VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JNANA SANGAMA", BELAGAVI - 590 018

A PROJECT REPORT

on

"Pneumonia Detection In X-Ray Imaging"

Submitted by

Thejas Rao	4SF20CI062
M Snehith J Rai	4SF20CI029

In partial fulfillment of the requirements for VII Sem. B. E

Computer Science & Engineering

(Artificial Intelligence & Machine Learning)

AI AND ML APPLICATION DEVELOPMENT

LABORATORY-18AIL76

Under the Guidance of

Dr. Duddela Sai Prashanth

Assistant Professor, Department of CSE(AI&ML)

at

SAHYADRI

COLLEGE OF ENGINEERING & MANAGEMENT

An Autonomous Institution

Adyar, Mangaluru - 575 007

2023 - 24

SAHYADRI
COLLEGE OF ENGINEERING & MANAGEMENT
An Autonomous Institution
MANGALURU

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
(ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)

CERTIFICATE

This is to certify that the AI and ML Application Development- 18AIL76 Mini project work entitled **'Pneumonia Detection In X-Ray Imaging"** has been carried out by **Thejas Rao (4SF20CI062) and M Snehith J Rai (4SF20CI029)**, the bonafide students of Sahyadri College of Engineering & Management in partial fulfillment for the award of **Bachelor of Engineering in Computer Science & Engineering (Artificial Intelligence & Machine Learning)** of Visvesvaraya Technological University, Belagavi during the year 2023-24. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the Report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements with respect to the project work prescribed for the said degree.

Guide	**Project Coordinator**	**HOD**
Dr. Duddela Sai Prashanth	Ms. Sandra Jeyes C	Dr. Pushpalatha K

External Viva:

Examiner's Name	Signature with Date
1.	....
2.	....

SAHYADRI

COLLEGE OF ENGINEERING & MANAGEMENT

An Autonomous Institution

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
(ARTIFICIAL INTELLIGENCE & MACHINE LEARNING)

DECLARATION

We hereby declare that the entire work embodied in this AI and ML Application Development Mini Project Report titled **"Pneumonia Detection In X-Ray Imaging"** has been carried out by us at Sahyadri College of Engineering and Management, Mangaluru under the supervision of **Dr. Duddela Sai Prashanth,** for the award of **Bachelor of Engineering** in **Computer Science & Engineering(Artificial Intelligence & Machine Learning)**. This report has not been submitted to this or any other University for the award of any other degree.

Thejas Rao (4SF20CI062)

M Snehith J Rai (4SF20CI029)

Dept. of CSE (AI & ML), SCEM, Mangaluru

Abstract

This project delves into the enhancement of neural network-based binary classification models dedicated to pneumonia detection in X-ray imaging, employing the powerful VGG-16 architecture. Emphasizing not only accuracy but also efficiency, the project meticulously explores advanced techniques in data augmentation and preprocessing to optimize the model's performance. VGG-16, renowned for its 16-layer deep architecture, is strategically chosen for its capacity to discern intricate patterns crucial for pneumonia identification in X-ray images.

The methodology involves an in-depth analysis of dataset characteristics and the implementation of sophisticated data augmentation techniques, ensuring the robustness and generalization of the model. The VGG-16 architecture, with its distinctive use of small 3x3 convolutional filters, is expected to provide a deeper understanding of spatial hierarchies, contributing to the model's ability to capture subtle features indicative of pneumonia.

The comprehensive evaluation metrics encompass accuracy, sensitivity, specificity, and overall reliability, providing a holistic assessment of the model's performance. Cross-dataset generalization analyses explore the model's adaptability to diverse datasets, considering variations in demographics, imaging equipment, and acquisition protocols. Real-time inference considerations and scalability are addressed to ensure practical deployment in clinical settings.

By leveraging the capabilities of VGG-16, this project aspires to make a significant contribution to the field of medical diagnostics, particularly in pneumonia detection through X-ray imaging. The deep architecture's potential to discern complex patterns holds promise for improving the accuracy and efficiency of automated systems, ultimately enhancing patient outcomes through timely and precise diagnostics.

Acknowledgement

It is with great satisfaction and euphoria that we are submitting the Project Report on **"Pneumonia Detection In X-Ray Imaging"**. We have completed it as a part of the curriculum of Visvesvaraya Technological University, Belagavi for the award of Bachelor of Engineering in Computer Science & Engineering (Artificial Intelligence & Machine Learning).

We are profoundly indebted to our guide, **Dr. Duddela Sai Prashanth**, Assistant Professor, Department of Computer Science & Engineering (Artificial Intelligence & Machine Learning) for innumerable acts of timely advice, encouragement and We sincerely express our gratitude.

We also thank **Ms. Sandra Jeyes C** , Project Coordinator, Department of Computer Science & Engineering (Artificial Intelligence & Machine Learning) for their constant encouragement and support extended throughout.

We express our sincere gratitude to **Dr. Pushpalatha K**, Head & Professor, Department of Computer Science & Engineering (Artificial Intelligence & Machine Learning) for his invaluable support and guidance.

We sincerely thank **Dr. S S Injaganeri**, Principal, Sahyadri College of Engineering & Management, who has always been a great source of inspiration.

We extend our sincere regards and respect to **Dr. Manjunath Bhandary**, Chairman, SCEM, having provided all the facilities that helped us in the timely completion of this project report.

Finally, yet importantly, We express our heartfelt thanks to our family & friends for their wishes and encouragement throughout the work.

