ResNetIncepX: A Fusion of ResNet50 and InceptionV3 for Pneumonia Detection Using Chest X-Rays

A Project Report

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In partial fulfillment of the requirements for the award of the degree

BACHELOR OF TECHNOLOGY
In
COMPUTER SCIENCE and ENGINEERING

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CERTIFICATE

This is to certify that the project report entitled **"ResNetIncepX: A Fusion of ResNet50 and InceptionV3 for Pneumonia Detection Using Chest X-Rays"** has been submitted by **A. Naga Naveen (211FA04561), V. Sumanth (211FA04593)** in partial fulfillment of the requirements for the **Major Project** course, as part of the academic curriculum of the B.Tech. CSE Program, **Department of Computer Science and Engineering (CSE)** at **VFSTR Deemed to be University**.

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DECLARATION

I/We hereby declare that the project work entitled **" ResNetIncepX: A Fusion of ResNet50 and InceptionV3 for Pneumonia Detection Using Chest X-Rays "** submitted in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology (B. Tech)** in **Computer Science and Engineering** at **VFSTR Deemed to be University** is a record of my/our original work.

This project has been carried out under the supervision of the Department of Computer Science and Engineering, VFSTR Deemed to be University. The work embodied in this thesis has not been submitted previously, in part or full, to any other University or Institution for the award of any degree or diploma.

I/We have duly acknowledged all sources of information and data used in the preparation of this project report and shall abide by the principles of academic integrity and ethical guidelines.

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Date:19-05-2025

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ABSTRACT

Pneumonia is a serious and potentially fatal respiratory infection that necessitates prompt and accurate diagnosis for effective treatment and improved patient care. Traditional diagnostic methods rely heavily on expert interpretation of chest X-rays, which can be subjective, inconsistent, and time intensive. With the advent of deep learning, automated medical image analysis has emerged as a powerful tool to enhance diagnostic precision and speed. In this study, we introduce ResIncepX, a hybrid deep learning model that integrates the strengths of ResNet50 and InceptionV3 architectures for the automated classification of pneumonia from chest X-ray images. While ResNet50 effectively captures deep spatial features through residual learning, InceptionV3 contributes by extracting multi-scale image patterns, enabling the model to learn diverse and discriminative features. The proposed model was evaluated on a publicly available dataset of 5,856 chest X-ray images, achieving an impressive accuracy of **95.19%**, surpassing the performance of the individual ResNet50 and InceptionV3 models. ResIncepX also demonstrated reduced misclassification rates and enhanced generalization, confirming its robustness and reliability. This hybrid approach presents a significant advancement in AI-driven medical diagnostics, offering a dependable solution for early and accurate pneumonia detection and supporting healthcare professionals in making timely clinical decisions.

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INTRODUCTION

1. INTRODUCTION

1.1.1 What is pneumonia?

Pneumonia is a serious respiratory infection that causes inflammation in the air sacs (alveoli) of one or both lungs. These air sacs may become filled with fluid or pus, leading to symptoms such as coughing, fever, chills, chest pain, and difficulty breathing. The condition can be caused by various infectious agents, including bacteria, viruses, and fungi. Pneumonia can affect people of all ages, but it poses a greater risk to infants, elderly individuals, and those with weakened immune systems. If not diagnosed and treated promptly, it can lead to severe complications or even death. Therefore, early and accurate detection of pneumonia is critical to improving patient outcomes and reducing mortality rates.

1.1.2 Global health and mortality rates

Pneumonia is a significant public health concern with a considerable global disease burden. It affects individuals of all ages but is particularly deadly among children under five and the elderly. According to the World Health Organization (WHO), pneumonia accounts for approximately 15% of all deaths in children under five, claiming over 700,000 young lives each year. The impact is more severe in low- and middle-income countries, where access to timely and adequate medical treatment is limited. In adults, especially those with chronic illnesses or compromised immune systems, pneumonia can lead to serious complications, prolonged hospitalization, and even death. Despite the availability of vaccines and antibiotics, pneumonia continues to cause millions of hospital admissions and remains a leading cause of morbidity and mortality globally. These statistics highlight the urgent need for early detection methods and improved healthcare strategies to manage and reduce pneumonia-related deaths.

1.1.3 Importance of early and accurate detection

Early and accurate detection of pneumonia is critical for effective treatment and improved patient outcomes. Delayed or incorrect diagnosis can lead to severe complications such as respiratory failure, sepsis, or even death, especially in vulnerable groups like children, the elderly, and individuals with weakened immune systems. Prompt identification enables timely medical intervention, reduces the risk of disease progression, shortens hospital stays, and lowers mortality rates. With advancements in medical imaging and artificial intelligence, automated detection systems can support healthcare providers in making faster and more reliable diagnoses, particularly in resource-limited settings.

1.2 Problem Statement

Pneumonia continues to be a leading cause of morbidity and mortality worldwide, particularly in vulnerable populations such as children, the elderly, and immunocompromised individuals. Traditional diagnostic methods, such as chest X-ray interpretation by radiologists, are time-consuming and prone to human error, leading to delays in diagnosis and treatment. Additionally, in many resource-limited settings, there is a shortage of trained healthcare professionals, further exacerbating the problem.

There is a pressing need for an automated, efficient, and accurate system to detect pneumonia at an early stage, which can significantly improve patient outcomes. The application of deep learning techniques, specifically Convolutional Neural Networks (CNNs), for automated pneumonia detection from chest X-rays presents an opportunity to address these challenges. However, despite progress in this area, achieving a high level of diagnostic accuracy remains a challenge due to factors like dataset quality, model generalization, and computational resource constraints.

This project aims to develop an automated deep learning model to detect pneumonia from chest X-ray images, providing an efficient and accurate tool to assist healthcare professionals in diagnosing the disease more reliably and quickly.

