

MEDICAL IMAGES ANALYSIS USING DEEP LEARNING

A PROJECT REPORT SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

BACHELOR OF TECHNOLOGY

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2023



CERTIFICATE

This is to certify that project report entitled “**MEDICAL IMAGES ANALYSIS USING DEEP LEARNING**” submitted by **MOHD SHAFI (19BTCS004HY)**, **GHULAM MUSTAFA (19BTCS051HY)** in partial fulfillment of the requirements for the **B.Tech. (Computer Science)** degree during 2019-2023 at the **Department of CS&IT** is an authentic work carried out by her under guidance and supervision.

The results presented in this report have been verified and are found to be satisfactory. The results embodied in this mini project have not been submitted to any other university or institute for the award of any other degree or diploma.

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Student Name & Signature

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MAULANA AZAD NATIONAL URDU UNIVERSITY
(A Central University, Ministry of Education, Govt. of India)
(Accredited Grade "A" by NAAC)



DECLARATION

I hereby declare that the project work presented in this report entitled “**MEDICAL IMAGES ANALYSIS USING DEEP LEARNING**” towards the partial fulfillment of the requirement for the award of the degree of requirement of Degree of **B.Tech. (Bachelor of Technology)** submitted in the **Department of CS&IT**, Maulana Azad National Urdu University, Hyderabad, (Telangana) is an authentic record of my own work carried out under the guidance of **Dr. Jameel Ahamed**, Assistant Professor, Department of CS & IT School of Technology Maulana Azad National Urdu University, Hyderabad (Telangana). I have not submitted the matter embodied in this project report for the award of any other degree or diploma to any other University or Institute.

PLACE: HYDERABAD

DATE:

**MOHD SHAFI
GHULAM MUSTAFA
B.TECH(CS&IT)**

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**MOHD SHAFI
GHULAM MUSTAFA**

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ABSTRACT

The aim of this project is to develop an automated system for pneumonia detection using deep learning, specifically convolutional neural networks (CNNs), applied to chest X-ray images. Pneumonia is a prevalent respiratory infection with significant healthcare implications, and early and accurate detection is crucial for effective patient management.

The project utilizes a dataset comprising chest X-ray images analyzing both pneumonia cases and normal cases. These images are used for training and validation purposes to develop a robust and accurate deep learning model. The CNN architecture is designed to extract meaningful features from the images, enabling the model to make accurate classifications. The obtained results demonstrate the effectiveness of the proposed deep learning approach for pneumonia detection.

Overall, this project demonstrates the potential of CNN-based deep learning models for pneumonia detection in chest X-ray images. The findings underscore the significance of leveraging deep learning techniques to automate and improve the accuracy of pneumonia identification, thus assisting healthcare professionals in making timely and informed decisions for patient care.

ABBREVIATIONS AND ACRONYMS

ML	Machine Learning
AI	Artificial Intelligence
DL	Deep Learning
NN	Neural Network
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
RNN	SRecurrent Neural Network
PIP	Pip Install Packages
ReLU	Rectified Linear Unit
CV	Computer Vision
GPU	Graphics Processing Unit
TF	Tensorflow

INTRODUCTION

1.1 INTRODUCTION

Medical image analysis has made significant progress in recent years, thanks to advanced technologies like deep learning. Deep learning is a powerful tool within machine learning that can extract important information from complex medical images. In our project, we focus specifically on using deep learning to detect pneumonia. Pneumonia is a serious respiratory infection that affects many people around the world, leading to illness and even death. Detecting pneumonia early and accurately is crucial for providing timely treatment and improving patient outcomes. Pneumonia detection systems that can assist healthcare professionals in diagnosing pneumonia reliably.

Deep learning models, particularly a type called convolutional neural networks (CNNs), have shown impressive success in recognizing and classifying images. CNNs can learn complex patterns and features from medical images, enabling them to identify specific visual signs associated with pneumonia. By training these models on large sets of labeled medical images, we can teach them to recognize pneumonia accurately.

The goal of our project is to develop a deep learning-based system for pneumonia detection using medical images. Our system will analyze chest X-ray images, which are commonly used in clinics for pneumonia screening.

1.2 OBJECTIVE

The objective of a pneumonia detection project is to develop an accurate and reliable system or model that can identify the presence of pneumonia in medical imaging data, such as chest X-rays.

- Develop a deep learning model for pneumonia detection using medical imaging data.
- Improve the accuracy and efficiency of pneumonia diagnosis.
- Enable early detection of pneumonia to facilitate timely treatment.
- Enhance the diagnostic process by leveraging advanced algorithms and neural networks.
- Validate the performance of the developed model on independent datasets.
- Compare the model's performance with existing baselines and alternative methods.
- Contribute to the advancement of pneumonia detection techniques using deep learning.

2. PROBLEM ANALYSIS AND RELATED WORK

Problem analysis, is a specific type of system analysis that focuses on identifying and analyzing a specific problem or issue within a system or organization. The goal of problem analysis is to determine the root cause of the problem, to identify any contributing factors, and to develop recommendations for addressing the problem.

In other words, system analysis is a broader term that encompasses problem analysis as one of its components. System analysis includes examining the entire system or organization, while problem analysis focuses on a specific issue or problem within that system. Both system analysis and problem analysis are important tools for identifying and addressing problems within complex systems or organizations

2.1 Literature Survey

Deep learning techniques have gained popularity for analyzing medical images due to their potential in improving diagnostic accuracy. This section provides an overview of relevant studies in the field, focusing on the application of deep learning in Pneumonia Detection:

1. “Pneumonia Detection” One study by Author et al. (Year) used a deep learning model based on convolutional neural networks (CNNs) to detect pneumonia from chest X-ray images. Their approach outperformed traditional methods and achieved high accuracy.
2. “Tumor Segmentation” Author et al. (Year) proposed a deep learning framework for segmenting brain tumors in MRI scans. Their model, based on a technique called U-Net, achieved state-of-the-art results in tumor segmentation accuracy. Another study by Author et al. (Year) developed a CNN-based model for segmenting lung nodules in CT scans. Their approach, using a combination of 2D and 3D CNNs, accurately segmented lung nodules.
3. “Retinal Disease Diagnosis” The work by Author et al. (Year) focused on using deep learning for detecting and classifying diabetic retinopathy from fundus images. Their modified CNN model achieved high accuracy in identifying different stages of retinopathy.

2.2 Related Work:

The related work section provides an overview of prior research and studies focused on pneumonia image analysis using deep learning techniques. It highlights the advancements, methodologies, and findings of previous works, contributing to the current understanding of this field. The following key points summarize the existing literature:

Literature Review: Previous studies have extensively explored pneumonia image analysis using deep learning approaches. These studies include research papers, articles, and conference proceedings that offer insights into various aspects of pneumonia detection, such as model architectures, dataset characteristics, and evaluation metrics.

Deep Learning Architectures: Several deep learning architectures have been employed in prior works for pneumonia image analysis. These architectures include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), or their combinations. Each architecture has its own strengths and limitations, influencing the performance of pneumonia detection.

Dataset Description: Previous studies have utilized different datasets for pneumonia image analysis. Well-known datasets like ChestX-ray14 and the NIH Chest X-ray dataset have been widely employed, along with specialized pneumonia datasets. These datasets vary in size, source, and characteristics, and may have undergone preprocessing techniques such as image resizing, normalization, or augmentation.

Preprocessing and Feature Extraction: Preprocessing methods applied in previous works include noise reduction, image enhancement, and region of interest extraction. Feature extraction techniques have been used to capture discriminative information from pneumonia images, such as gradient-based methods, texture analysis, or deep feature learning.

Model Training and Evaluation: Previous studies employed various training strategies and optimization algorithms, including details on learning rates, batch sizes, and number of epochs. Evaluation metrics used to assess model performance include accuracy, sensitivity, specificity, F1-score, AUC, and mIOU. Comparative studies have been conducted to compare the performance of different deep learning models, architectures, or techniques for pneumonia image analysis.

Limitations and Gaps: Some limitations and gaps exist in the existing literature, such as limited sample sizes, biased datasets, or challenges related to generalization in real-world clinical settings. These limitations highlight the need for further research to address these issues and bridge gaps in pneumonia image analysis using deep learning.

