers progressively identify more complex, disease-specific patterns within chest X-ray images. The model concludes with global average pooling, fully connected layers, and a softmax activation for classifying images into lung disease categories. Furthermore, ResNet50 leverages transfer learning, initializing its weights with those pre-trained on massive datasets like ImageNet. This strategy proves particularly beneficial when working with limited labeled medical data, boosting performance and training.

InceptionV3:

InceptionV3 is a deep convolutional neural network designed to improve computational efficiency and classification accuracy by using a modular structure called inception blocks. Instead of stacking standard convolutional layers, the model employs multiple filter sizes within the same layer, allowing it to extract spatial features at different scales. This architecture reduces the number of parameters and computational cost while maintaining high performance. InceptionV3 consists of several key components, including factorized convolutions, asymmetric convolutions, and auxiliary classifiers that help with gradient propagation. The network is structured into multiple stages, beginning with initial convolutional layers for low-level feature extraction, followed by multiple inception modules that capture complex patterns. The final layers include global average pooling and fully connected layers, which lead to the final classification. This efficient design enables InceptionV3 to handle complex image recognition tasks while reducing the risk of overfitting.
The working principle of InceptionV3 relies on inception modules, which process input data through multiple convolutional filters simultaneously. This multi-path approach allows the model to learn fine-grained details and broader contextual information within an image. Additionally, factorized convolutions break down larger kernels into smaller ones, improving computational efficiency without sacrificing performance. The network also incorporates batch normalization, which helps stabilize training and accelerates convergence. Throughout the architecture, auxiliary classifiers act as additional output layers, providing extra supervision and preventing gradient vanishing in deeper layers. As the network processes an image, it extracts fundamental features in the early layers and progressively learns more complex structures in deeper layers. The final classification is performed using global average pooling, a fully connected layer, and a softmax activation function, which assigns

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ISSN: 0970-2555
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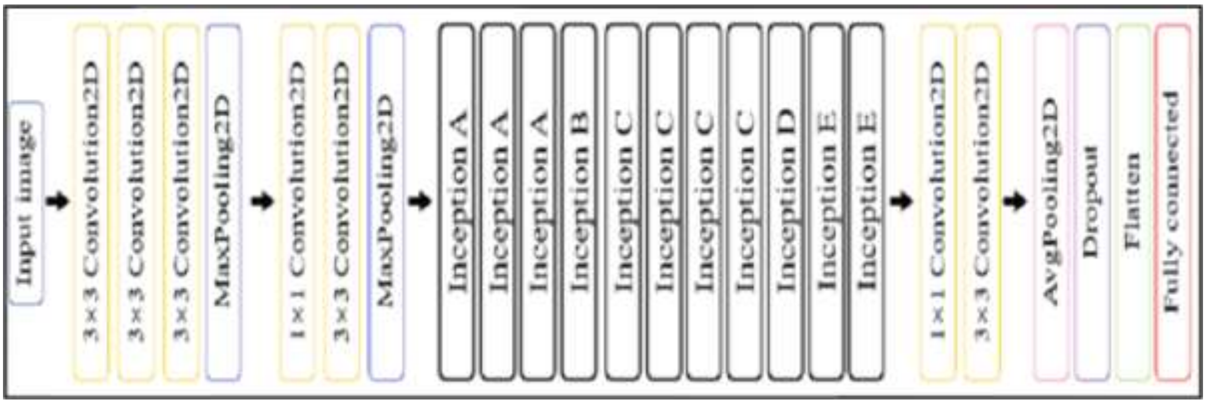
probability scores to different lung disease categories. Like ResNet50, InceptionV3 benefits from transfer learning, where pre-trained weights from large datasets such as ImageNet enhance its ability to generalize well on medical imaging tasks, including lung disease classification.

Fig-8 : InceptionV3 Architecture



Both models were implemented using transfer learning, leveraging pre-trained weights from ImageNet to enhance feature extraction. This approach ensures better generalization and improved accuracy in distinguishing between different lung conditions.

Model Training

The training process involves designing the model structure, setting up optimization techniques, and using callbacks to enhance performance and prevent overfitting.

1. Model Architecture

This model's architecture uses a pre-trained base network like ResNet50 or InceptionV3, which is then enhanced with specific classification layers. The output from the base network goes into a GlobalAveragePooling2D layer, followed by a Dropout layer (with a 0.5 rate) to prevent overfitting. Next, a dense layer with 1024 units and ReLU activation is used. Finally, a dense layer with num_classes units and a softmax activation function is applied. The softmax function ensures the predicted probabilities for all classes add up to one, which is ideal for multi-class classification..