1.2.1 Limitations of traditional diagnosis

Traditional pneumonia diagnosis primarily relies on clinical symptoms, physical examinations, and medical imaging techniques, such as chest X-rays. However, these methods have several limitations:

1. Time-Consuming: Chest X-ray interpretation is often slow, requiring radiologists to manually examine and diagnose each image. This delays the initiation of appropriate treatment.

2. Subjectivity: Radiologists' interpretations of X-rays are subject to human error and variability, which can lead to misdiagnosis, especially in subtle cases or when the disease presents atypically.

3. Dependence on Expertise: Accurate diagnosis heavily depends on the skill and experience of the radiologist, making it difficult to achieve consistent results, particularly in areas with a shortage of trained professionals.

4. Limited Access in Remote Areas: In many rural and underdeveloped regions, there may be

limited access to radiology services and diagnostic facilities. This increases the risk of undiagnosed or misdiagnosed cases.

5. Cost and Resource Intensive: The need for physical examinations, follow-up tests, and expert radiologists makes the traditional diagnostic approach costly and resource-heavy, especially in low-resource settings.

1.2.2 Need for automated, reliable, and quick detection using technology

The limitations of traditional pneumonia diagnosis highlight the need for an automated, reliable, and quick detection system. Automated detection using technologies such as artificial intelligence (AI) and machine learning (ML) can address these challenges by providing improved diagnostic accuracy. AI-based systems can analyze chest X-ray images with high precision, reducing human error and identifying patterns that might be overlooked by radiologists. These systems also offer the advantage of speed, providing timely diagnoses that are crucial in emergency situations. Additionally, automated models ensure consistency in results, eliminating variations in interpretation between radiologists. Furthermore, these technologies can be deployed on a large scale, making them accessible in remote or underserved areas where there is a shortage of trained professionals. Automated detection also helps reduce healthcare costs by minimizing the need for repeated consultations and physical exams. Overall, there is a clear need for technology-driven solutions to enhance the accuracy, efficiency, and accessibility of pneumonia diagnosis.

1.3 Motivation

Pneumonia is a serious lung infection that continues to be a major cause of illness and death worldwide, particularly in young children and the elderly. Traditional diagnostic methods such as chest X-rays require expert interpretation, which can be time-consuming and often unavailable in rural or under-resourced areas. This project is motivated by the urgent need for an automated, reliable, and rapid diagnostic tool that can assist healthcare professionals in accurately detecting pneumonia. By leveraging deep learning techniques, especially Convolutional Neural Networks (CNNs) and hybrid architectures like Inception and ResNet, the project aims to build a model capable of analyzing chest X-ray images with high accuracy and consistency. The motivation lies in enhancing diagnostic efficiency, reducing dependence on specialists, and ultimately contributing to improved patient outcomes, particularly in areas with limited access to medical care.

1.3.1 Why this project was chosen

This project was chosen due to the growing global need for faster, more accurate, and accessible diagnostic tools in the medical field, especially for critical conditions like pneumonia. Pneumonia remains a significant health burden, particularly in regions with limited healthcare infrastructure where expert radiologists are not always available. Manual interpretation of chest X-rays can be time-consuming and prone to human error. With the rise of artificial intelligence and deep learning, there is a strong opportunity to automate the detection process and support clinical decisions. This project combines both social relevance and technical challenge — offering a meaningful way to apply deep learning models such as CNN, ResNet, and Inception to real-world medical imaging problems, making it both impactful and innovative.

1.3.2 Real-world impact and relevance

The real-world impact and relevance of this project lie in its potential to significantly improve healthcare delivery, especially in resource-constrained environments. An AI-powered pneumonia detection system can assist doctors by providing quick and accurate analysis of chest X-ray images, reducing diagnostic time and minimizing human error. This is particularly valuable in rural or underdeveloped areas where experienced radiologists may not be available. Early and reliable diagnosis can lead to timely treatment, lowering the risk of severe complications or death. Additionally, such a system can help manage high patient volumes in busy hospitals, support telemedicine services, and contribute to the broader goal of integrating intelligent technologies into everyday clinical practice, thereby enhancing overall healthcare efficiency and accessibility.

1.4 Objectives

The primary objective of this project is to develop an efficient deep learning model capable of detecting pneumonia from chest X-ray images with high accuracy. The project aims to evaluate and compare the performance of different deep learning architectures, including CNN, Inception, ResNet, and hybrid models, to determine the most effective approach for classification. Another key objective is to enhance diagnostic accuracy through optimized preprocessing, model tuning, and the integration of advanced architecture. Ultimately, the goal is to create a reliable, automated diagnostic tool that can support medical professionals and improve early detection and treatment of pneumonia.

1.4.1 Develop a deep learning model to detect pneumonia

The goal is to develop a deep learning model that can automatically detect pneumonia from chest X-ray images. By training the model on a large dataset of labeled images, the system learns to identify patterns and features associated with pneumonia. Using Convolutional Neural Networks (CNNs) and other advanced architectures, the model is designed to classify images as pneumonia-positive or normal with high accuracy. This automated approach aims to assist radiologists and healthcare professionals in making faster, more reliable diagnoses.

1.4.2 Evaluate performance with different architectures

To ensure the effectiveness of the pneumonia detection system, the project involves evaluating the performance of multiple deep learning architectures. Models such as CNN, Inception, ResNet, Xception, and VGG16 are trained and tested on the same dataset to compare their accuracy, precision, recall, and other performance metrics. This evaluation helps in identifying the strengths and weaknesses of each model, allowing for the selection or combination of architectures that offer the best diagnostic accuracy. The comparative analysis ensures that the final system is both efficient and reliable in real-world clinical settings.

CHAPTER 2:

LITERATURE SURVEY

2 LITERATURE SURVEY

2.1 Literature review

This section reviews recent advancements in pneumonia detection using deep learning techniques from credible journals and conferences.