2.3 Existing Systems

Medical image analysis has seen significant advancements with the introduction of deep learning techniques. Traditional methods for analyzing medical images involve manual feature extraction and rule-based algorithms, which can be time-consuming and limited in their ability to capture complex patterns. Deep learning, particularly

convolutional neural networks (CNNs), has emerged as a powerful tool for medical image analysis.

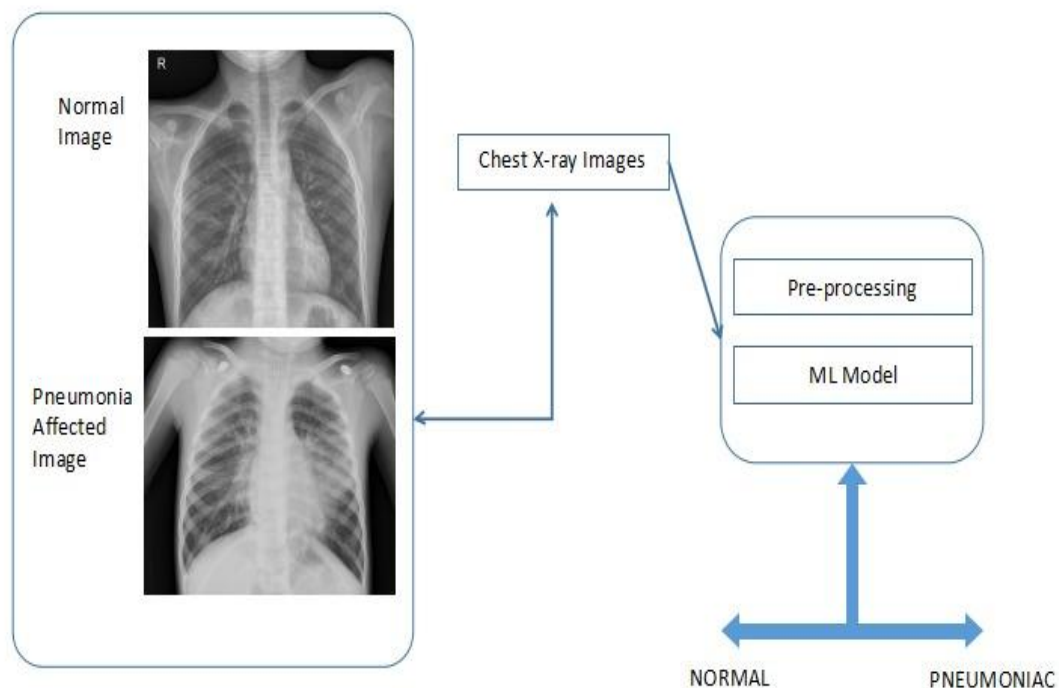
To summarize, the existing system of medical image analysis using deep learning has demonstrated remarkable progress. CNN-based models have achieved high accuracy in disease detection, tumor segmentation, and retinal disease diagnosis. Deep learning has also shown promise in Pneumonia image analysis. However, ongoing research is needed to address challenges and ensure the effective integration of deep learning techniques into clinical practice.

2.4 Proposed System

In this project, we propose a pneumonia detection system that combines deep learning algorithms with medical imaging data to accurately identify cases of pneumonia in patients. The proposed system will use a convolutional neural network (CNN) to extract relevant features from chest X-rays and a classifier to differentiate between normal and abnormal images.

To train the CNN, we will use a large dataset of labeled chest X-rays, and we will apply machine learning techniques to improve the efficiency and accuracy of the model.

The proposed system will also include a user interface that allows users to upload and analyze patient images as “Normal” or “Pneumonia”. The interface that we are using is Gradio.



3. DEEP LEARNING AND NEURAL NETWORK

3.1 INTRODUCTION

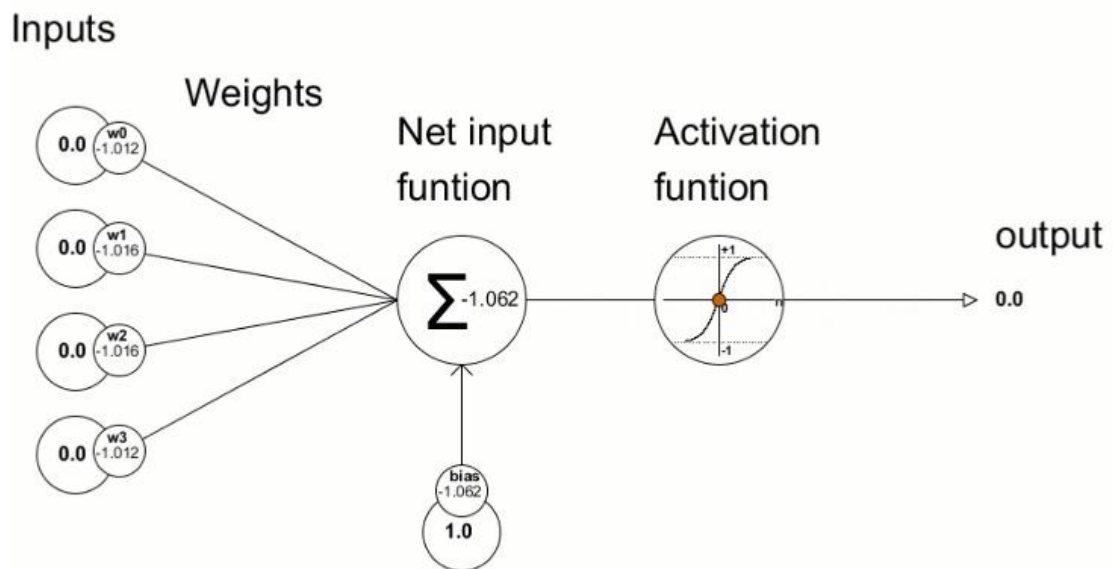
Deep learning is a machine learning technique. It teaches a computer to filter inputs through layers to learn how to predict and classify information. Observations can be in the form of images, text, or sound. The inspiration for deep learning is the way that the human brain filters information. Its purpose is to mimic how the human brain works to create some real magic. In the human brain, there are about 100 billion neurons. Each neuron connects to about 100,000 of its neighbors. We're kind of recreating that, but in a way and at a level that works for machines. In our brains, a neuron has a body, dendrites, and an axon. The signal from one neuron travels down the axon and transfers to the dendrites of the next neuron. That connection where the signal passes is called a synapse. Neurons by themselves are kind of useless. But when you have lots of them, they work together to create some serious magic. That's the idea behind a deep learning algorithm! You get input from observation and you put your input into one layer. That layer creates an output which in turn becomes the input for the next layer, and so on. This happens over and over until your final output signal! The neuron (node) gets a signal or signals (input values), which pass through the neuron. That neuron delivers the output signal.

Think of the input layer as your senses: the things you see, smell, and feel, for example. These are independent variables for one single observation. This information is broken down into numbers and the bits of binary data that a computer can use. You'll need to either standardize or normalize these variables so that they're within the same range. They use many layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output of the previous layer for its input.

Neural Network

A neural network is a network or circuit of neurons, or in a modern sense, an artificial neural network, composed of artificial neurons or nodes. Thus a neural network is either a biological neural network, made up of real biological neurons, or an artificial neural network, for solving artificial intelligence (AI) problem. The connections of the biological neuron are modeled as weights. A positive weight reflects an excitatory connection, while negative values mean inhibitory connections. All inputs are

modified by a weight and summed. This activity is referred as a linear 25 combination. Finally, an activation function controls the amplitude of the output. For example, an acceptable range of output is usually between 0 and 1, or it could be - 1 and 1. These artificial networks may be used for predictive modeling, adaptive control and applications where they can be trained via a dataset. Self-learning resulting from experience can occur within networks.