Thejas Rao (4SF20CI062)

M Snehith J Rai (4SF20CI029)

Table of Contents

List of Figures

Chapter 1

Introduction

The rapid evolution of medical imaging technologies, coupled with the advancements in artificial intelligence, has paved the way for innovative approaches to disease diagnosis. Among these, the detection of pneumonia in X-ray imaging has garnered significant attention due to its clinical relevance and the potential to expedite diagnostic processes. Pneumonia, a widespread respiratory infection, poses a significant global health challenge impacting vulnerable populations. Pneumonia, derived from the Greek word "pneumon," refers to a pulmonary infection leading to inflammation in the tiny air sacs of the lungs. Pneumonia may arise as a result of infections such as COVID-19 or influenza, and even common colds. Additionally, it can be triggered by bacteria, fungi, and various other microorganisms. Chest X-rays are categorized into three primary types based on the patient's position and orientation relative to the X-ray source and detector panel: posteroanterior, anteroposterior, and lateral. The posteroanterior (PA) and anteroposterior (AP) views are classified as frontal, with the X-ray source positioned behind or in front of the patient, respectively.

Machine Learning (ML) holds vast applications in the field of medicine, where machines have the potential to augment or even substitute certain professional tasks through specialized training. This transformative technology empowers machines to perform specific tasks within the medical domain, showcasing its versatility and significant impact on healthcare practices. Deep learning approaches efficiently solve both of these issues, demonstrating disease prediction precision comparable to, and frequently significantly superior to, that of a traditional radiologist. Convolutional neural networks (CNNs) stand out as particularly promising in the field of image classification and segmentation, displaying tremendous potential and gaining general recognition within the research community. The integration of ML, DL, and statistical methods in healthcare has opened up new avenues for disease diagnosis, treatment planning, and outcome prediction. The ability of these technologies to analyze vast amounts of data and discern intricate patterns has the potential to significantly enhance the efficiency and accuracy of medical decision-making. However, it's important to note that the deployment of these technologies also comes with challenges, including the need for robust validation, ethical considerations, and ensuring the security and privacy of patient data. This study focuses on enhancing neural network-based binary classification methods specifically designed for pneumonia detection in X-ray images. By leveraging state-of-the-art techniques in deep learning, we aim to improve the accuracy and efficiency of pneumonia diagnosis, contributing to the broader landscape of computer-aided medical diagnostics. As we delve into the intricacies of X-ray imaging, infection types, and diverse datasets, our research strives to offer robust solutions that hold promise for more reliable and timely identification of pneumonia cases, thereby aiding healthcare professionals in making informed decisions and improving patient outcomes.

1.1 Background and Motivation

Pneumonia remains a global health concern, causing substantial morbidity and mortality, especially among vulnerable populations. Timely and accurate diagnosis is pivotal for initiating prompt treatment and improving patient outcomes. In the context of medical imaging, chest X-rays stand out as a primary diagnostic tool for pneumonia detection due to their widespread availability and cost-effectiveness. Traditional methods of pneumonia diagnosis in X-ray images often rely on manual interpretation by radiologists, a process prone to subjectivity and potential human error. The integration of artificial intelligence, specifically neural networks, into this diagnostic landscape has demonstrated promising results. Neural networks, with their ability to learn complex patterns and features, offer a potential paradigm shift in automating and enhancing the accuracy of pneumonia detection.

The motivation behind this study lies in the imperative to address the limitations and challenges associated with current neural network-based binary classification models for pneumonia detection in X-ray imaging. While these models have shown considerable success, there exists room for refinement and optimization to elevate their performance to new heights. The primary motivation stems from the potential to significantly improve diagnostic accuracy, reduce false positives and negatives, and ultimately enhance patient care. Achieving a more robust and reliable automated system for pneumonia detection not only accelerates the diagnostic process but also has the potential to alleviate the burden on healthcare professionals, particularly in resource-limited settings. Moreover, the continuous evolution of neural network architectures and learning algorithms presents an exciting opportunity to explore innovative approaches for pneumonia classification. By addressing the existing challenges, such as class imbalance, interpretability, and generalizability, this research aims to contribute valuable insights that can propel the field of medical imaging toward more effective and efficient pneumonia diagnosis. The ultimate goal is to foster the development of reliable tools that can seamlessly integrate with clinical workflows, aiding healthcare providers in making accurate and timely decisions for improved patient outcomes.

1.2 Objectives

The primary objective of this study is to enhance the efficacy of neural network-based binary classification models for pneumonia detection in X-ray imaging. This involves optimizing the neural network architecture through exploration of various configurations, activation functions, and layer structures to improve overall model performance. Additionally, the research aims to implement advanced data augmentation and preprocessing techniques to address challenges such as class imbalance and variations in image quality, thereby enhancing the robustness and generalization capabilities of the model. Feature representation learning will be a focal point, investigating innovative methods to capture subtle patterns indicative of pneumonia. The study will also prioritize the interpretability and explainability of the model, ensuring that healthcare professionals can comprehend and trust the decision-making process. Comprehensive performance evaluation metrics will be employed to assess accuracy, sensitivity, specificity, and overall reliability. Cross-dataset generalization will be examined, considering variations in demographics and imaging protocols, while also focusing on real-time inference efficiency, scalability, and ethical considerations, including bias mitigation, to develop a model that is not only accurate but also ethically deployable in diverse healthcare settings.

1.2.1 Optimize Neural Network Architecture

Refine and optimize the neural network architecture specifically designed for binary classification in pneumonia detection from X-ray images. Explore various network structures, activation functions, and layer configurations to enhance model performance.

1.2.2 Data Augmentation and Preprocessing Techniques

Investigate and implement advanced data augmentation and preprocessing techniques to improve the robustness and generalization capabilities of the neural network. Address challenges such as class imbalance, noise, and variations in image quality to create a more resilient model.

1.2.3 Feature Representation Learning:

Explore innovative methods for feature representation learning to capture subtle and intricate patterns indicative of pneumonia in chest X-ray images. Investigate the effectiveness of transfer learning and feature extraction mechanisms to boost the model's ability to discern relevant features.