2. Loss Function

For multi-class classification tasks, Categorical Cross-Entropy is used to measure the model's performance. It is defined as:

$L= -\sum_{i=1}^{N} y_i \log (\hat{y}_i)$

Where, y_i is the actual class label in one-hot encoded format. $\hat{y}_i$ is the predicted probability for class i.N represents the number of classes.

3.Optimization Algorithm

The model parameters are updated using the Adam optimizer, which combines momentum and adaptive learning rates. The update rule is given by:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

$$\theta_t = \theta_{t-1} - \frac{\alpha}{\sqrt{\hat{v}_t}+\epsilon}\hat{m}_t$$

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During optimization, mt and vt represent the first and second moment estimates, respectively. mt tracks the running average of the gradients, while vt tracks the running average of their squared values. Decay parameters β1 and β2, typically set to 0.9 and 0.999 respectively, govern the influence of past gradients on these estimates. The computed gradient at time step t, denoted as gt, is used to update the model's parameters. The learning rate, α (e.g., 0.001), scales the parameter updates at each iteration. A small constant, ε, is added to the denominator to prevent division by zero and ensure numerical stability.

4. Performance Metric

Model performance is assessed by calculating its accuracy, which is determined by:

Accuracy = $\frac{Correct\ predictions}{Total\ prediction}$

A higher accuracy score indicates that the model is correctly identifying lung disease conditions.

5. Training Enhancements (Callbacks)

To optimize training and prevent overfitting, EarlyStopping and ReduceLROnPlateau are implemented.EarlyStopping monitors validation loss and halts training if no further improvement is observed over a specified number of epochs:If $L_{val}(t) \geq L_{val}(t-p)$ for p epochs, training stops.

ReduceLROnPlateau dynamically adjusts the learning rate when the validation loss stabilizes, making the model learn more effectively.$\alpha_{new}=\alpha_{current}\times$factor, if loss does not improve for p epochs.where the factor is typically set to 0.5 and p represents the patience parameter.

By integrating these strategies, the model learns efficiently, reduces overfitting, and achieves high accuracy in lung disease classification.

Workflow of Each Epoch

Fig-9:Workflow of each epoch

Performance Analysis:

In this study, accuracy was the key metric for evaluating the models' ability to correctly classify lung disease cases. ResNet50 achieved an accuracy of 92.99%, while InceptionV3 achieved a higher accuracy of 94.92%. This suggests InceptionV3 is better at extracting relevant features and distinguishing between tuberculosis, COVID-19, pneumonia, and healthy cases. The use of inception modules likely contributes to this improved performance by allowing the model to analyze patterns at multiple scales. While slightly less accurate, ResNet50 still performed well, likely due to its deep residual learning framework, which is designed for efficient training of very deep networks. Overall, these accuracy results highlight the potential of deep learning for medical image classification and its usefulness in automated lung disease diagnosis.

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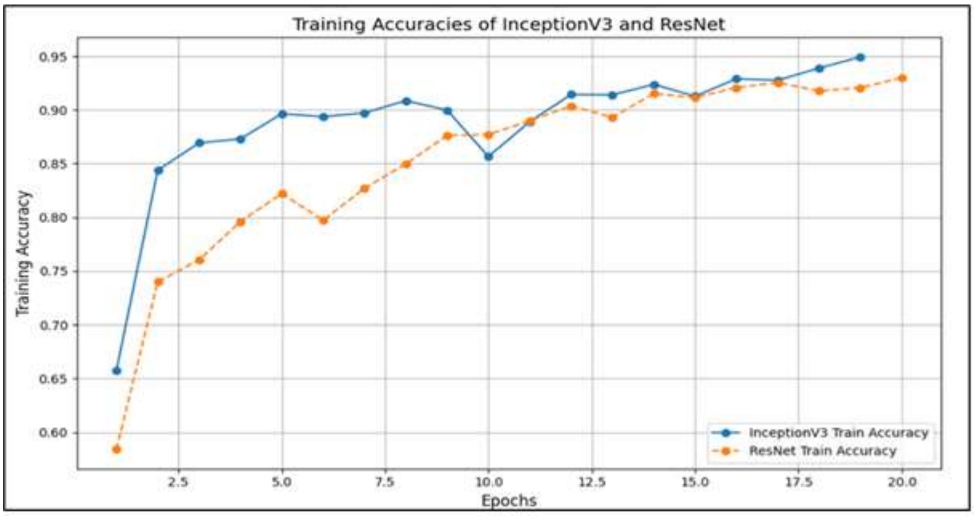