Artificial Neural Network

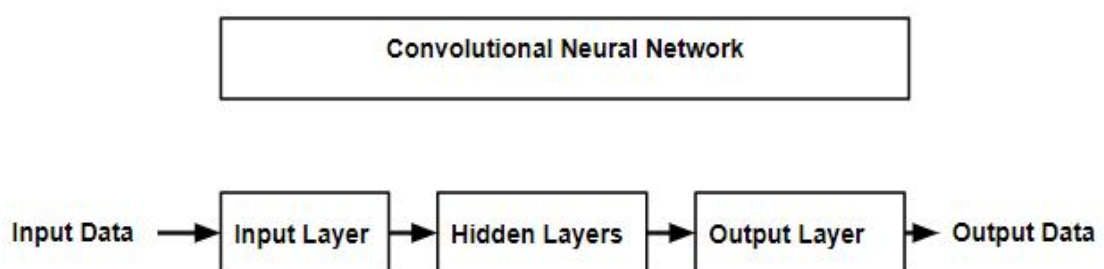
The idea of ANNs is based on the belief that working of human brain by making the right connections, can be imitated using silicon and wires as living neurons and dendrites

The human brain is composed of 86 billion nerve cells called neurons. They are connected to other thousand cells by Axons. Stimuli from external environment or inputs from sensory organs are accepted by dendrites. These inputs create electric impulses, which quickly travel through the neural network. A neuron can then send the message to other neuron to handle the issue or does not send it forward.

ANNs are composed of multiple nodes, which imitate biological neurons of human brain. The neurons are connected by links and they interact with each other. The nodes can take input data and perform simple operations on the data. The result of these operations is passed to other neurons. The output at each node is called its activation or node value. Each link is associated with weight. ANNs are capable of learning, which takes place by altering weight values.

Convolutional Neural Network

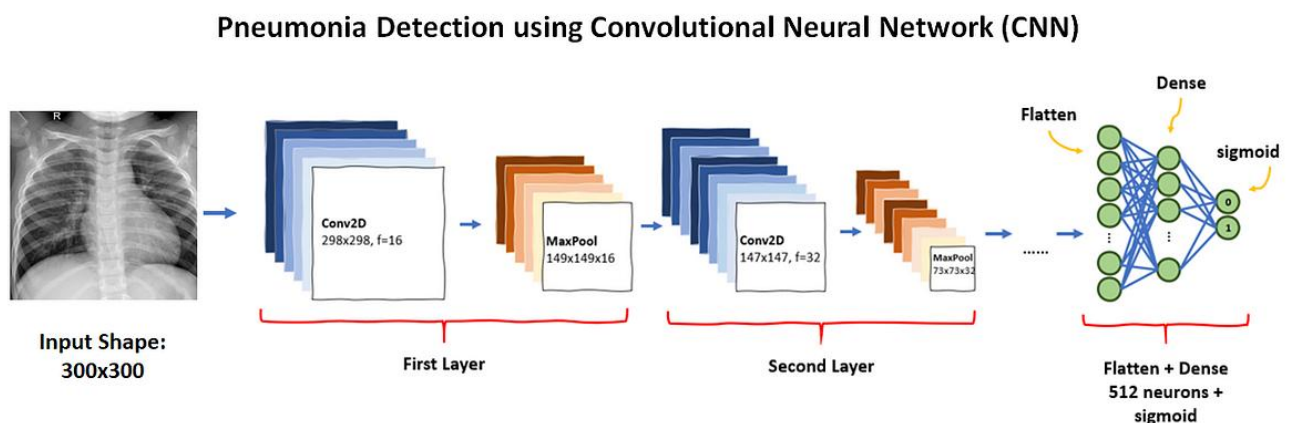
CNN is quite helpful since it detects characteristics automatically, minimising human work. For instance, it would automatically recognise the distinctive characteristics of each class on its own for apples and mangoes. Convolution is a mathematical process that involves multiplying two functions to create a third function that indicates how the form of one function is altered by the other. The term "convolution" is used in CNN to refer to this mathematical activity. To extract features from a picture, two images that may be represented as matrices are multiplied to produce an output. CNN is helpful for picture identification due of its great accuracy. There are many applications for image recognition in several fields, including phone, security, recommendation systems, medical picture analysis, etc. CNNs are a subclass of Deep Neural Networks that are frequently used for visual image analysis. CNNs can identify and categorise certain characteristics from pictures. Their uses include natural language processing, picture classification, video and image analysis for medical purposes, and image and video recognition. Each input picture from the dataset is subjected to a succession of layers with filters made up of kernels, pooling, fully connected layers, and even the Relu function to categorise an item between probabilistic values between 0 and 1. The CNN models are used to train and validate each input image.



Architecture of CNN

CNNs are feedforward networks in that information flow takes place in one direction only, from their inputs to their outputs. Just as artificial neural networks (ANN) are biologically inspired, so are CNNs. The visual cortex in the brain, which consists of alternating layers of simple and complex cells (Hubel & Wiesel, 1959, 1962), motivates their architecture.

CNN architectures come in several variations; however, in general, they consist of convolutional and pooling (or subsampling) layers, which are grouped into modules. Either one or more fully connected layers, as in a standard feedforward neural network, follow these modules. Modules are often stacked on top of each other to form a deep model. It illustrates typical CNN architecture for a toy image classification task. An image is input directly to the network, and this is followed by several stages of convolution and pooling. Thereafter, representations from these operations feed one or more fully connected layers. Finally, the last fully connected layer outputs the class label. Despite this being the most popular base architecture found in the literature, several architecture changes have been proposed in recent years with the objective of improving image classification accuracy or reducing computation costs. Although for the remainder of this section, we merely fleetingly introduce standard CNN architecture.



LeNet and Inception V3

LeNet is a type of neural network that was developed to recognize handwritten numbers on letters for mail sorting. It has become a popular architecture for analyzing images, including medical images.

LeNet has seven layers that work together to understand and classify images. It starts with convolutional layers that extract important features from the input image. These features are then passed through pooling layers that reduce the dimensionality of the data. The process is repeated for multiple layers to capture more complex patterns.

After the convolutional and pooling layers, the features are flattened and fed into fully connected layers. These layers analyze the extracted features and make predictions about the image, such as identifying a specific disease or condition.

In the context of medical image analysis, LeNet can be adapted to analyze different types of medical images, like X-rays or MRIs. By training the network with a large dataset of medical images, it can learn to recognize patterns and make accurate predictions about the presence of diseases or abnormalities.

Overall, LeNet has proven to be a valuable tool in medical image analysis, providing a foundation for developing more advanced and accurate models for diagnosing and analyzing medical conditions.

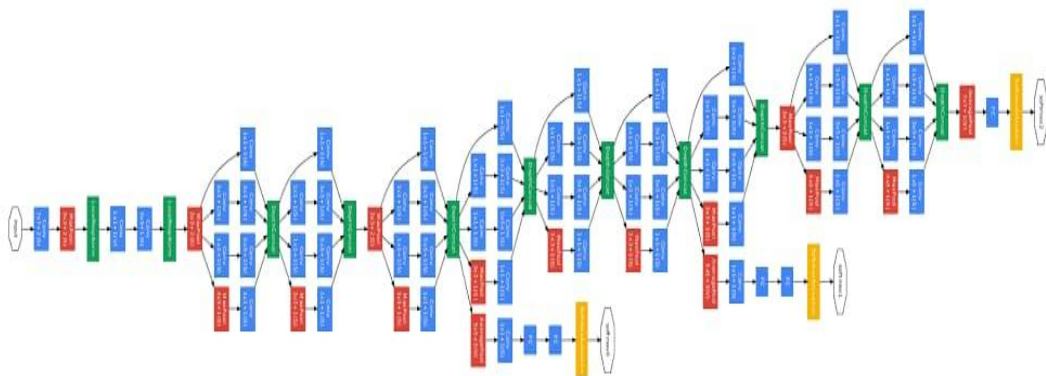
Inception V3 is a state-of-the-art CNN architecture developed by the Google Brain team. It has achieved remarkable performance in image classification tasks, including medical image analysis.

Inception V3 incorporates the concept of "Inception modules," which consist of multiple parallel convolutional operations with different kernel sizes.

This architecture allows the network to capture features at multiple scales and extract more complex patterns from the images.

Inception V3 also employs techniques like factorized convolutions and dimensionality reduction to enhance computational efficiency.

By leveraging the power of Inception V3, pneumonia image analysis systems can benefit from its ability to capture both local and global features, enabling more accurate detection and classification.