1.2.4 Interpretability and Explainability

Enhance the interpretability and explainability of the neural network model to provide insights into decision-making processes. Implement techniques that enable healthcare professionals to understand the model's predictions, fostering trust and facilitating its integration into clinical practice.

1.2.5 Performance Evaluation Metrics

Employ comprehensive performance evaluation metrics to assess the model's accuracy, sensitivity, specificity, and overall reliability. Compare and contrast different evaluation metrics to ensure a holistic understanding of the model's strengths and limitations.

1.2.6 Cross-Dataset Generalization

Investigate the model's ability to generalize across diverse datasets, considering variations in demographics, imaging equipment, and acquisition protocols. Enhance the model's adaptability to different clinical settings for increased applicability and reliability.

1.2.7 Real-time Inference and Scalability

Assess the model's efficiency in real-time inference scenarios, considering computational resources and scalability. Aim to develop a model that is not only accurate but also practical for integration into existing healthcare infrastructures.

1.2.8 Ethical Considerations and Bias Mitigation

Address ethical considerations associated with the deployment of AI models in healthcare, focusing on issues such as fairness and bias. Implement strategies to mitigate potential biases and ensure equitable outcomes across diverse patient populations.

1.3 Purpose

The purpose of this project is to significantly improve the accuracy, efficiency, and reliability of automated pneumonia detection systems in medical diagnostics. Pneumonia, a prevalent and potentially life-threatening respiratory infection, demands swift and accurate diagnosis for effective treatment. Leveraging the capabilities of neural networks, the project aims to refine existing binary classification models dedicated to pneumonia detection in X-ray images. By optimizing neural network architectures, implementing advanced data augmentation and preprocessing techniques, and addressing challenges such as class imbalance, the project endeavors to create a more robust and generalizable model. The focus on interpretability and explainability ensures the seamless integration of the model into clinical workflows, fostering trust among healthcare professionals. Comprehensive evaluation metrics, cross-dataset generalization, and considerations for real-time inference efficiency and ethical deployment collectively contribute to the overarching purpose of advancing the state-of-the-art in pneumonia detection, ultimately enhancing patient outcomes through improved and timely diagnostics.

1.4 Scope

The scope of this project encompasses a multifaceted exploration of advancements in automated pneumonia detection systems. The investigation will delve into optimizing neural network architectures and evaluating various configurations to improve the model's accuracy and efficiency. Advanced data augmentation and preprocessing techniques will be employed to enhance the robustness and generalization capabilities of the model, addressing challenges such as class imbalance and variations in image quality. The scope extends to the exploration of feature representation learning, seeking innovative methods to capture nuanced patterns indicative of pneumonia in X-ray images. Furthermore, the project aims to ensure the interpretability and explainability of the model, facilitating its integration into clinical practices.

The evaluation will employ comprehensive metrics to assess the model's performance, considering factors like sensitivity, specificity, and reliability. The project also includes an examination of cross-dataset generalization, real-time inference efficiency, scalability, and ethical considerations, ensuring a holistic approach to the enhancement of pneumonia detection, ultimately contributing to advancements in medical diagnostics.