K. Liharika et al. [1] introduced a pneumonia detection model based on DenseNet, EfficientNet, and a hybrid Inception-ResNet. Both DenseNet and EfficientNet resulted in 91% accuracy, whereas the hybrid one boosted the performance to between 92% and 95%.

Eva Rianti et al. [2] worked on the application of transfer learning in detecting pneumonia. Transfer models like Xception, VGG16, and ResNet50 were used for the classification of chest X-rays. The authors documented classification accuracy levels of 82% using Xception, 87% using VGG16, and 94.06% using ResNet50. These outcomes are indicative of the success of deep transfer learning methods in pneumonia classification.

Subrat Kumar Kabi et al. [3] compared ensemble models for the diagnosis of pneumonia by combining SVM, CatBoost, and Logistic Regression. The ensemble model achieved better than individual models.

Shengnan Hao et al. [4] introduced a deep learning framework using YOLO-based object detection for pneumonia localization in chest X-rays. The study focused on detecting multiple lesions within the lungs to aid early diagnosis. The YOLO-CXR model achieved improved accuracy and sensitivity in identifying pneumonia-infected regions.

Yeongbong Jin et al. [5] compared gender-specific performance in classifying pneumonia using DenseNet121, InceptionV3, ResNet50, and Xception. DenseNet121 had more than 90% accuracy, whereas InceptionV3 performed at 93% on the female dataset. ResNet50 had less accuracy in both female and mixed-gender groups, highlighting the influence of the composition of the dataset.

Mudasir Ali et al. [6] proposed a system for pneumonia detection based on EfficientNetV2L, which recorded the highest classification accuracy of 94.02%. The research highlighted the importance of model architecture in enhancing feature extraction and classification performance.

Nazmus Syed et al. [7] explored model fine-tuning and augmentation techniques to enhance pneumonia detection performance. The study utilized LSTM and customized VGG19 models, achieving over 91% and 92.94% accuracy, respectively.

Amer Kareem et al. [8] proposed a hybrid AI-based pneumonia detection system. Their research highlighted accuracy as a key performance metric, demonstrating that hybrid models improve predictive capabilities compared to standalone classifiers.

Mr. M. Rajeev Kumar [9] explored a pneumonia detection method that uses DL architecture with VGG16 and attention mechanisms, which achieved a high classification accuracy of 93.53%. The study highlighted the effectiveness of transfer learning and feature enhancement techniques in improving diagnostic performance on chest X-ray images.

Thenmozhi M. [10] proposed an automated machine learning framework using CNN for using chest X-ray pictures to diagnose pneumonia. Their framework was highly sensitive and specific to bridge the diagnostic gap due to a shortage of radiologists and improve early disease detection for improved patient outcomes.

In general, these studies emphasize the progress in detecting pneumonia. Although CNNs, EfficientNet, hybrid models, and ResIncepX exhibit high accuracy, issues like dataset bias and model interpretability are still topics for future work. The combination of deep learning methods continues to improve pneumonia diagnosis, providing better accuracy and lower computational complexity.

2.2 Limitations

Pneumonia detection using deep learning techniques, while promising, has several limitations. One significant challenge is dataset bias, where an imbalanced or unrepresentative dataset can lead to poor generalization in real-world applications, especially when the data lacks diversity across demographics such as age, gender, or race. Additionally, the quality and quantity of data play a critical role in the performance of these models. Incomplete, noisy, or inaccurately labelled data can hinder the model's accuracy. Another limitation is the interpretability of the models; deep learning models, particularly convolutional neural networks (CNNs), are often considered "black boxes," making it difficult to understand the rationale behind their predictions, which is crucial in medical contexts where clinicians need to trust and explain the results. Moreover, these models are susceptible to overfitting, where they perform well on training data but fail to generalize to new, unseen data. The computational complexity of training deep learning models, which often require powerful GPUs and large storage capacities, can make them less feasible for healthcare settings with limited resources. Furthermore, the challenge of generalization to real-world data arises because models trained on curated datasets may struggle with variations in image quality and resolution in real-world clinical environments. The limited availability of labeled data, crucial for training deep learning models, can also be a barrier, as accurately annotating medical images is labor-intensive and requires expert knowledge. Issues like class imbalance, where healthy chest X-rays significantly outnumber those showing pneumonia, can cause models to be biased toward the majority class, affecting their performance. Lastly, these models are highly dependent on high-quality imaging; poor-quality chest X-rays due to noise, improper positioning, or low resolution can lead to false positives or negatives, reducing the accuracy of the model. These limitations underscore the challenges that need to be addressed to improve the practical deployment of deep learning-based pneumonia detection systems.

CHAPTER 3:

PROPOSED SYSTEM

3 PROPOSED SYSTEM

The proposed system for pneumonia detection uses deep learning to automatically identify pneumonia from chest X-ray images. It begins with collecting data from public sources like Kaggle, followed by preprocessing techniques such as image resizing and augmentation to improve model performance. The dataset is split into training and testing sets , and multiple models like CNN, InceptionV3, ResNet50, Xception, and VGG16 are trained. A hybrid model combining InceptionV3 and ResNet50 is also developed to enhance accuracy. The models are evaluated using metrics like accuracy and F1-score to select the best-performing one for reliable pneumonia detection.