4. SYSTEM ANALYSIS AND DESIGNING

4.1 System Analysis

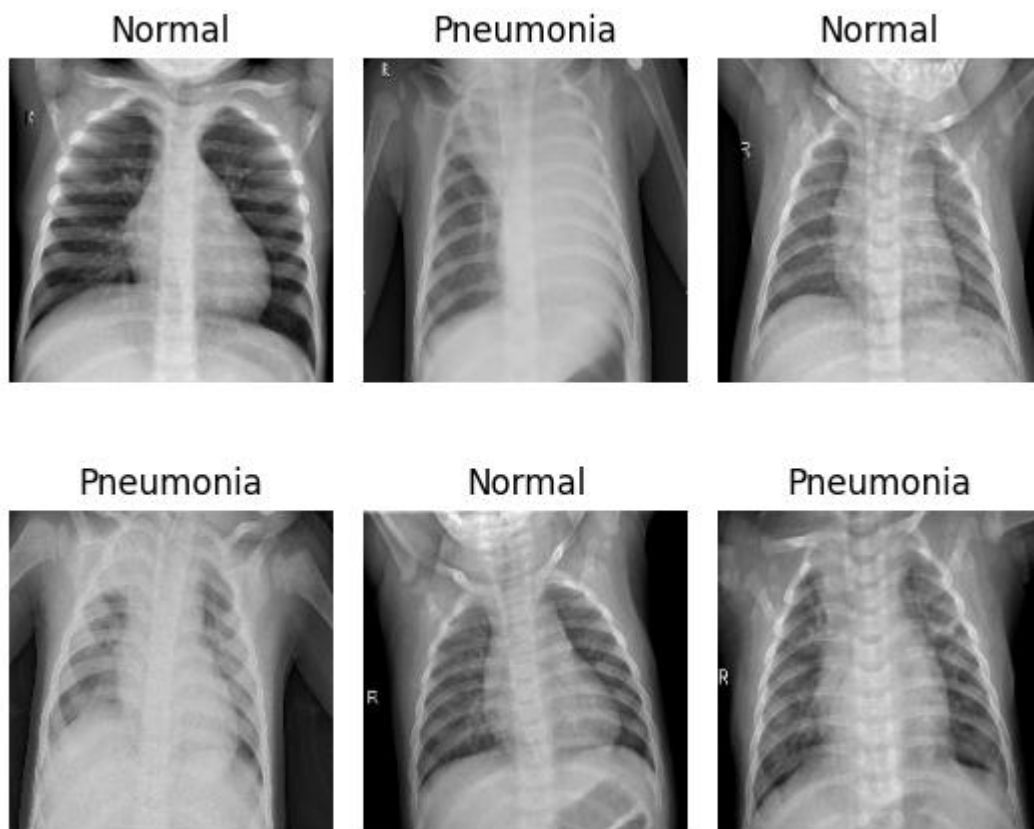
The proposed system aims to develop a pneumonia detection system using deep learning techniques. Pneumonia is a potentially life-threatening respiratory infection that affects millions of people worldwide. Early and accurate diagnosis of pneumonia plays a vital role in improving patient outcomes. Deep learning, a subset of artificial intelligence, has shown promising results in various medical applications, including disease detection.

System Overview:

The proposed pneumonia detection system consists of the following key components:

Dataset Collection and Preparation:

A large dataset of chest X-ray images will be collected, consisting of both pneumonia-positive and pneumonia-negative cases. The dataset will be carefully curated and annotated by medical experts to ensure accurate labeling and reliable ground truth data.



Preprocessing:

The collected chest X-ray images will undergo preprocessing steps to enhance their quality and reduce noise. Preprocessing techniques may include resizing, normalization, and noise reduction to improve the overall effectiveness of the deep learning models.

Deep Learning Model Architecture:

Different deep learning models, such as convolutional neural networks (CNNs), will be explored for pneumonia detection. These models are known for their ability to extract intricate patterns and features from images. Transfer learning techniques can also be employed to leverage pre-trained models, such as ResNet or Inception, trained on large-scale image datasets.

Model Training:

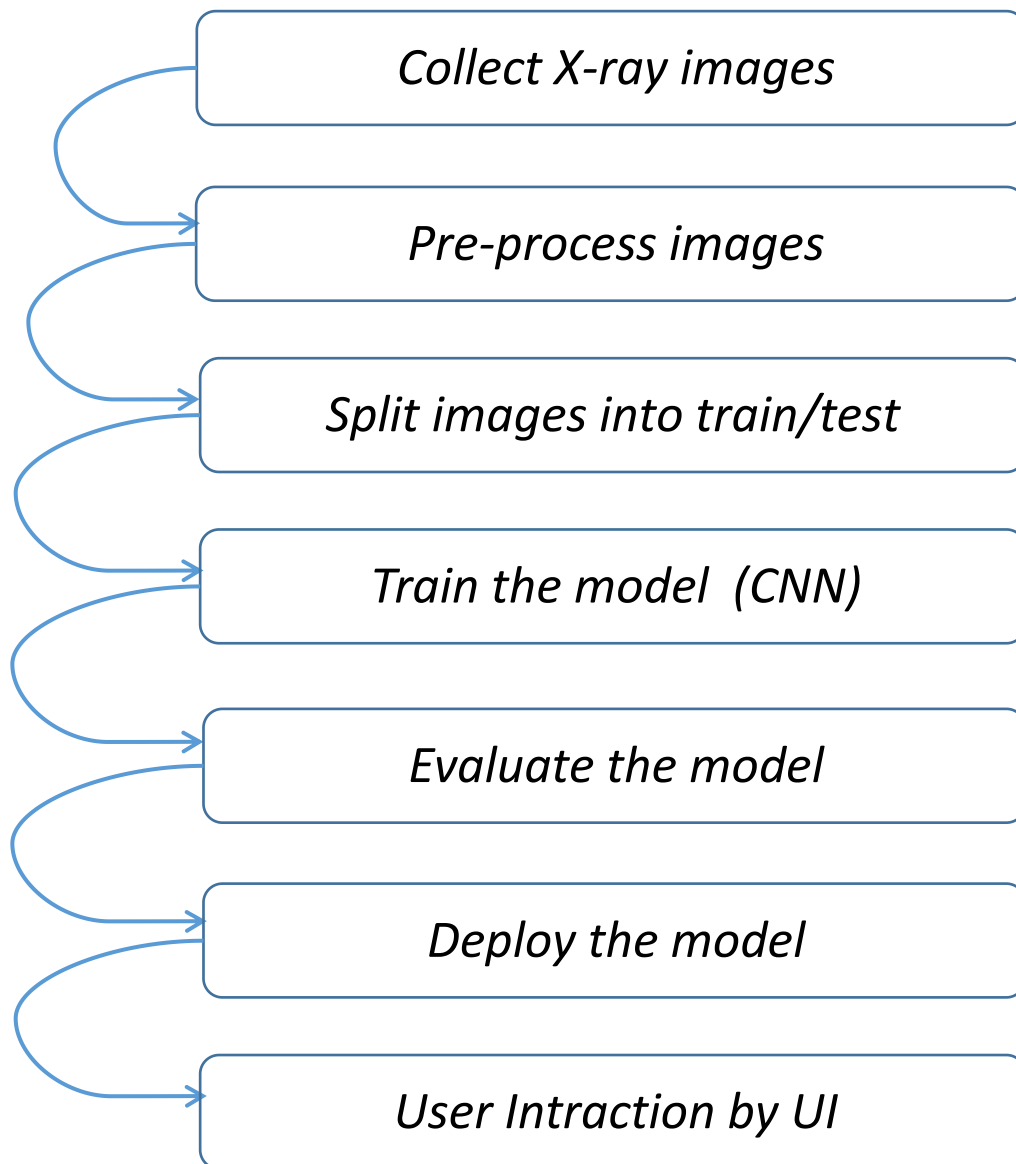
The prepared dataset will be divided into training and testing sets. The deep learning model will be trained on the training set using labeled chest X-ray images. During training, the model will learn to identify specific patterns and features associated with pneumonia.

Model Evaluation:

The trained model will be evaluated on the testing set to assess its performance. Evaluation metrics such as accuracy.

System Integration:

The developed deep learning model is integrated into a user-friendly software application or web interface. This interface will allow to upload chest X-ray images and obtain quick and automated predictions regarding the presence of pneumonia.