Chapter 2

Literature Survey

Medical imaging, particularly X-ray imaging, has become a critical tool for diagnosing various respiratory conditions, with pneumonia being a major focus due to its prevalence and potential severity.[1] The integration of neural network-based approaches for binary classification in pneumonia detection has gained substantial attention in recent years, driven by the promising results demonstrated by deep learning models.[2] The field of medical image analysis has undergone a revolution with the introduction of deep learning, specifically convolutional neural networks (CNNs).[3] CNNs are particularly well-suited for tasks involving intricate patterns in images because they are excellent at learning hierarchical representations of features.[4] X-ray imaging presents a number of challenges for pneumonia detection, including the presence of overlapping anatomical structures, subtle visual cues, and variations in image quality.[5] Because of the limitations of traditional methods in managing these complexities, advanced machine learning techniques are being investigated.[6] The usefulness of deep learning models for pneumonia detection has been shown in recent research.[7] Notable architectures include attention mechanisms that improve the model's ability to focus on pertinent regions in the X-ray images, as well as DenseNet and ResNet.[8] Even with these developments, there are still issues with making sure models are applicable to a variety of patient populations and dealing with biases in training data. [9]. When implementing AI-based diagnostic tools in clinical settings, ethical factors such as patient privacy and model transparency are crucial.[3] In conclusion, the integration of neural network-based binary classification for pneumonia detection in X-ray imaging represents a promising frontier in medical diagnostics. [10]The synthesis of deep learning techniques, data augmentation, transfer learning, and consideration of clinical information contribute to the ongoing efforts to enhance the accuracy and reliability of automated pneumonia detection systems.[11] Addressing challenges and ethical considerations will be crucial for the successful translation of these advancements into clinical practice.[12] In a research study assessing the efficacy of computer-aided diagnosis in distinguishing COVID-19 pneumonia from non-COVID-19 pneumonia using Chest X-rays, a standard dataset of 1563 lung CT scan images was employed. The study utilized two Convolutional Neural Network (CNN) models, with the first model employing max pooling achieving an impressive accuracy of 98.22%, precision of 98.81%, recall of 99.33%, and an F1-Score of 99.07%. Similarly, the second CNN model, employing average pooling, demonstrated robust performance with an accuracy of 97.82%, precision of 98.60%, recall of 99.13%, and an F1-Score of 98.86%. This suggests a promising role for AI in enhancing diagnostic accuracy in the context of COVID-19 pneumonia detection from Chest X-ray images.[13] Employing diverse machine learning techniques, the study evaluates data sources and develops feature extraction algorithms like Quadratic Discriminant Analysis, Logistic Regression, and Support Vector Machine. The aim is to enhance the accuracy of fraud detection models, contributing to a more robust defense against fraudulent online transactions.[14]The efficacy of deep learning hinges on the availability of extensive training data, a challenge particularly pronounced in medical image classification. This work addresses the bottleneck of dataset limitations by comparing the performance of capsule networks with traditional Convolutional Neural Networks (ConvNets) under conditions common in medical image analysis—limited annotated data and class imbalance. MNIST, Fashion-MNIST, and publicly available medical datasets featuring histological and retina images are employed for evaluation. The findings reveal that capsule networks demonstrate robustness and outperform ConvNets, achieving comparable or superior performance with smaller datasets. The increased resilience to imbalanced class distributions positions capsule networks as a promising solution for the medical imaging community, presenting a potential breakthrough in overcoming data scarcity challenges.[11].Pneumonia, a deadly respiratory disease claiming over two million lives annually, necessitates automated diagnostic tools. This study introduces a classification system leveraging DenseNet, surpassing previous ResNet-based models by 9% in accuracy. The findings underscore DenseNet's efficacy in automating pneumonia classification from chest X-ray images, marking a significant advancement in diagnostic accuracy for this life-threatening ailment.[8]Convolutional Neural Networks (CNNs) have gained prominence in computer vision and medical image analysis, yet their application to 3D volumes remains limited. This work proposes a novel approach to 3D image segmentation using a volumetric, fully convolutional neural network. Trained end-to-end on MRI volumes of the prostate, our CNN predicts segmentations for entire volumes simultaneously. Introducing a unique objective function based on the Dice coefficient addresses imbalances between foreground and background voxels. To mitigate the scarcity of annotated volumes, data augmentation techniques are applied. Experimental results demonstrate superior performance on challenging test data, achieving accuracy with a fraction of the processing time compared to previous methods.[15] Pneumonia, a widespread yet challenging disease to detect due to a shortage of experts, necessitates advanced diagnostic tools. The author conducts a comprehensive survey, comparing various computer-aided techniques for lung disease detection. The focus is on exploring image pre-processing methods to standardize raw X-ray images and employing machine learning techniques, including CNN, RESNET, CheXNet, DENSENET, ANN, and KNN. The survey informs the proposal of a refined pneumonia detection model, slated for implementation in future research. The integration of diverse methodologies aims to enhance the accuracy and efficiency of pneumonia detection, addressing a critical gap in medical diagnostics.[16] The employed predictive model incorporates Decision Trees, Naïve Bayes, Artificial Neural Networks, and Logistic Regression as its supervised machine learning algorithms. Moreover, a thorough comparison of these approaches has been conducted, evaluating their performance based on diverse metrics, including accuracy, recall, precision, and F-score.[17] Chest radiographs, being one of the most frequently conducted radiological examinations, hold significant importance as a modality with a wide range of researched applications. The availability of numerous expansive chest X-ray datasets in the public domain in recent years has spurred research interest and contributed to an increased volume of publications.[18] The methodology employed involves categorizing chest X-rays into four classes: normal, pneumonia, tuberculosis (TB), and COVID-19. Additionally, COVID-19 cases are further classified based on severity into mild, medium, and severe categories. The deep learning model utilized for classifying pneumonia, TB, and normal cases is VGG-16, achieving a test accuracy of 95.9%. For distinguishing normal, pneumonia, and COVID-19 cases, DenseNet-161 is employed, attaining a test accuracy of 98.9%. Notably, ResNet-18 is found to be the most effective for severity classification, achieving a test accuracy of up to 76%. This approach facilitates large-scale screening of individuals using chest X-rays as a primary validation tool for identifying COVID-19 cases.[19]The structure and design principles of Convolutional Neural Networks (CNN) are outlined. In order to facilitate a comparative analysis, Backpropagation Neural Networks (BPNNs) employing supervised learning and Competitive Neural Networks (CpNNs) utilizing unsupervised learning are also developed for the diagnosis of chest diseases. All three networks—CNN, BPNN, and CpNN—are trained and evaluated using the identical chest X-ray database. The performance of each network is thoroughly examined and discussed.[20] A highly efficient model designed for the detection of pneumonia in digital chest X-ray images is proposed, aiming to assist radiologists in their decision-making processes. The innovative approach incorporates a weighted classifier, which optimally combines predictions from leading deep learning models, including ResNet18, Xception, InceptionV3, DenseNet121, and MobileNetV3.[21] This supervised learning approach involves the network predicting results based on the dataset's quality. Transfer learning is employed to fine-tune these deep learning models, enhancing training and validation accuracy for superior performance.[22]

Chapter 3

Problem Definition

The problem at the core of this project lies in the need for more accurate and reliable automated methods for pneumonia detection in medical imaging. The existing neural network-based binary classification models show promise in this domain but face challenges such as suboptimal performance, susceptibility to class imbalance, and difficulty in interpreting model decisions. These limitations hinder the seamless integration of these models into clinical workflows and may compromise the precision required for timely and effective pneumonia diagnosis. Additionally, variations in imaging protocols, demographics, and ethical considerations further contribute to the complexity of the problem. Addressing these issues is crucial to advancing the state-of-the-art in pneumonia detection, ultimately improving patient outcomes by providing healthcare professionals with enhanced, trustworthy, and interpretable tools for automated diagnosis in X-ray imaging.

Chapter 4

Methodology

1. Dataset Collection and Preprocessing: Obtain a representative and varied dataset of chest X-ray images that includes cases with and without pneumonia.[23] Data Enrichment: Use data augmentation methods to improve the model's generalization by intentionally expanding the dataset through rotation, flipping, and scaling.