Fig-10:Accuracies of InceptionV3 and ResNet50

Training loss measures the difference between the predicted and actual values during the learning process, with lower values indicating better performance. In this study, ResNet50 achieved a training loss of 0.33, while InceptionV3 had a slightly higher loss of 0.41. The lower loss in ResNet50 suggests that the model was able to fit the training data more effectively, learning intricate patterns with minimal error. However, InceptionV3, despite having a slightly higher loss, demonstrated better generalization as indicated by its higher accuracy. The use of techniques like batch normalization and residual learning in ResNet50 contributed to faster convergence and reduced loss. The balance between training loss and accuracy shows that both models effectively captured essential features, ensuring reliable classification of lung diseases.

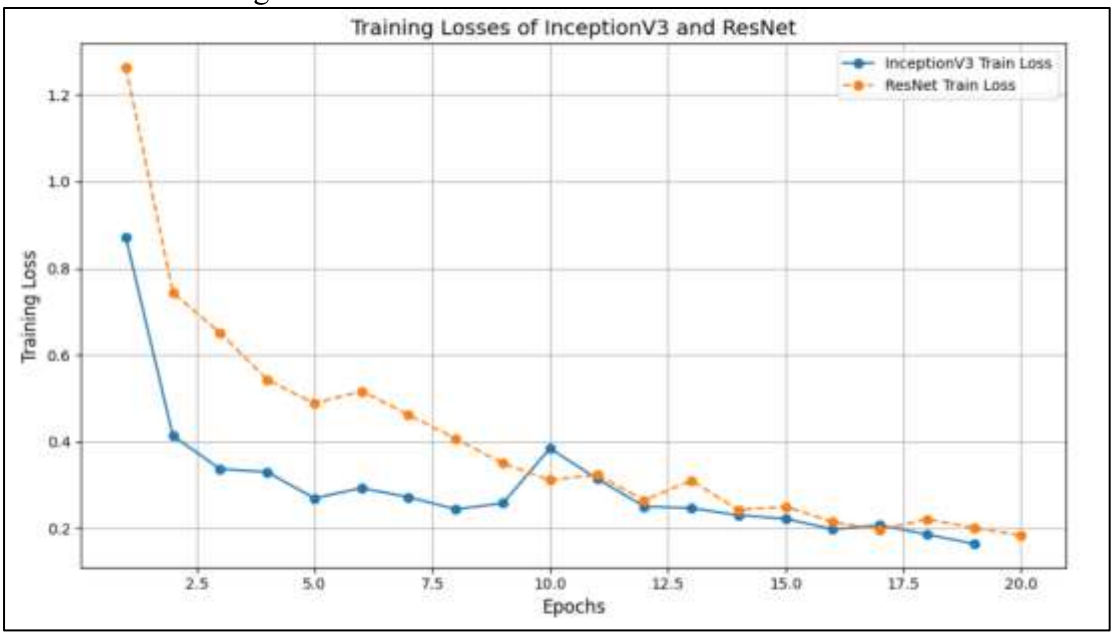

Fig-11: Training losses of InceptionV3 and ResNet50

Classification:

InceptionV3 was chosen as the optimal model for lung disease classification due to its superior accuracy of 94.92%, outperforming ResNet50. This model analyzes chest X-ray images, extracting key features through a series of convolutional layers. Its unique inception modules improve feature detection by examining patterns at various scales, effectively distinguishing between COVID-19, tuberculosis, pneumonia, and healthy cases. Global average pooling reduces dimensionality while retaining crucial information as the image propagates through the network. Finally, a fully connected

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ISSN: 0970-2555
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layer followed by a SoftMax activation function assigns probability scores to each disease category. The category with the highest probability is assigned as the predicted label, providing a robust and automated system for lung disease diagnosis.

Model	**Accuracy(%)**
InceptionV3	94.92
ResNet50	92.99

Table 1: comparison of accuracies of both models

V. RESULT

To make lung disease classification accessible and user-friendly, a web-based application was developed. The platform includes a simple interface where users can upload a chest X-ray image through an input form. Upon submission, a "Classify" button processes the image using the trained model to determine the lung condition. The results are then displayed on a separate page, providing the predicted
disease along with a confidence score indicating the model's certainty. This application streamlines the diagnosis process, offering a quick and efficient solution for lung disease detection without requiring specialized medical expertise.