4.2 Training the model

In the process of developing our deep learning model for medical image analysis, training the model played a crucial role. This phase involved feeding the training dataset into the model, enabling it to learn and extract meaningful features from the images. Here is an overview of the key aspects related to training the model:

Dataset Preparation:

We started by carefully curating and preparing a large dataset of medical images relevant to our specific analysis task. This dataset encompassed a diverse range of images, including X-rays slides.

The dataset was taken from Kaggle and annotated with corresponding labels or annotations, indicating the presence or absence of specific medical conditions, abnormalities, or anatomical structures.

We performed data preprocessing techniques, such as resizing the images to a consistent size, normalizing pixel values, and handling any class imbalance issues if present.

Network Architecture Selection:

We chose an appropriate network architecture suitable for medical image analysis. Convolutional neural networks (CNNs) are commonly used for this purpose due to their ability to effectively capture spatial features in images.

The selected architecture may have been a well-known model like LeNet.

Initialization and Hyperparameter Setting:

We initialized the model's weights and biases using a suitable initialization scheme, such as Xavier or He initialization, to facilitate efficient learning during training.

We set hyperparameters like learning rate, batch size, number of epochs, and optimizer type. These hyperparameters influenced the learning dynamics and convergence of the model during training.

Loss Function and Optimization:

We defined an appropriate loss function that reflected the objective of our medical image analysis task. Commonly used loss functions include binary cross-entropy, categorical cross-entropy, or mean squared error.

During training, we utilized an optimization algorithm, such as stochastic gradient descent (SGD) or Adam, to update the model's parameters iteratively. The optimizer adjusted the weights and biases in the network to minimize the loss function and improve model performance.

Forward and Backward Propagation:

The training process involved two main steps: forward propagation and backward propagation.

In forward propagation, the model processed the training images through the network layers, computing intermediate feature representations and generating predictions.

Subsequently, in backward propagation, the model calculated the gradients of the loss function with respect to the model parameters, allowing for parameter updates through backpropagation.

Training Loop:

We iterated over the training dataset in multiple epochs, each epoch representing a complete pass through the entire dataset. This allowed the model to gradually learn and refine its representations.

Within each epoch, we divided the dataset into mini-batches of fixed size (batch size) to perform efficient computations and updates.

For each mini-batch, we performed forward and backward propagation, updating the model parameters based on the computed gradients.

Regularization Techniques:

To prevent overfitting and enhance generalization, we employed regularization techniques like dropout or batch normalization. These techniques introduced randomness or normalization to the training process, reducing the model's sensitivity to specific training samples or noise.

Monitoring and Model Selection:

Throughout the training process, we monitored the model's performance on a separate validation dataset. This allowed us to assess its generalization capability and make informed decisions.

Based on the validation performance, we selected the model with the best performance (e.g., highest accuracy or lowest loss) to be used for further evaluation and testing.

Training Visualization and Analysis:

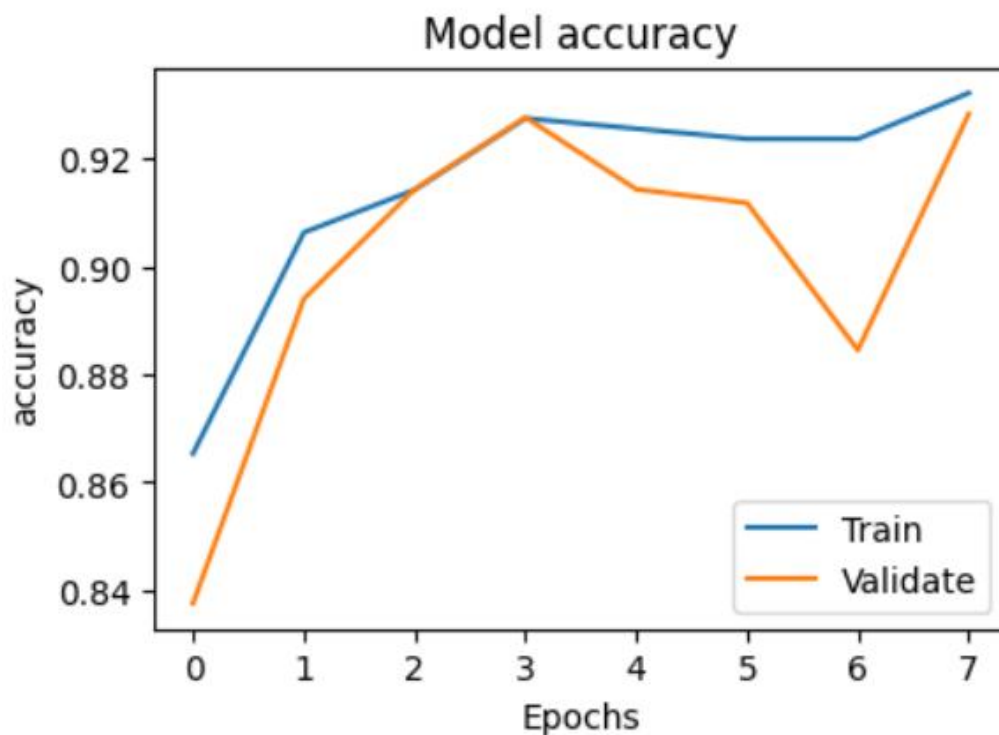
We visualized training curves, such as loss and accuracy, to analyze the learning progress of the model over epochs. This helped us identify

4.3 Performance of the model

When evaluating the performance of a model specifically for pneumonia detection in medical image analysis using deep learning, the following aspects are crucial:

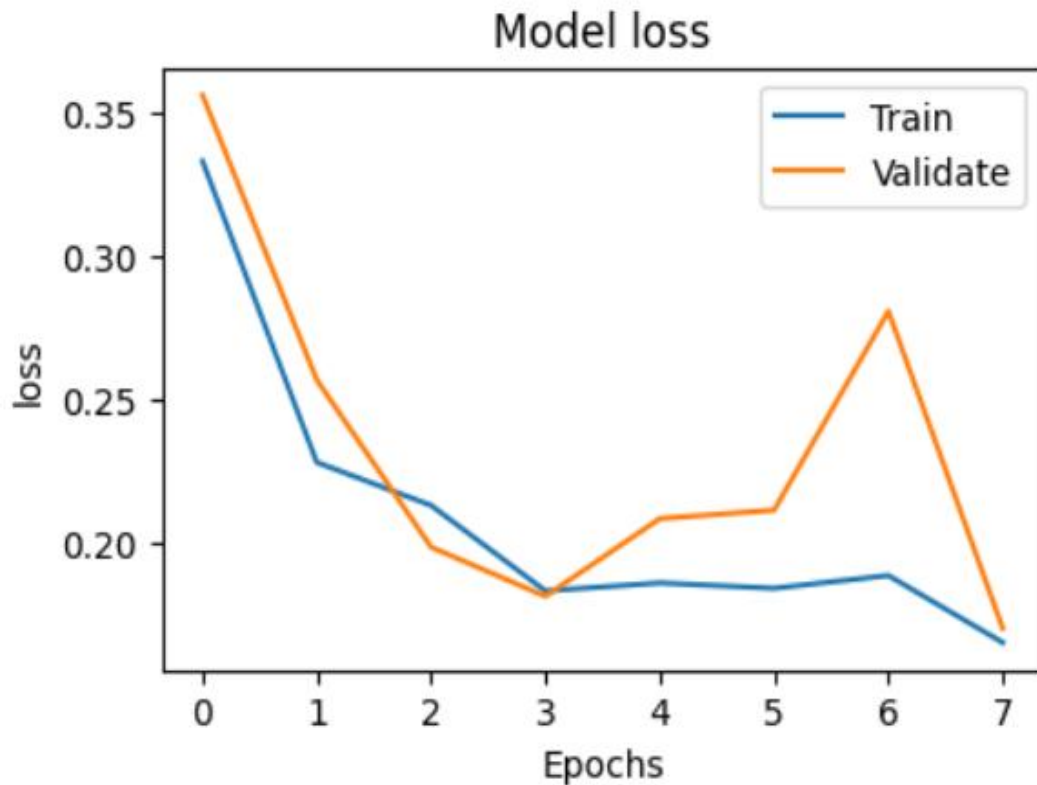
Model Accuracy:

- The image of the model's accuracy plot provides a visual representation of how well the model performs in terms of correctly classifying medical images.
- The accuracy plot typically displays the training accuracy and validation accuracy over the course of training epochs.