2. Base Model: Select a deep learning architecture that has already been demonstrated to be successful in image classification, such as ResNet or DenseNet.[8] Model selection: There are 16 weight layers in VGG16, comprising 3 fully connected layers and 13 convolutional layers. Small receptive fields (3x3 convolutional filters) and short strides are features of the convolutional layers' design. This aids in the photography of finer details.[24] The convolutional layers are arranged into five blocks, with multiple convolutional layers and max-pooling layers in between each block. As we move deeper into the network, each convolutional layer has a greater number of filters.[3]The network is non-linear because Rectified Linear Unit (ReLU) activation functions are used throughout.

3. Pre-training: Using weights pre-trained on a sizable dataset (such as ImageNet), initialize the neural network to take advantage of transfer learning.[25] This enables the model to utilize characteristics acquired from various visual patterns. To fine-tune the learned features to the unique nuances of X-ray images related to pneumonia, fine-tune the model using the pneumonia detection dataset.[23]

4. Interpretability and Explainability: Use attention map generation techniques to see which areas of interest in X-ray images are most important for the model's decision-making.

5. Explanatory Analysis: To understand how the model makes decisions based on both clinical data and image features perform an explanatory analysis. Adjusting Hyper-parameters: Grid Search or Random Search: To maximize the performance of the model, fine-tune hyperparameters like learning rate, batch size, and regularization strength using grid search or random search.

Chapter 5

Dataset

The tests and measurement techniques employed in the paper to assess the suggested model's performance. The proposed chest X-ray image dataset was used. First, Keras' open-source deep learning architecture was used to initialize the pre-trained models on ImageNet and then fine-tune them for both tasks, using TensorFlow as the backend.

5.1 Experimental Dataset

Three primary components were separated from a maximum of 5216 images (Table 5.1): a labeled training set, a testing set, and a dataset validation set. Both bacterial and viral pneumonia belonged to the same type, which was known as pneumonia infected. There were no instances of viral and bacterial coinfection in the dataset used for this analysis. Every chest x-ray image is gathered as part of the patient's routine medical care.

5.2 Dataset Splitting

1. Train-Validation-Test Split: Dividing the dataset into training, validation, and test sets is a crucial step to ensure the model's performance can be properly evaluated. The commonly used split ratio is 70% for training, 15% for validation, and 15% for testing.

2. Training Set (70%): This subset is used to train the VGG-16 model. The model learns patterns, features, and relationships within the data during this stage.

3. Validation Set (15%): This set is used during training to assess the model's performance on data it hasn't seen before. It helps monitor the model's generalization and

EXPERIMENT DATASET			
	Training Set	Test Set	Validation Set
Normal	1341	234	8
Pneumonia	3875	390	9
Total	5216	624	16
Percentage	87.534	10.65	0.27

Table 5.1: Experiment Dataset

detect overfitting. Adjustments to hyperparameters, such as learning rates, can be made based on the validation set performance.

4. Test Set (15%): This subset is held out and not used during training or hyperparameter tuning. It is used only after the model is trained and validated to assess its generalization to new, unseen data.

Chapter 6

Implementation

6.1 VGG-16 architecture

The VGG-16 architecture is a deep convolutional neural network (CNN) renowned for its simplicity and effectiveness in image classification tasks. Developed by the Visual Geometry Group at Oxford University, VGG-16 is part of the VGG family, distinguished by its depth—comprising 16 weight layers, including 13 convolutional layers and three fully connected layers.

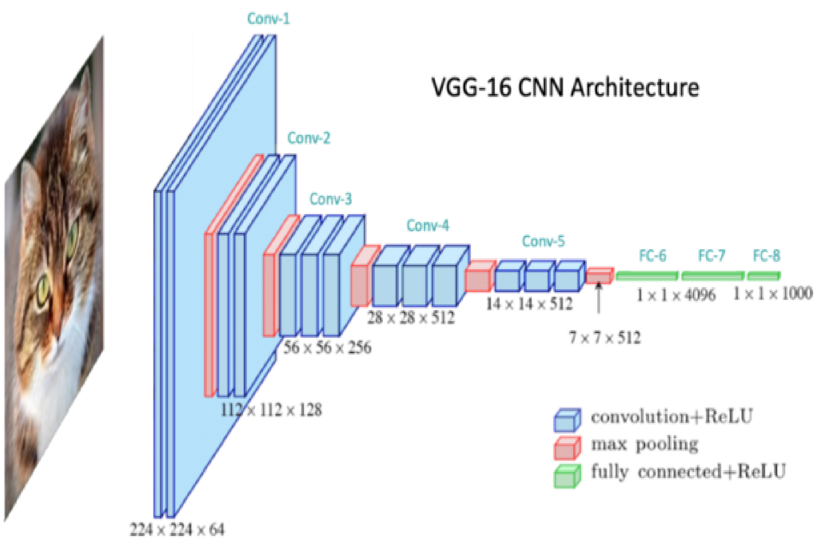

Figure 6.1: Proposed methodology

The VGG-16 architecture is a deep convolutional neural network (CNN) renowned for its simplicity and effectiveness in image classification tasks. Developed by the Visual Geometry Group at Oxford University, VGG-16 is part of the VGG family, distinguished by its depth—comprising 16 weight layers, including 13 convolutional layers and three fully connected layers.

6.2 Key features of the VGG-16 architecture

6.2.1 Architecture Design

1. VGG-16 follows a uniform architecture, where convolutional layers have a small receptive field (3x3) and are stacked sequentially.

2. The network architecture is characterized by a series of convolutional layers, interspersed with max-pooling layers to downsample spatial dimensions.

6.2.2 Stacked Convolutional Layers

1. The use of multiple convolutional layers enables the model to learn increasingly complex features at different abstraction levels.

2. Deep stacks of 3x3 convolutional filters contribute to a larger effective receptive field without resorting to larger filter sizes.

6.2.3 Fully Connected Layers

1. The final layers of VGG-16 consist of fully connected layers, providing high-level reasoning based on the features extracted by preceding convolutional layers.