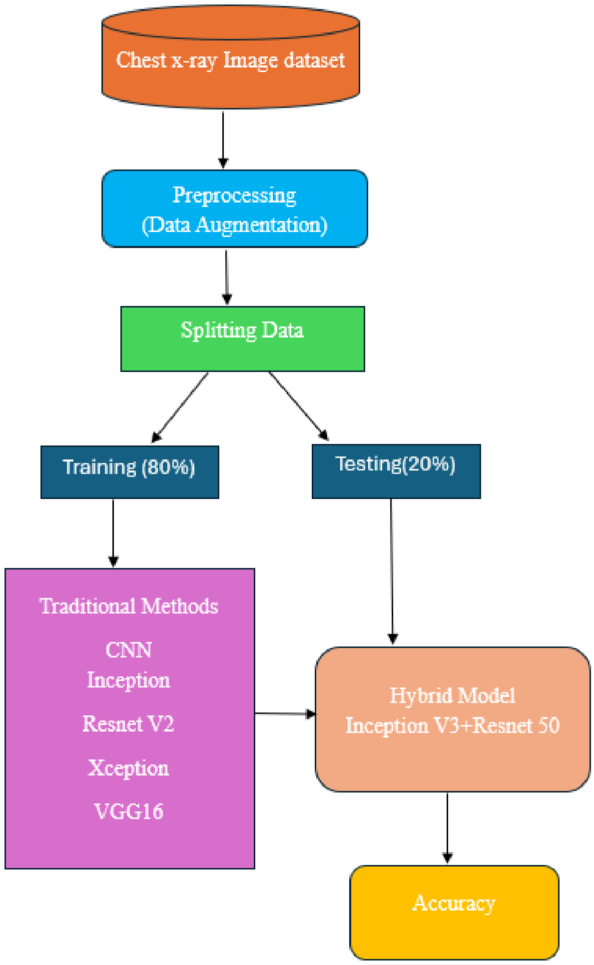


Figure 1. Workflow of the system

3.1 Input dataset

The dataset used in this study is Kaggle's Chest X-ray Pneumonia dataset, which contains 5,863 X-ray images categorized into two classes: pneumonia and normal. It is divided into training, testing, and validation sets to ensure a balanced evaluation of the model. Specifically, the training set includes 3,875 pneumonia and 1,341 normal images, the test set has 390 pneumonia and 234 normal images, and the validation set contains 8 images from each class. This dataset plays a crucial role in training and validating the proposed ResIncepX model, contributing to improved accuracy in pneumonia detection using deep learning.

Figure 2. Various types in the dataset

3.1.1 Detailed Features of the Dataset

The Chest X-ray Pneumonia dataset used in this study comprises 5,863 chest radiograph images categorized into two main classes: **Normal** and **Pneumonia**. The pneumonia class is further subdivided into **Bacterial Pneumonia** and **Viral Pneumonia**, as illustrated in the figure. Each X-ray image is labeled accordingly, helping the model learn and distinguish between healthy lungs and those affected by different types of pneumonia.

- **Normal**: These images show clear lungs with no signs of infection or inflammation. The lung fields appear transparent with visible ribs and normal heart and diaphragm outlines.
- **Bacterial Pneumonia**: These X-rays display localized opacities or patches indicating bacterial infection, often appearing in specific lung lobes.
- **Viral Pneumonia**: These images typically exhibit more diffuse and hazy opacities across the lungs, as viruses usually cause a more widespread inflammation compared to bacteria.

The dataset is divided into training, testing, and validation subsets to support robust model development. Each image is grayscale, uniformly formatted, and suitable for use in deep learning models like CNNs and hybrid architectures.

3.2 Data Pre-processing

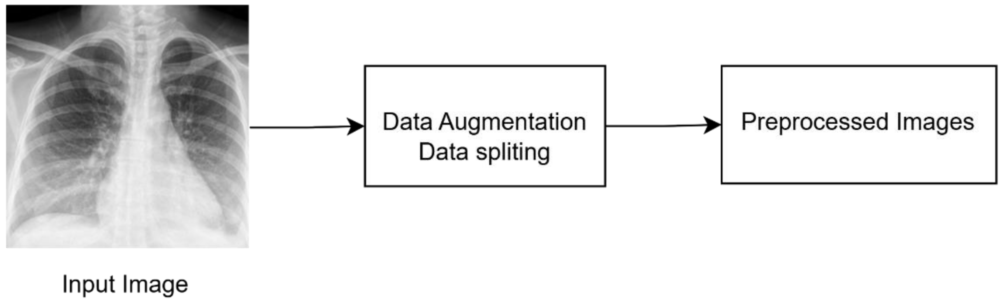


Figure 3. Pre-processing Overview

Data preprocessing is a crucial step in preparing chest X-ray images for deep learning-based pneumonia detection. It ensures that the input data is clean, consistent, and suitable for model training. The preprocessing pipeline in this study involves three key steps: applying data augmentation and splitting the dataset into appropriate subsets.

3.2.1 Data Augmentation Techniques

To enhance the diversity of the dataset and prevent overfitting, data augmentation techniques are applied. These include random rotations, horizontal flips, brightness shifts, and zoom operations. Augmentation simulates a wider range of imaging conditions and helps the model generalize well to real-world scenarios.