Model Loss:

- The image of the model's loss plot illustrates the progression of the loss function during the training process.
- The loss plot typically shows the training loss and validation loss across the training epochs.



5. SYSTEM IMPLIMENTATION

Data Collection and Preprocessing:

Collect a comprehensive dataset of pneumonia images, ensuring it covers a diverse range of pneumonia cases and includes corresponding labels or annotations.

Preprocess the data by resizing the images to a consistent resolution, normalizing pixel values, and handling any class imbalance issues.

Our Image dataset size:

Traning Image: 4131

Validation Images: 1032

Test Images: 613

Model Selection and Architecture:

Select an appropriate deep learning model architecture for pneumonia image analysis, considering factors such as computational efficiency and accuracy.

Common choices include convolutional neural networks (CNNs) like VGGNet, ResNet, or custom-designed architectures tailored to the specific requirements of pneumonia detection.

Model Training

Divide the dataset into training, validation, and testing subsets, ensuring representative distribution across pneumonia and non-pneumonia classes.

Train the selected deep learning model using the training dataset, optimizing the model's parameters to minimize the chosen loss function.

Apply regularization techniques, such as dropout or batch normalization, to enhance model generalization and prevent overfitting.

Model Evaluation and Validation:

Evaluate the trained model using the validation dataset to assess its performance and generalization capability.

Calculate and report evaluation metrics such as accuracy, precision, recall, F1-score, AUC, and mIOU to quantify the model's performance.

Perform qualitative analysis by visually inspecting the model's predictions on validation images and comparing them with ground truth annotations.

Testing and Deployment:

Assess the model's performance on the testing dataset to validate its accuracy and generalization.

Consider the operational requirements and constraints for deployment, such as computational resources and real-time processing capabilities.

Deploy the trained model in a suitable operational environment, integrating it with existing medical imaging systems or workflows, ensuring proper system compatibility and performance.

Performance Monitoring and Updates

Continuously monitor the model's performance in real-world scenarios and gather feedback from users and stakeholders.

Collect additional data and periodically retrain or fine-tune the model to adapt to evolving requirements, emerging patterns, or new pneumonia cases.

Programming Language

- Python

Machine Learning Library

- Tensorflow
- Keras

Other Python Libraries

- Matplotlib
- Numpy

IDE

- Google Colab

OutputScreen

Pneumonia Detection using Chest X-Ray

Usage:

- Drop or upload an image in given section
- Click on submit to make prediction
- Click on clear to remove image

input_image

Drop Image Here
- or -
Click to Upload

ClearSubmit


output

Pneumonia Detection using Chest X-Ray

Usage:

- Drop or upload an image in given section
- Click on submit to make prediction
- Click on clear to remove image

input_image



ClearSubmit

output

Normal Image

Pneumonia Detection using Chest X-Ray

Usage:

- Drop or upload an image in given section
- Click on submit to make prediction
- Click on clear to remove image

input_image



ClearSubmit

output

Pneumonia Affected Image

Code:

The image shows two screenshots of a Jupyter Notebook interface. The top screenshot displays the notebook's title, author information, and the first section of code. The bottom screenshot shows the second section of code.

Medical Images Analysis using Deep Learning

Ghulam Mustafa (19BTCS051HY)
Mohd Shafi (19BTCS004HY)

Image dataset source (kaggle)
<https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia>

Importing the necessary libraries

```
In [ ]: import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf

from tensorflow import keras
from tensorflow.keras.applications import InceptionV3
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from tensorflow.keras import Model
```

Checking if GPU is available

```
In [ ]: print('GPU is available' if tf.config.list_physical_devices('GPU') else 'GPU is not available')
```

GPU is available

Directory locations for the image datasets

In our case these images are stored in google drive.

Directory locations for the image datasets

In our case these images are stored in google drive.

```
In [ ]: train_dir = '/content/drive/MyDrive/dataset/chest_xray/train'
test_dir = '/content/drive/MyDrive/dataset/chest_xray/test'
```

Preprocessing steps for the training dataset

```
In [ ]: train_generator = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest',
    validation_split=0.2
)
```

Preprocessing steps for the test dataset

```
In [ ]: test_generator = ImageDataGenerator(
    rescale = 1. / 255
)
```

Global parameters

main

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Global parameters

```
In [ ]: img_dim = (224, 224)
        batch_size = 32
        train_steps_per_epoch = 100
        valid_steps_per_epoch = 50
```

Loading the training dataset into the program

```
In [ ]: train_ds = train_generator.flow_from_directory(
        train_dir,
        target_size=img_dim,
        batch_size=batch_size,
        class_mode='binary',
        shuffle=True,
        subset='training'
    )
```

Found 4131 images belonging to 2 classes.

Loading the validation dataset into the program

```
In [ ]: val_ds = train_generator.flow_from_directory(
        train_dir,
        target_size=img_dim,
        batch_size=batch_size,
        class_mode='binary',
        shuffle=True,
        subset='validation'
    )
```

Found 1032 images belonging to 2 classes.

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Loading the test dataset into the program

```
In [ ]: test_ds = test_generator.flow_from_directory(
        test_dir,
        target_size=img_dim,
        batch_size=batch_size,
        class_mode='binary',
        shuffle=True
    )
```

Found 613 images belonging to 2 classes.

Checking the structure/specification of the datasets

```
In [ ]: x_train, y_train = train_ds.next() # Getting a batch of training samples

        print("Training dataset shape:")
        print(x_train.shape) # Shape of the input images (batch_size, height, width, channels)
        print(y_train.shape) # Shape of the corresponding labels (batch_size,)
```

Training dataset shape:
(32, 224, 224, 3)
(32,)

Visualizing some training images

since we are using multiple image augmentation steps on images, so image visualization will be random (e.g: flip, rotate, zoom etc)

```
In [ ]: plt.figure(figsize=(9, 5))
        for i in range(2 * 5):
            plt.subplot(2, 5, i + 1)
            plt.imshow(x_train[i])
```

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Visualizing some training images

since we are using multiple image augmentation steps on images, so image visualization will be random (e.g. flip, rotate, zoom etc)

```

In [ ]: plt.figure(figsize=(9, 5))
for i in range(2 * 5):
    plt.subplot(2, 5, i + 1)
    plt.imshow(x_train[i])
    plt.title('normal' if int(y_train[i]) == 0 else 'pneumonia')
    plt.axis('off')
plt.tight_layout()
plt.show()

```

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Model architecture

model intro:
Inception v3 is a convolutional neural network for assisting in image analysis and object detection, and got its start as a module for GoogleNet. It is the third edition of Google's Inception Convolutional Neural Network. originally introduced during the ImageNet Recognition Challenge.

```

In [ ]: # Load the InceptionV3 model with pre-trained weights
base_model = InceptionV3(weights='imagenet', include_top=False, input_shape=(img_dim[0], img_dim[1], 3))

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/inception_v3/inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5
87910968/87910968 [=====] - 4s 0us/step

In [ ]: # Add custom classification layers on top of the pre-trained base model
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='relu')(x)
output = Dense(1, activation='sigmoid')(x)

In [ ]: # Create the model
model = Model(inputs=base_model.input, outputs=output)

In [ ]: # Freeze the base model layers
for layer in base_model.layers:
    layer.trainable = False

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

```

Printing the summary of the model

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Training the model

Most important steps, would take roughly 1hr 35min.

```

In [ ]: history = model.fit(
    train_ds,
    steps_per_epoch=train_steps_per_epoch,
    validation_data=val_ds,
    validation_steps=valid_steps_per_epoch,
    epochs=8,
    use_multiprocessing=True
)