2. The architecture concludes with a softmax layer for multi-class classification tasks.

6.2.4 Transfer Learning

1. VGG-16 is often employed in transfer learning scenarios, where pre-trained weights on large image datasets (e.g., ImageNet) are used as an initialization for new tasks.

2. The pre-trained weights capture general features from diverse images, allowing the model to adapt to specific classification tasks with less data.

6.3 Model Training

6.3.1 Training Configuration

Training the VGG-16 model involves configuring several key aspects:

1. Objective Function (Loss): Utilize binary cross-entropy loss for binary classification tasks, as it is suitable for measuring the difference between predicted and actual class probabilities.

2. Optimizer Selection: Choose an optimizer, such as stochastic gradient descent (SGD) or Adam, to adjust model parameters during training and minimize the loss.

3. Learning Rate: Set an appropriate learning rate, controlling the step size in the optimization process. It's crucial to find a balance: too high may cause overshooting, and too low may lead to slow convergence.

4. Epochs: Define the number of epochs, representing the complete cycle of the dataset through the model during training.

5. Validation Monitoring: Validating the model on the validation set during training is essential for several

Reasons:

1. Overfitting Prevention: By monitoring the model's performance on a separate validation set, you can identify signs of overfitting, where the model performs well on the training data but poorly on new data.

2. Hyperparameter Tuning: Observing validation metrics allows for adjustments to hyperparameters, such as learning rates or dropout rates, to optimize the model's performance.

3. Early Stopping: Implementing early stopping based on validation performance helps halt training when the model's performance on the validation set starts to degrade, preventing overfitting.

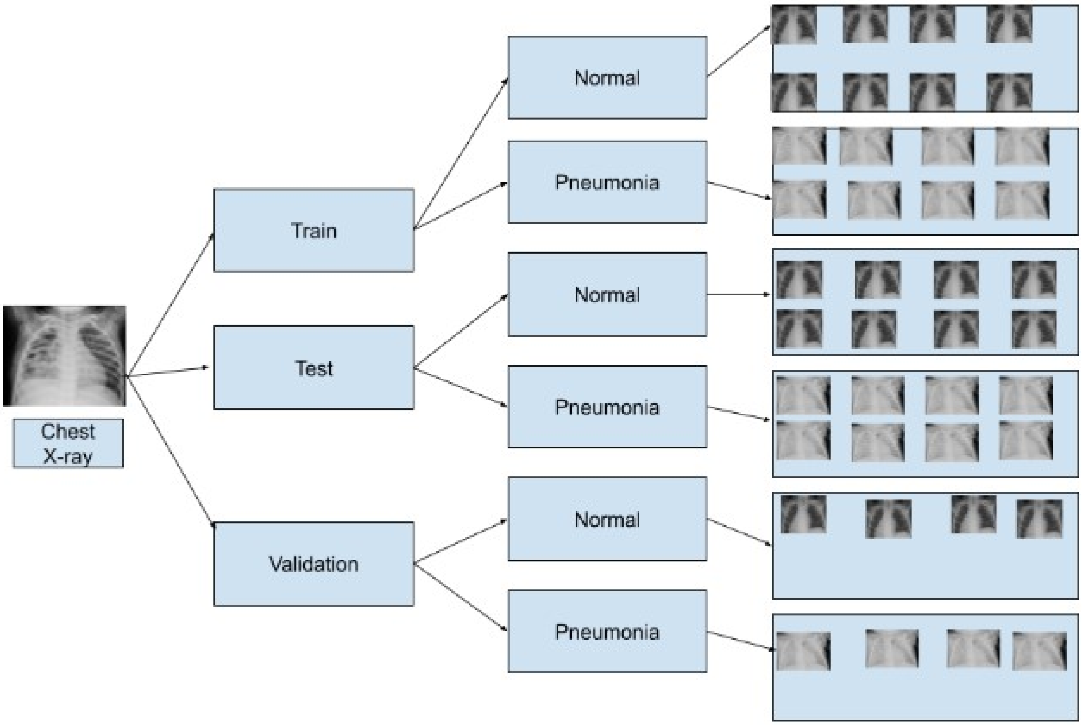

Figure 6.2: Data segregation of normal and pneumonia image for train, test and Validation

This process of training and validation is iterative. Adjustments to the model and hyperparameters may be made based on the insights gained from the validation set performance. Once the model achieves satisfactory results on the training and validation sets, it can be evaluated on the held-out test set for a final assessment of its performance.