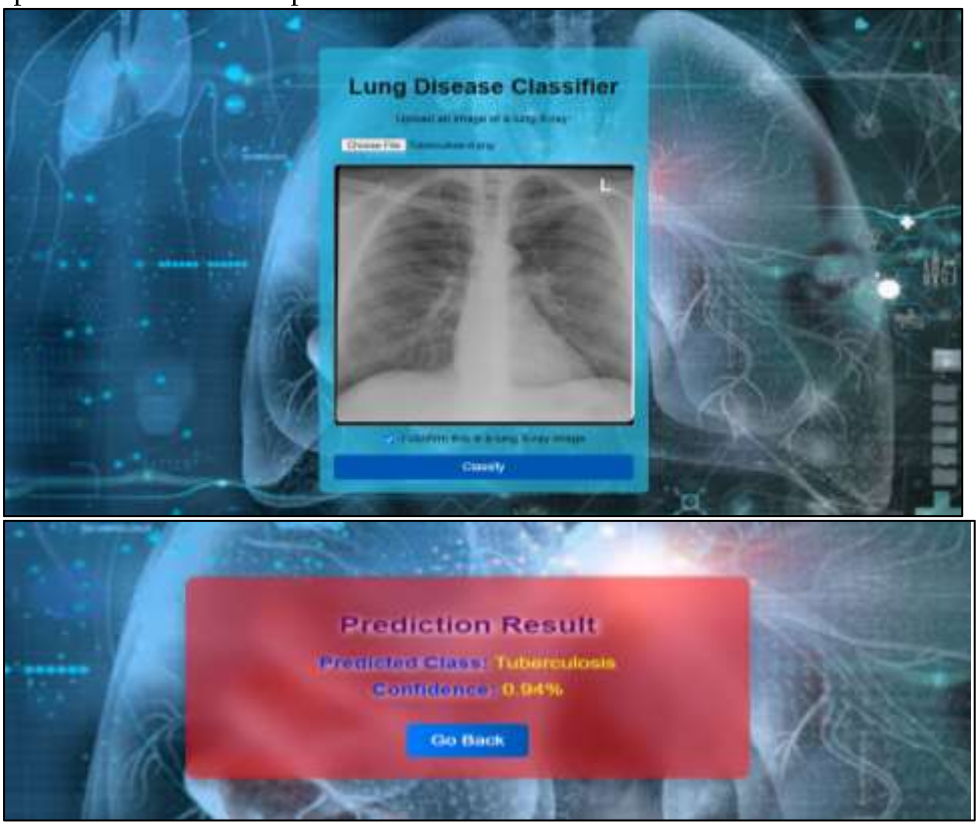

Fig -12 : User Interface for Lung Disease Classification

VI. FUTURE SCOPE

Integrating AI models like InceptionV3 with X-ray systems during the scanning process can significantly enhance disease detection by enabling real-time image analysis. This integration facilitates the immediate identification of abnormalities such as lung diseases, fractures, or tumors, allowing healthcare providers to receive instant insights. As a result, diagnostic accuracy improves, waiting times decrease, and clinical decision-making becomes more efficient. AI-driven X-ray systems can also automate critical alerts, ensuring prompt medical attention for severe cases. Additionally, incorporating AI into these systems enhances workflow efficiency, strengthens remote diagnostics, and provides consistent analysis, especially in regions with limited access to specialized healthcare professionals.

VII. CONCLUSION

This project developed a deep learning approach for classifying lung diseases from chest X-ray images. Leveraging the InceptionV3 architecture with transfer learning, the model successfully detected and categorized several conditions: COVID-19, Tuberculosis, Viral Pneumonia, and healthy lung. Data augmentation and preprocessing techniques were employed to bolster model robustness and improve generalization with the limited dataset. EarlyStopping and ReduceLROnPlateau callbacks optimized training efficiency, preventing overfitting and ensuring convergence. Fine-tuning further enhanced the model's accuracy, creating a reliable tool for scalable predictions. This work highlights the potential of deep learning in medical diagnostics, offering an efficient solution for healthcare providers. The model's capabilities can be expanded to include additional diseases, proving especially valuable in regions with limited access to radiology specialists, ultimately improving the speed and accuracy of lung disease diagnosis.

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