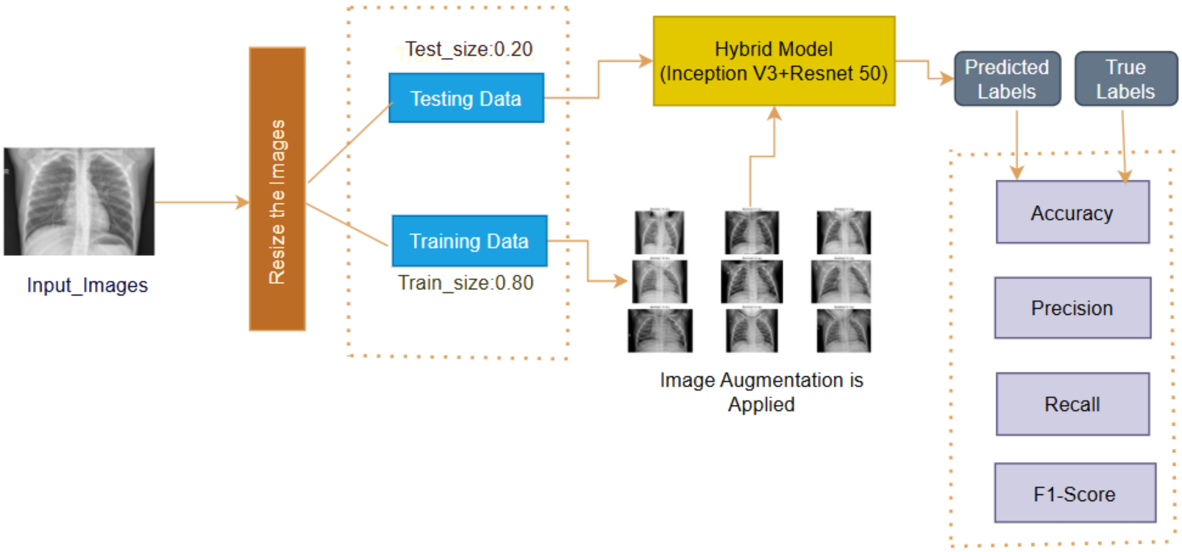
3.2.2 Data Splitting

The dataset is divided into three subsets: training, validation, and testing. This ensures that the model is evaluated on unseen data, which is crucial for assessing its generalization capabilities. The training set is used to fit the model, the validation set helps fine-tune hyperparameters, and the testing set provides an unbiased performance estimate.

3.3 Model Building

The model building and training phase is central to the success of any deep learning project, particularly in medical image classification. In this study, a systematic approach has been taken to design, build, and train models capable of detecting pneumonia from chest X-ray images. This phase involves experimenting with both traditional deep learning models and a proposed hybrid model, which is designed to harness the combined strengths of multiple architectures for improved performance.

figure 4. Architecture of the proposed mode



3.3.1 Traditional Models

Traditional deep learning models like CNN, VGG16, ResNet-50, and InceptionV3 have shown strong performance in pneumonia detection. CNN extracts key features from chest X-ray images using convolutional layers. VGG16 uses 16 layers with small filters to perform image classification efficiently. ResNet-50 solves training issues in deep networks by using skip connections (residual learning). InceptionV3 captures features at multiple scales using different filter sizes in parallel, improving accuracy while managing computational load. These models are used as benchmarks for performance comparison in pneumonia detection tasks.

1. Convolutional Neural Network (CNN)

Definition:

A Convolutional Neural Network (CNN) is a type of deep learning model specifically designed for processing structured grid data like images. CNNs use convolutional layers to automatically extract spatial hierarchies of features, reducing the need for manual feature extraction.

Key Components:

Convolutional Layer: Applies filters to extract local features.

Activation Function (ReLU): Introduces non-linearity.

Pooling Layer: Reduces spatial dimensions.

Fully Connected Layer: Makes predictions based on extracted features.

Formulas:

- **Convolution Operation:**

$$y(i,j) = \frac{\Sigma}{m}\frac{\Sigma}{n} x(i+m, j+n).\, \omega(m,n)$$

- **ReLU Activation:**

$$f(x) = \max(0, x)$$

2. VGG16

Definition:

VGG16 is a deep CNN architecture that consists of 16 weight layers, primarily using 3×3 convolutional filters with a stride of 1 and padding of 1, followed by max-pooling layers and fully connected layers. It emphasizes depth over width, allowing the network to learn more complex features.

Architecture Highlights:

13 convolutional layers

3 fully connected layers

Fixed filter size (3×3) and max pooling (2×2)

Formula (Output size after convolution):

$$o = \frac{(I - K + 2P)}{s} + 1$$

Where:

- I: input size
- K: kernel size
- P: padding
- S: stride

3. ResNet-50

Definition:

ResNet-50 is a 50-layer deep convolutional neural network that introduces **residual learning** via **skip connections**. This helps address the **vanishing gradient problem** and enables training of deeper networks effectively.

Formula:

$$y = F(x, \{W_i\} + x$$

4. Inception V3

Definition:

Inception V3 is an advanced CNN architecture designed to efficiently use **computational resources** while maintaining high accuracy. It uses **Inception modules** which allow the network to perform multiple types of convolutions (1×1, 3×3, 5×5) in parallel, capturing spatial features at various scales.

Key Features:

- Factorized convolutions (e.g., 3×3 = 3×1 + 1×3)
- Use of **1×1 convolutions** to reduce dimensions before expensive operations
- Auxiliary classifiers to improve convergence

  Formula:

$$y = [conv_{1\times1}(x)||conv_{3\times3}(x)||conv_{5\times5}(x)||maxpool(x)]$$

Where || denotes concatenation along the channel axis.

3.3.2 Hybrid Model Implementation

The hybrid model combines the strengths of **ResNet50** and **InceptionV3** to enhance pneumonia detection accuracy. ResNet50 contributes deep residual learning through skip connections, allowing the model to train deeper layers without degradation. InceptionV3 adds the ability to capture multi-scale spatial features using parallel convolutional filters. By merging the feature extraction capabilities of both models—typically by concatenating their learned feature maps or using ensemble averaging—this hybrid approach increases the network's ability to detect subtle patterns in chest X-ray images. As a result, it achieves higher accuracy and generalization compared to using either model individually.

Implementation Steps of Hybrid Model (ResNet50 + InceptionV3)

- **Import Libraries**

  Import essential libraries like TensorFlow, Keras, NumPy, Matplotlib, etc.
- **Load and Preprocess Dataset**

  Load chest X-ray images from the Kaggle dataset.

  Normalize the image pixel values (e.g., rescale to [0, 1]).

Resize images to a uniform size (e.g., 224×224).

Apply data augmentation (rotation, flipping, zooming) to increase variability.

- **Load Pretrained Models**

  Load ResNet50 and InceptionV3 without their top (classification) layers.

  Set include_top=False and load weights from imagenet.

  Freeze the base layers to retain pretrained knowledge.

- **Feature Extraction**

  Pass input images through both ResNet50 and InceptionV3.

  Extract output feature maps from both models.

- **Feature Concatenation or Fusion**

  Concatenate or average the outputs of both models to create a combined feature vector.