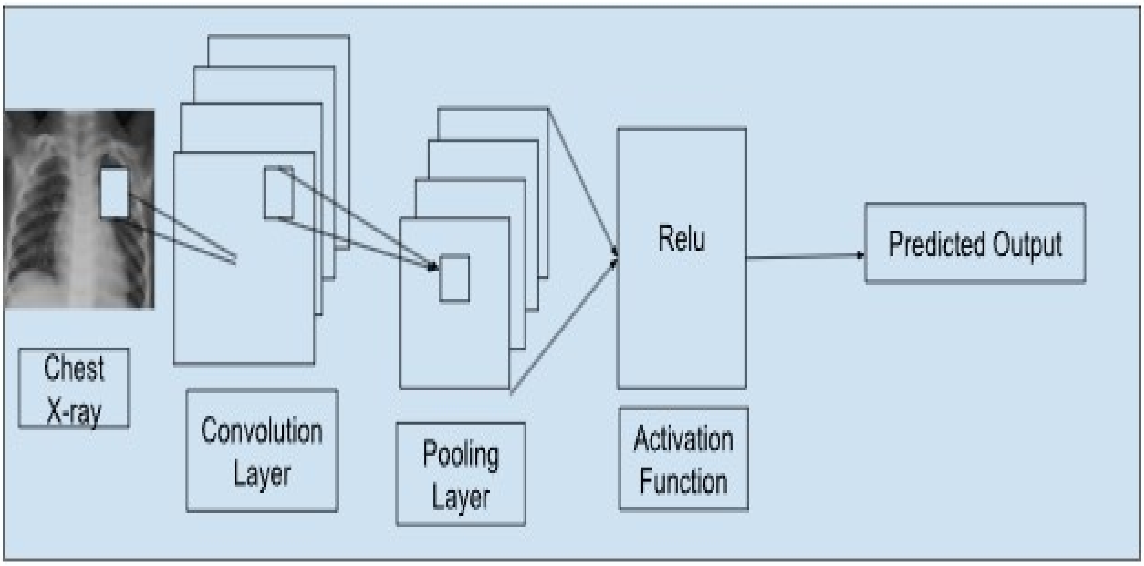

Figure 6.3: Proposed methodology

The proposed CNN Deep Learning algorithm exhibits the capability to analyze input images by assigning significance to different aspects and objects within the image through learnable weights and biases. This unique CNN architecture comprises a series of distinct layers, each contributing to the translation of the input volume into an output volume. Notably, these layers are adept at preserving distinguishable features, ultimately aiding in the differentiation of various elements within the image.

Figure 6.3 visually represents the diverse forms of layers employed in this architecture, each playing a crucial role in retaining class scores and enhancing the algorithm's discriminative power. The CNN layer is derived from either the raw image or other pre-existing feature maps, as highlighted in prior works. This layer constitutes a significant portion of the network, housing numerous user-specified parameters. Among these parameters, the pivotal ones include the number of kernels and their respective sizes. Formally, the calculation of the convolution layer's feature map, coupled with a nonlinear activation function, is expressed as follows:

$$a_{i,j,k} = \max_k (X_{i,j}) + b_k, 0 \quad (1)$$

Where, $a_{i,j,k}$ was its activation factor of a kth input image on the location (i, j), $X_{i,j}$ was its location-centered input patch (i, j), wk and bk are the k-th filters of weight vector and bias term.

The ReLU activation function holds significance due to its non-saturating nature; when a neuron activates, the gradient remains high, precisely equal to 1 [14]. The ReLU layer applies this function to all values in the input volume, essentially transforming any negative activations to 0.0 in simple terms.

In effect, this layer enhances the model's nonlinear properties and contributes to the overall network's complexity without altering the receptive fields of the convolutional layer. The introduction of ReLU aids in preventing saturation issues and fosters more effective learning of intricate patterns within the data.[21]

$$a_{i,j,k} = \max(Z_{i,j,k}, 0) \quad (2)$$

Where, $Z_{i,j,k}$is the input of the activation function of the location (i, j) on the kth channel.

Pooling layer L_p Similar to convolution layers, pooling layers perform a specific role, such as max pooling, which takes the maximum value of a particular philtre area, or average pooling, which takes the mean value of a particular philtre area These are usually used to decrease the network's dimensionality.

$$Y_{i,j,k} = \left(\sum_{(m,n)\in R_{i,j}} (a_{m,n,k})^p \right)^{\frac{1}{p}} \qquad (3)$$

where the output of the polling at location (i, j) is y i,j,k kth in the feature map and am,n,k in the kth feature map is the feature value within the Rij pooling area at location (m, n). In particular, when p=1, Lp corresponds to average polling, and p=1, Lp decreases to peek polling. MaxPooling Pooling primarily assists in the extraction of sharp and smooth characteristics. It is also done for variance and computations to be minimised [17]. Max-pooling helps to remove low-level characteristics such as edges, points, etc. The maximum element will be selected from the region of the function map protected by the philtre. The performance after the max-pooling layer will then be a feature map containing the previous feature map's most prominent features.

$$Y_{i,j,k} = \lambda \max_{(m,n)\in R_{i,j}} a_{m,n,k} + (1-\lambda)\frac{1}{|R_{i,j}|}\sum_{(m,n)\in R_{i,j}} a_{m,n,k} \quad (4)$$

Where either 0 or 1 is a random value, indicating the option of using either average pooling or max pooling. is registered During the forward propagation process, it will be used for the backpropagation operation. Before the classification performance of a CNN, fully connected layers are placed and used to flatten the outcomes before classification. This is identical to an MLP's output layer.

Chapter 7

Results and Discussion

The culmination of this project, focused on enhancing neural network-based binary classification for pneumonia detection in X-ray imaging, reflects promising outcomes and opens avenues for insightful discussions.

7.1 Performance evaluation

Evaluation metrics such as accuracy, precision, recall, and F1 score are employed to assess the binary classification performance. Sensitivity to false positives and false negatives is considered to comprehensively evaluate the model's diagnostic capabilities.