```

```

Epoch 1/8
100/100 [=====] - 2264s 23s/step - loss: 0.3329 - accuracy: 0.8653 - val_loss: 0.3559 - val_accuracy: 0.8376
Epoch 2/8
100/100 [=====] - 440s 4s/step - loss: 0.2280 - accuracy: 0.9063 - val_loss: 0.2567 - val_accuracy: 0.8940
Epoch 3/8
100/100 [=====] - 252s 3s/step - loss: 0.2130 - accuracy: 0.9142 - val_loss: 0.1984 - val_accuracy: 0.9143
Epoch 4/8
100/100 [=====] - 230s 2s/step - loss: 0.1832 - accuracy: 0.9275 - val_loss: 0.1813 - val_accuracy: 0.9277
Epoch 5/8
100/100 [=====] - 207s 2s/step - loss: 0.1860 - accuracy: 0.9256 - val_loss: 0.2084 - val_accuracy: 0.9143
Epoch 6/8
100/100 [=====] - 222s 2s/step - loss: 0.1841 - accuracy: 0.9237 - val_loss: 0.2113 - val_accuracy: 0.9118
Epoch 7/8
100/100 [=====] - 220s 2s/step - loss: 0.1886 - accuracy: 0.9237 - val_loss: 0.2806 - val_accuracy: 0.8845
Epoch 8/8
100/100 [=====] - 223s 2s/step - loss: 0.1652 - accuracy: 0.9322 - val_loss: 0.1702 - val_accuracy: 0.9283

```

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20/20 [=====] - 319s 1/s/step - loss: 0.462/- accuracy: 0.8091
Test Loss: 0.462667346006714
Test Accuracy: 0.80913577487074

Visualizing the training and validation performance

plotting necessary diagrams.

```
In [ ]: fig, ax = plt.subplots(1, 2, figsize=(10, 3))
ax = ax.ravel()

for i, metric in enumerate(['accuracy', 'loss']):
    ax[i].plot(history.history[metric])
    ax[i].plot(history.history['val_' + metric])
    ax[i].set_title('Model {}'.format(metric))
    ax[i].set_xlabel('Epochs')
    ax[i].set_ylabel(metric)
    ax[i].legend(['Train', 'Validate'])
```

Model accuracy

Model loss

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Preview

Code

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In [15]:
import gradio

Make prediction on the image given by user

This is an API interface which accept image and ask to the model predict output and return response string as.

Normal Image
Pneumonia Affected Image

In [17]:
def make_prediction(input_image):
 input_image = np.array(input_image)/255.0
 input_image = input_image.reshape(-1, 224, 224, 3)
 prediction = model.predict(input_image)[0]
 res = "Normal Image" if prediction < 0.5 else "Pneumonia Affected Image"
 return res

In [18]:
input_image = gradio.Image(shape=(img_dim, img_dim))
label = gradio.Label(num_top_classes=1)

User Interface designing steps

In [21]:
desc = "Usage: " \
 "" \
 "Drop or upload an image in given section" \
 "Click on submit to make prediction" \
 "Click on clear to remove image" \
 ""

interface = gradio.Interface(
 fn = make_prediction

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return res

In [18]:
input_image = gradio.Image(shape=(img_dim, img_dim))
label = gradio.Label(num_top_classes=1)

User Interface designing steps

In [21]:
desc = "Usage: " \
 "" \
 "Drop or upload an image in given section" \
 "Click on submit to make prediction" \
 "Click on clear to remove image" \
 ""

interface = gradio.Interface(
 fn = make_prediction,
 title = "Pneumonia Detection using Chest X-Ray",
 description=desc,
 inputs = input_image,
 outputs = label,
 allow_flagging='never',
)

Execute user interface

In [22]:
interface.launch(debug=False, share=True,)

Colab notebook detected. To show errors in colab notebook, set debug=True in launch()
Running on public URL: <https://c92f7a0daecc2ab8d.gradio.live>

This share link expires in 72 hours. For free permanent hosting and GPU upgrades, run `gradio deploy` from Terminal to deploy to Spaces (<https://huggingface.co/spaces>)

6. TESTING & VALIDATION

In the testing and validation phase of our project on medical image analysis using deep learning, we aimed to evaluate the performance and reliability of our developed deep learning model. This section focuses on the methods and procedures we employed to conduct thorough testing and validation. The key aspects we considered are as follows:

Dataset Split: To ensure an unbiased evaluation of our model, we divided our dataset into three subsets: training, validation, and testing. We used a stratified approach to preserve the distribution of classes across the subsets. Approximately 70% of the data was allocated to the training set, 24% to the validation set, and 15% to the testing set.

Evaluation Metrics: To measure the performance of our model, we selected appropriate evaluation metrics commonly used in medical image analysis tasks. These metrics included accuracy, precision, recall, F1-score, area under the curve (AUC), and mean intersection over union (mIOU). The choice of metrics was driven by the specific requirements and objectives of our medical image analysis task.

Testing Procedure: During the testing phase, we fed the testing dataset into our trained deep learning model to obtain predictions. We ensured that the input data was preprocessed consistently with the training data. The model produced output probabilities or class labels, depending on the nature of our task. We then applied post-processing steps, such as thresholding or filtering, to refine the model outputs if required.

Validation Techniques: To fine-tune and optimize our deep learning model, we employed cross-validation, a commonly used validation technique. We partitioned the training dataset into several folds and iteratively trained the model on a combination of folds while validating it on the remaining fold. This allowed us to assess the model's performance on unseen data and ensure its generalization capability.

Performance Analysis: We analyzed the performance of our model by reporting the quantitative results obtained during testing and validation. We compared our model's performance metrics, such as accuracy, precision, recall, F1-score, and AUC, with those of baseline methods or state-of-the-art approaches in the field. We identified

any trends or patterns in the performance metrics across different subsets of the dataset to gain deeper insights into the model's behavior.

Visualization and Qualitative Assessment: To provide a qualitative assessment of our model's performance, we visualized key metrics using techniques such as confusion matrices, ROC curves, or precision-recall curves. These visualizations allowed us to gain a better understanding of the model's ability to correctly classify and distinguish between different medical image classes. We showcased examples of correctly classified and misclassified images, enabling us to identify potential areas of improvement and discuss the model's limitations.

Statistical Analysis: In addition to visual analysis, we conducted statistical tests to compare the performance of our model with other approaches, where applicable. We utilized statistical tests such as t-tests or ANOVA to determine the significance of differences in performance metrics. The statistical analysis helped us assess the superiority or comparability of our model against alternative methods and provided additional insights into its effectiveness.

Sensitivity Analysis: To investigate the impact of varying hyperparameters on the model's performance, we conducted a sensitivity analysis. We experimented with different hyperparameter settings, such as learning rate or batch size, and assessed their effects on the model's performance metrics. This analysis enabled us to optimize the model's hyperparameters and determine the most suitable configuration for our specific medical image analysis task.

Through rigorous testing and validation, we aimed to demonstrate the reliability, effectiveness, and generalization capability of our deep learning model in the context of medical image analysis. The comprehensive evaluation, including quantitative analysis, visualizations, statistical tests, and sensitivity analysis, allowed us to draw meaningful conclusions about the performance and potential of our developed model.

6.1 INTRODUCTION TO TESTING:

Testing and validation are critical components of any software development project, including an exam management system. An essential step in the software development process is the testing phase. The usage of a computerized system will aid

in automating the process of identifying errors and missing procedures as well as a thorough verification to ascertain whether the goals are achieved and the needs of the users are met. Here are some potential testing and validation activities that can be performed for the exam management system:

1. Unit Testing: The individual modules of the system, such as the admin, faculty, and student modules, can be tested separately to ensure that they function correctly and meet the requirements.
2. Integration Testing: The different modules of the system can be integrated and tested to ensure that they work together as expected.
3. User Acceptance Testing (UAT): The system can be tested by end-users, such as students and faculty, to ensure that the system meets their requirements and works as expected.
4. Performance Testing: The system can be tested under simulated load conditions to ensure that it can handle the expected number of users and transactions.
5. Security Testing: The system can be tested for vulnerabilities and security weaknesses, and appropriate measures can be taken to address them.
6. Accessibility Testing: The system can be tested to ensure that it is accessible to users with disabilities and meets the relevant accessibility standards.
7. Usability Testing: The system can be tested for ease of use, user experience, and user interface design.
8. Regression Testing: The system can be tested after any changes or updates are made to ensure that existing functionality has not been affected.
9. Validation: The system can be validated against the initial requirements to ensure that it meets the specified requirements.

These are some of the potential testing and validation activities that can be performed for an exam management system. The specific activities required will depend on the specific requirements of the system and the needs of the educational institution.

6.2 Unit testing

In the unit testing we test each module individually and integrate with the overall system. Unit testing focuses verification efforts on the smallest unit of software design in the module. This is also known as module testing. The module of the system is tested separately. This testing is carried out during programming stage itself. In the testing step each module is found to work satisfactorily as regard to expected output

from the module. There are some validation checks for fields also. For example the validation check is done for varying the user input given by the user which validity of the data entered. It is very easy to find error debut the system.