  Flatten the result to prepare it for dense layers.

- **Add Custom Classification Head**

  Add fully connected (Dense) layers after fusion.

  Use activation functions like ReLU and Dropout to prevent overfitting.

  End with a softmax or sigmoid layer (for binary classification).

- **Compile the Model**

  Use an optimizer like Adam.

  Set loss function to binary cross-entropy.

  Track metrics like accuracy, precision, and recall.

- **Train the Model**

  Fit the model using training data.

  Validate performance on the validation set.

- **Evaluate Performance**

  Test the hybrid model on the unseen test set.

  Generate metrics: accuracy, confusion matrix, F1-score.

3.4 Methodology of the system

The proposed system for pneumonia detection is structured around a robust pipeline involving data acquisition, preprocessing, model training, evaluation, and deployment. The methodology begins with collecting chest X-ray images from a reliable and publicly available dataset (such as Kaggle's Chest X-ray Pneumonia dataset), which includes labeled images categorized into pneumonia and normal cases. These images undergo a preprocessing stage where data augmentation techniques like flipping, rotation, scaling, and brightness adjustment are applied to enhance generalization and prevent overfitting.

The pre-processed dataset is then divided into training, validation, and testing subsets. Multiple deep learning models are explored and trained, including traditional convolutional neural networks (CNN), InceptionV3, ResNet50, and VGG16. Each of these models is fine-tuned to learn critical features from the X-ray images that differentiate between healthy lungs and pneumonia-infected lungs.

To enhance classification accuracy and leverage the strengths of different architectures, a hybrid model combining ResNet50 and InceptionV3 is implemented. The outputs from both networks are merged using a fusion technique (such as concatenation), followed by dense layers that classify the image based on the learned features. The final classification layer uses a sigmoid activation function for binary output (pneumonia or normal).

After training, the model's performance is evaluated using the test dataset. Metrics such as accuracy, precision, recall, and F1-score are calculated to assess the model's effectiveness. The best-performing model is then saved for deployment, allowing real-time prediction on new X-ray images. This systematic methodology ensures a high-performing and reliable tool to assist in the early detection of pneumonia, supporting medical professionals in diagnosis and treatment planning.

3.5 Model Evaluation

Model evaluation is a crucial step in validating how well the trained deep learning models perform on unseen data. In this pneumonia detection project, various models like CNN, VGG16, InceptionV3, ResNet50, and a hybrid ResNet50+InceptionV3 were assessed using a combination of statistical metrics. These metrics help determine the model's reliability and accuracy in detecting pneumonia from chest X-rays.

The following metrics and their formulas were used:

1.Accuracy:

Accuracy measures the proportion of correct predictions (both positive and negative) among the total number of cases evaluated.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

2.Precision:

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. It is useful to measure how many predicted pneumonia cases are correct.

$$Precision = \frac{TP}{TP + FP}$$

3.Recall:

Recall measures the ability of the model to detect actual positive cases (i.e., pneumonia cases).

$$Recall = \frac{TP}{TP + FN}$$

4.F1-Score:

F1-score is the harmonic mean of precision and recall. It provides a balance between the two, especially in cases of class imbalance.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + recall}$$

5.Confusion Matrix

A confusion matrix summarizes the performance of a classification model by displaying the counts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

	Predicted Positive	**Predicted Negative**
Actual Positive	TP	FN
Actual Negative	FP	TN

Table 1. Confusion matrix true labels

CHAPTER 4:

IMPLEMENTATION

4 IMPLEMENTATION

4.1 Environment setup

To successfully run the provided code and execute the project, certain environmental requirements must be met. The project is designed to operate on a system running Windows 10 (or later) with Python 3.10 installed. For optimal performance and smooth execution of deep learning tasks, it is recommended to use a machine with at least 16GB of RAM and a dedicated GPU, such as an NVIDIA GTX 1660 or higher, along with a modern processor like an Intel Core i7 10th generation or newer. Alternatively, the project can also be run efficiently in cloud-based environments like Google Colaboratory or Kaggle Notebooks, which offer free GPU resources and eliminate the need for high-end local hardware.

To ensure a clean and well-organized development setup, it is essential to create a Python virtual environment. The project relies on several key libraries, including TensorFlow for building and training deep learning models, Scikit-learn for computing evaluation metrics, NumPy for numerical computations, and Matplotlib and Seaborn for data visualization tasks. Together, these libraries enable robust image classification workflows, from data preprocessing and model training to performance evaluation and visualization of metrics like confusion matrices, ROC curves, and precision-recall curves, ultimately enhancing the functionality, accuracy, and interpretability of the model.