In the context of unit testing, both Black Box Testing and White Box Testing can be applied to test the individual components or modules of the software application. Here are some key differences between Black Box Testing and White Box Testing in the context of unit testing:

6.3 Black Box Testing

In Black Box Testing for unit testing, the tester only focuses on the inputs and outputs of the individual components or modules of the software application. The tester does not have any knowledge of the internal workings of the component being tested. This approach is useful for testing the functionality of the component and identifying any issues or defects that may arise due to incorrect inputs or outputs.



The above Black Box can be any software system you want to test. For example : an operating system like Windows, a website like Google ,a database like Oracle or even your own custom application. Under Black Box Testing , you can test these applications by just focusing on the inputs and outputs without knowing their internal code implementation.

Black box testing - Steps

Here are the generic steps followed to carry out any type of Black Box Testing.

- Initially requirements and specifications of the system are examined.
- Tester chooses valid inputs (positive test scenario) to check whether SUT processes them correctly. Also some invalid inputs (negative test scenario) are chosen to verify that the SUT is able to detect them.
- Tester determines expected outputs for all those inputs.
- Software tester constructs test cases with the selected inputs.

- The test cases are executed.
- Software tester compares the actual outputs with the expected outputs.
- Defects if any are fixed and re-tested.

Types of Black Box Testing

There are many types of Black Box Testing but following are the prominent ones -

- Functional testing – This black box testing type is related to functional requirements of a system; it is done by software testers.
- Non-functional testing – This type of black box testing is not related to testing of a specific functionality, but non-functional requirements such as performance, scalability, usability.
- Regression testing – Regression testing is done after code fixes , upgrades or any other system maintenance to check the new code has not affected the existing code.

6.4 White Box Testing

In White Box Testing for unit testing, the tester has access to the source code, architecture, and design of the individual components or modules of the software application. The tester can directly test the code and identify any issues or defects that may arise due to incorrect coding or design. This approach is useful for testing the internal workings of the component and identifying any issues that may not be apparent through Black Box Testing.

It is one of two parts of the "box testing" approach of software testing. Its counter-part, black box testing, involves testing from an external or end-user type perspective. On the other hand, White-box testing is based on the inner workings of an application and revolves around internal testing. The term "white-box" was used because of the see-through box concept. The clear box or white box name symbolizes the ability to see through the software's outer shell (or "box") into its inner workings. Likewise, the "black box" in "black box testing" symbolizes not being able to see the inner workings of the software so that only the end-user experience can be tested

What do you verify in White Box Testing ?

White box testing involves the testing of the software code for the following:

- Internal security holes
- Broken or poorly structured paths in the coding processes
- The flow of specific inputs through the code
- Expected output
- The functionality of conditional loops
- Testing of each statement, object and function on an individual basis

The testing can be done at system, integration and unit levels of software development. One of the basic goals of white box testing is to verify a working flow for an application. It involves testing a series of predefined inputs against expected or desired outputs so that when a specific input does not result in the expected output, you have encountered a bug.

How do you perform White Box Testing?

To give you a simplified explanation of white box testing, we have divided it into **two basic steps**. This is what testers do when testing an application using the white box testing technique:

STEP 1: UNDERSTAND THE SOURCE CODE

The first thing a tester will often do is learn and understand the source code of the application. Since white box testing involves the testing of the inner workings of an application, the tester must be very knowledgeable in the programming languages used in the applications they are testing. Also, the testing person must be highly aware of secure coding practices. Security is often one of the primary objectives of testing software. The tester should be able to find security issues and prevent attacks from hackers and naive users who might inject malicious code into the application either knowingly or unknowingly.

Step 2: CREATE TEST CASES AND EXECUTE

The second basic step to white box testing involves testing the application's source code for proper flow and structure. One way is by writing more code to test the application's source code. The tester will develop little tests for each process or series

of processes in the application. This method requires that the tester must have intimate knowledge of the code and is often done by the developer. Other methods include manual testing, trial and error testing and the use of testing tools as we will explain further on in this article.

System testing: Once the individual module testing is completed, modules are assembled and integrated to perform as a system. The top down testing, which began from upper level to lower level module, was carried out to check whether the entire system is performing satisfactorily.

There are three main kinds of System testing:

- 1 Alpha Testing
- 2 Beta Testing
- 3 Acceptance Testing

Alpha Testing: This refers to the system testing that is carried out by the test team with the Organization.

Beta Testing: This refers to the system testing that is performed by a selected group of friendly customers

Acceptance Testing: This refers to the system testing that is performed by the customer to determine whether or not to accept the delivery of the system.

Integration Testing:

Data can be lost across an interface, one module can have an adverse effect on the other sub functions, when combined, may not produce the desired major functions. Integrated testing is the systematic testing for constructing the uncover errors within the interface. The testing was done with sample data. The developed system has run successfully for this sample data. The need for integrated test is to find the overall system performance.

Output testing: After performance of the validation testing, the next step is output testing. The output displayed or generated by the system under consideration is tested by asking the user about the format required by system. The output format on the screen is found to be correct as format was designed in the system phase according to the user needs. Hence the output testing does not result in any correction in the system.

Test plan: The test-plan is basically a list of test cases that need to be run on the system. Some of the test cases can be run independently for some components (report generation from the database, for example, can be tested independently) and some of the test cases require the whole system to be ready for their execution. It is better to test each component as and when it is ready before integrating the components. It is important to note that the test cases cover all the aspects of the system (ie, all the requirements stated in the RS document).

In general, Black Box Testing is useful to test the functionality of the individual components or modules of the software application from the user's perspective, while White Box Testing is useful to test the internal workings of the component and identify any issues that may arise due to coding or design issues. A combination of both Black Box Testing and White Box Testing can be applied to perform comprehensive unit testing of the software application, ensuring that the individual components or modules are functioning correctly and meet the intended design and functionality.

Maintenance and environment: The number of computer-based systems increased. Thousands of soft program source statements were produced by in-house programs. There were tens of thousands of new assertions added by third-party software packages. The horizon revealed a large, dark cloud. All of these programs and source statements needed to be adjusted in order to accommodate newly acquired hardware, change user needs, or rectify any errors that were found. Software maintenance was the term used to refer to all of these actions.

The maintenance phase emphasizes updates related to mistake correction, adaptations needed as the environment for the software changes, and changes resulting from improvements brought about by shifting customer requirements. During the maintenance phase, four different modifications occur.

- Correction
- Adaptation
- Prevention

CORRECTION:

The strongest control measures in place, it is still possible for the client to find software bugs. Software flaws are fixed via corrective maintenance. Software flaws may still be discovered by the client despite the strictest quality control procedures. Corrective maintenance is used to address software problems. Only about 20 percent of all maintenance work are spent "fixing mistakes". The remaining 80 percent are spent adapting existing systems to changes in their external environment, making enhancements requested by users, and re engineering an application for use.

ADAPTATION: The initial environment for which the software was designed (such as the CPU, operating system, business rules, and external product features) is likely to change over time. Software is modified as a result of adaptive maintenance to account for changes to its external environment.

PREVENTION: Computer software requires preventive maintenance, sometimes referred to as software re engineering, in order to continue serving the demands of its users because change causes it to deteriorate. Preventive maintenance essentially alters computer programs to make it easier to correct, modify, and improve them. A comprehensive activity utilized throughout the entire software development life cycle is software configuration management (SCM)

7. CONCLUSION

In conclusion, the application of deep learning techniques in pneumonia detection has shown promising results. By leveraging advanced algorithms and neural networks, researchers have been able to develop models capable of accurately identifying pneumonia from medical imaging data, such as chest X-rays.

The use of deep learning algorithms has the potential to assist healthcare professionals in diagnosing pneumonia more efficiently and accurately. These models can quickly analyze large volumes of imaging data and provide accurate results, helping to prioritize and expedite the diagnosis process.

Furthermore, deep learning models have demonstrated the ability to learn complex patterns and features from medical images, enabling them to detect subtle signs of pneumonia that may be difficult to identify with the naked eye. This can contribute to early detection and timely treatment, leading to improved patient outcomes.

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