4.2 Sample code

```
import tensorflow as tf

from tensorflow.keras.applications import InceptionV3, ResNet50

from tensorflow.keras.applications.inception_v3 import preprocess_input as

inception_preprocess

from tensorflow.keras.applications.resnet50 import preprocess_input as resnet_preprocess

from tensorflow.keras.layers import Dense, GlobalAveragePooling2D, Concatenate, Input

from tensorflow.keras.models import Model

from tensorflow.keras.preprocessing.image import ImageDataGenerator

from tensorflow.keras.optimizers import Adam
```

```
from sklearn.metrics import confusion_matrix, classification_report
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
# Load dataset with preprocessing
train_datagen = ImageDataGenerator(preprocessing_function=inception_preprocess,
rotation_range=30, width_shift_range=0.2,
height_shift_range=0.2, shear_range=0.2, zoom_range=0.2,
horizontal_flip=True, validation_split=0.2)
test_datagen = ImageDataGenerator(preprocessing_function=inception_preprocess)
train_generator = train_datagen.flow_from_directory('/content/chest_xray/train',
target_size=(224, 224),
batch_size=32, class_mode='categorical')
validation_generator = train_datagen.flow_from_directory('/content/chest_xray/val',
target_size=(224, 224),
batch_size=32, class_mode='categorical')
test_generator = test_datagen.flow_from_directory('/content/chest_xray/test',
target_size=(224, 224),
batch_size=32, class_mode='categorical', shuffle=False)
# Define input shape
input_shape = (224, 224, 3)
inputs = Input(shape=input_shape)
# Load pre-trained models without top layers
inception = InceptionV3(weights='imagenet', include_top=False, input_tensor=inputs)
resnet = ResNet50(weights='imagenet', include_top=False, input_tensor=inputs)
```

```
# Extract feature maps
inception_output = GlobalAveragePooling2D()(inception.output)
resnet_output = GlobalAveragePooling2D()(resnet.output)
# Concatenate features from both models
merged = Concatenate()([inception_output, resnet_output])
# Fully connected layers
x = Dense(512, activation='relu')(merged)
x = Dense(256, activation='relu')(x)
# Get num_classes from train_generator before defining the model
num_classes = train_generator.num_classes
x = Dense(num_classes, activation='softmax')(x)  # Now using num_classes variable
# Create model
model = Model(inputs=inputs, outputs=x)
# Compile model
model.compile(optimizer=Adam(learning_rate=0.0001), loss='categorical_crossentropy',
metrics=['accuracy'])
# Train model
history = model.fit(train_generator, validation_data=validation_generator, epochs=11)
# Evaluate model
train_loss, train_acc = model.evaluate(train_generator)
val_loss, val_acc = model.evaluate(validation_generator)
test_loss, test_acc = model.evaluate(test_generator)
print(f'Train Accuracy: {train_acc:.4f}, Validation Accuracy: {val_acc:.2f}, Test Accuracy:
{test_acc:.4f}')
# prompt: build a cofusion matrix for the above
```

```
# Predict on the test set
y_pred = model.predict(test_generator)
y_pred_classes = np.argmax(y_pred, axis=1)
# Get true labels
y_true = test_generator.classes
# Compute the confusion matrix
cm = confusion_matrix(y_true, y_pred_classes)
# Plot the confusion matrix
plt.figure(figsize=(6, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=test_generator.class_indices.keys(),
yticklabels=test_generator.class_indices.keys())
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
# Print classification report
print(classification_report(y_true, y_pred_classes,
target_names=test_generator.class_indices.keys()))
# ROC Curve and AUC
fpr, tpr, thresholds = roc_curve(y_true, y_pred_prob[:, 1])  # Use the probability of the
positive class
roc_auc = auc(fpr, tpr)
# Plot ROC Curve
plt.figure(figsize=(6, 6))
```

```
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC Curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
# Precision-Recall Curve
precision, recall, _ = precision_recall_curve(y_true, y_pred_prob[:, 1])
average_precision = average_precision_score(y_true, y_pred_prob[:, 1])
# Plot Precision-Recall Curve
plt.figure(figsize=(6, 6))
plt.plot(recall, precision, color='green', lw=2, label=f'Precision-Recall Curve (AP =
{average_precision:.2f})')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc='lower left')
plt.show()
```

CHAPTER-5:

EXPERIMENTATION AND RESULT ANALYSIS

5 EXPERIMENTATION AND RESULT ANALYSIS

This chapter presents a detailed account of the experiments conducted, the evaluation metrics employed, and the analysis of the results obtained from the proposed hybrid deep learning model, ResIncepX—a fusion of ResNet50 and InceptionV3—developed for pneumonia detection from chest X-ray images.

5.1 Experimental Setup

The experimentation was performed using the Kaggle Chest X-ray Pneumonia dataset, comprising 5,863 X-ray images divided into training, validation, and test sets. The training process was executed on a GPU-enabled environment with the following configuration:

- **Framework:** TensorFlow/Keras
- **Optimizer:** Adam
- **Learning rate:** 0.0001
- **Batch size:** 32
- **Epochs:** 11

Data augmentation techniques (rotation, flipping, contrast adjustment) were applied to improve generalization and avoid overfitting.

5.2 Performance Metrics

The performance of the proposed model was evaluated using the following metrics:

- **Accuracy**: Correct predictions / Total predictions
- **Precision**: TP / (TP + FP)
- **Recall (Sensitivity)**: TP / (TP + FN)
- **Score**: 2 × (Precision × Recall) / (Precision + Recall)
- **AUC (Area Under the Curve)**: Overall ability to distinguish between classes

These metrics are crucial for assessing classification models, especially in medical applications where false negatives can have serious consequences.

5.3 Results and Analysis

5.3.1 Comparison Hybrid Model with Traditional Models

DL model success depends on their capability to accurately analyze and classify data in making predictions. To assess their performance, certain key metrics are employed, including accuracy, precision, recall, and the F1 score. Accuracy describes the overall accuracy of the model at classification, while precision determines the proportion of accurate positive instances out of all the predicted positives. Recall, on the other hand, seeks to minimize false negatives while maximizing true positive cases. The F1 score attempts to balance precision with recall and offers an overall measure of the model's reliability to undertake classification operations. These checks when combined result in a whole analysis of predictive capacity of the model, and the comparison among different models in terms of correctness is depicted by Table [2]

Model	Accuracy (%)
EfficientNetV2L	94.02
InceptionResNetV2	88.9
InceptionV3	94.78
ResNet50	92.56
Hybrid Model (InceptionV3 + ResNet50)	**95.19**

Table 2: Comparison of traditional models with hybrid models

5.3.2 Performance Metrics of Hybrid Model

The hybrid ResNet50-InceptionV3 model was assessed on the major performance indicators of precision, recall, F1-score, and overall accuracy. The model was found to be highly capable of classifying both pneumonia and normal conditions accurately. For the normal cases, it had an accuracy of 0.94, i.e., 94% of the instances predicted as normal were accurately classified, and a recall of 0.90, i.e., 90% of the actual normal cases were correctly identified, giving an F1-score of 0.92. For the detection of pneumonia, the model had a precision of 0.94 and a remarkable recall of 0.97, giving an F1-score of 0.95. The overall accuracy of 95.19% further emphasizes the effectiveness and reliability of the hybrid model in distinguishing pneumonia from chest X-ray images.

	Precision	Recall	F1-Score	Accuracy
Hybrid Model	94	90	92	95.19

Table 3: Performance Metrics

5.3.3 Confusion Matrix Analysis

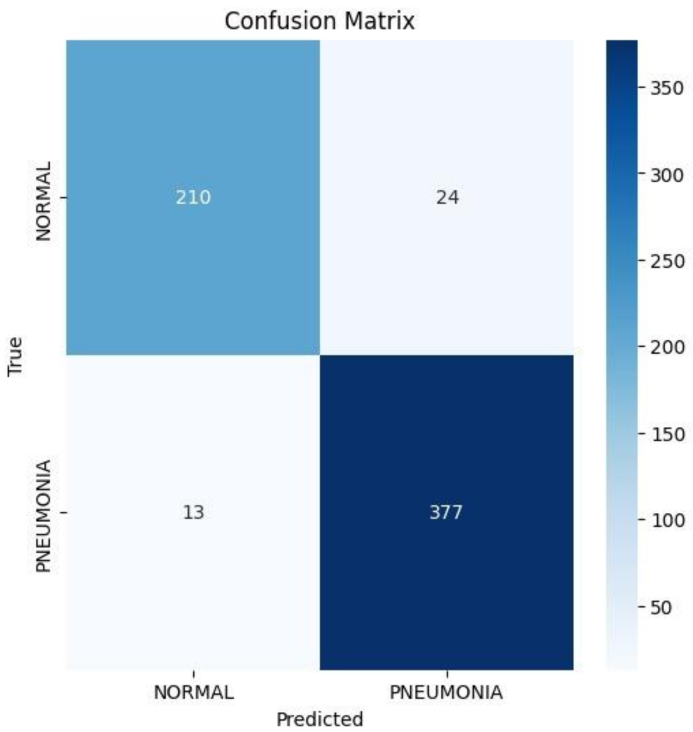


Figure 5: Confusion matrix for the hybrid ResIncepX model

Interpretation:

- **True Positives (PNEUMONIA correctly predicted):** 377
- **True Negatives (NORMAL correctly predicted):** 210
- **False Positives (NORMAL misclassified as PNEUMONIA):** 24
- **False Negatives (PNEUMONIA misclassified as NORMAL):** 13

The matrix highlights that the model achieves excellent discrimination, with very few misclassifications in both categories.

5.3.4 Receiver Operating Characteristic (ROC) Curve

The ROC curve illustrates the trade-off between the **True Positive Rate (TPR)** and **False Positive Rate (FPR)** across various threshold settings. The area under the ROC curve (AUC) quantifies the overall model performance.

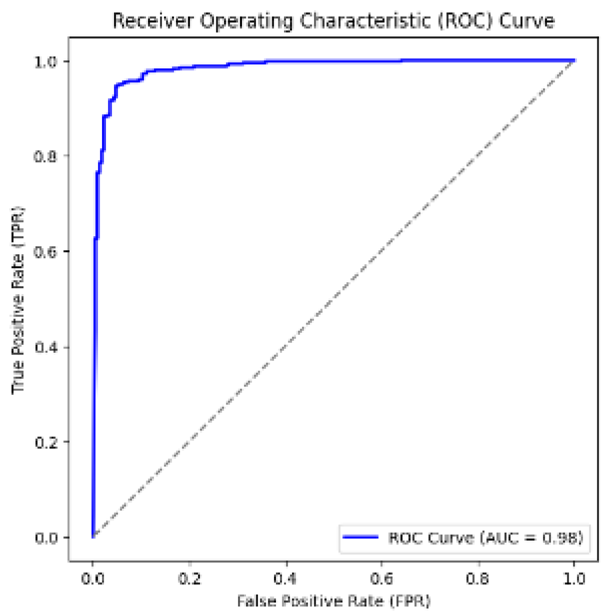


Figure 6: Receiver Operating Characteristic (ROC) Curve

Interpretation:

- **AUC = 0.98** indicates near-perfect discrimination between NORMAL and PNEUMONIA cases.
- The curve staying near the top-left corner signifies high sensitivity and specificity.

CHAPTER-6:

CONCLUSION

5 CONCLUSION

In the realm of modern healthcare, the early and accurate detection of pneumonia remains a critical challenge with profound implications for patient outcomes. Pneumonia, a potentially life-threatening respiratory infection, requires timely diagnosis to prevent complications and reduce mortality rates. Traditional diagnostic methods, such as manual evaluation of chest X-rays by radiologists, can be time-consuming and subject to inter-observer variability. Our study addresses this pressing clinical need by harnessing the synergistic power of deep learning through a hybrid architecture combining ResNet50 and InceptionV3. By leveraging the complementary strengths of these two state-of-the-art convolutional neural networks, we have achieved a significant breakthrough in pneumonia detection. Our hybrid model attains an impressive overall accuracy of 95.19%, along with superior precision and recall metrics, outperforming conventional deep learning architectures used in this domain. These performance metrics highlight the robustness and reliability of our model in distinguishing between normal and pneumonia cases, offering a promising tool to assist radiologists in clinical practice. Notably, the high accuracy underscores the model's capacity to reduce diagnostic errors and support faster decision-making, ultimately improving patient care and treatment outcomes. Compared to prior research, our approach establishes a new benchmark in automated pneumonia detection, paving the way for broader applications in medical image analysis. Looking ahead, incorporating advanced techniques such as data augmentation, real-time deployment, and integration into clinical workflows can further elevate the model's practical utility. Our work thus opens new avenues for research and innovation, reaffirming the transformative potential of deep learning in enhancing healthcare delivery and patient well-being.

CHAPTER-7:

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