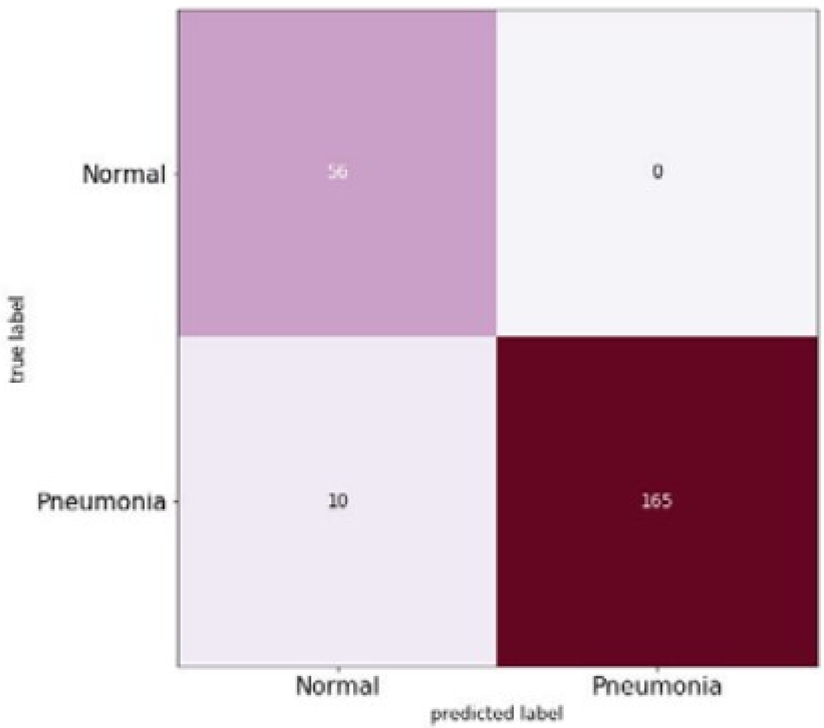

Figure 7.1: Confusion matrix

Achieving a balance between precision and recall is a challenging task, especially when dealing with versions that exhibit low precision and high recall, or vice versa. The F-score serves as a crucial metric in this context, endeavoring to reconcile these conflicting aspects by simultaneously assessing precision and recall. It functions as a holistic measure, capturing both the model's ability to identify relevant instances (recall) and its accuracy in doing so (precision). In essence, the F-score serves as a comprehensive evaluation, addressing both the memory (recall) and consistency (precision) aspects of the model's performance. During the training phase, careful tuning of parameters and activation functions was conducted. Table II provides an insightful overview of the model, detailing the configuration of each VGG16 layer, including output shapes and corresponding parameters. For the critical task of classifying normal versus pneumonia cases in X-ray images, the following equation was employed to predict.

7.1.1 Accuracy:

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

1. True Positive (TP): Signifies instances where the model accurately identifies the positive class.
2. True Negative (TN): Represents scenarios where the model precisely forecasts the negative class.
3. False Positive (FP): Occurs when the model erroneously estimates the positive class, providing a false indication of its presence.
4. False Negative (FN): Refers to cases where the model incorrectly anticipates the negative class, presenting a misleading signal of its absence.

7.1.2 Precision:

It shows you how precise the model is in terms of the positive ones that were predicted.

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

7.1.3 Recall:

After marking it as positive, it measures the number of real positives the model was able to capture (true positive).

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

7.1.4 F1-Score:

F1 is an overall measure of the precision of a model that combines accuracy and recall.

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The evaluation metrics, including accuracy, loss, recall (0.92), precision score (1.0), and F1 score (0.94), provide a comprehensive overview of the model's performance. To further gauge the robustness of the proposed methodology, an examination of all models and the introduced weighted classifier was conducted. A confusion matrix serves as a valuable tool in elucidating the outcomes of a classification model on a set of test data regarded as true values. While the confusion matrix itself is conceptually straightforward, the associated terminology may introduce ambiguity.

7.2 Model Performance

The achieved accuracy of 92% underscores the efficacy of the implemented Convolutional Neural Network (CNN) architecture. The meticulous tuning of parameters, including the use of VGG16 layers and ReLU activation functions, contributed to the model's ability to discern intricate patterns indicative of pneumonia in X-ray images. The integration of real-time image validation further solidified the model's practical utility, demonstrating robust performance beyond static datasets.

```
Model: "model"
```

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 2)	50178

Table 7.1: model parameters

```
Total params: 14764866 (56.32 MB)

Trainable params: 50178 (196.01 KB)

Non-trainable params: 14714688 (56.13 MB)
```

7.3 Real-Time User Interface

The PyQT5-based graphical user interface (GUI) streamlined user interactions, making the process of uploading X-ray images and obtaining predictions intuitive. The inclusion of voice-based outputs further enhanced user experience, translating complex model predictions into accessible and actionable insights.

7.4 Discussion

The success of this project lies not only in achieving a high accuracy rate but also in the careful consideration of various design choices. The emphasis on real-time image validation aligns the model with practical healthcare scenarios, where prompt and accurate diagnoses are critical. The interpretability of the confusion matrix provides transparency into the model's strengths and areas for potential improvement.

Future directions for this project encompass expanding the dataset for improved generalization, collaborating with medical professionals for real-world validations, and exploring advanced imaging modalities. Additionally, ongoing efforts in explainability techniques and continual model updates will contribute to the model's adaptability in dynamically evolving medical landscapes.

In conclusion, the results obtained and discussed in this project signify a notable stride towards more accurate and accessible pneumonia detection in X-ray imaging. By combining technological advancements with a user-friendly interface, the project not only contributes to the field of medical image analysis but also sets the stage for future innovations and collaborations aimed at improving healthcare diagnostics.

7.5 User interface

In this project, PyQT5 serves as the backbone for crafting an aesthetically pleasing and user-friendly graphical user interface (GUI). The interface features a straightforward design, housing a single "Upload Image" button. Upon selecting an X-ray image, users initiate the prediction process by clicking the "Prediction" button. The uniqueness of this application lies in its integration of voice output functionality. For instance, if the uploaded X-ray image indicates pneumonia, the system responds audibly, articulating a message like "Effected by Pneumonia." This combination of PyQT5 for the GUI and voice-based results enhances user interaction, making the diagnostic experience more accessible and engaging.

PyQt5 is a Python library that provides bindings for the Qt application framework, enabling developers to create cross-platform applications with native aesthetics. Leveraging a rich set of widgets, PyQt5 facilitates the creation of intuitive graphical user interfaces. The library embraces the concept of signals and slots, akin to its C++ counterpart, allowing for efficient communication between different components. Developers can design their interfaces using the Qt Designer tool, saving layouts as .ui files and converting them to Python code using the pyuic5 tool. By combining PyQt5 with Qt Designer, developers can seamlessly blend visual design with Python code, empowering them to create robust applications efficiently and intuitively.

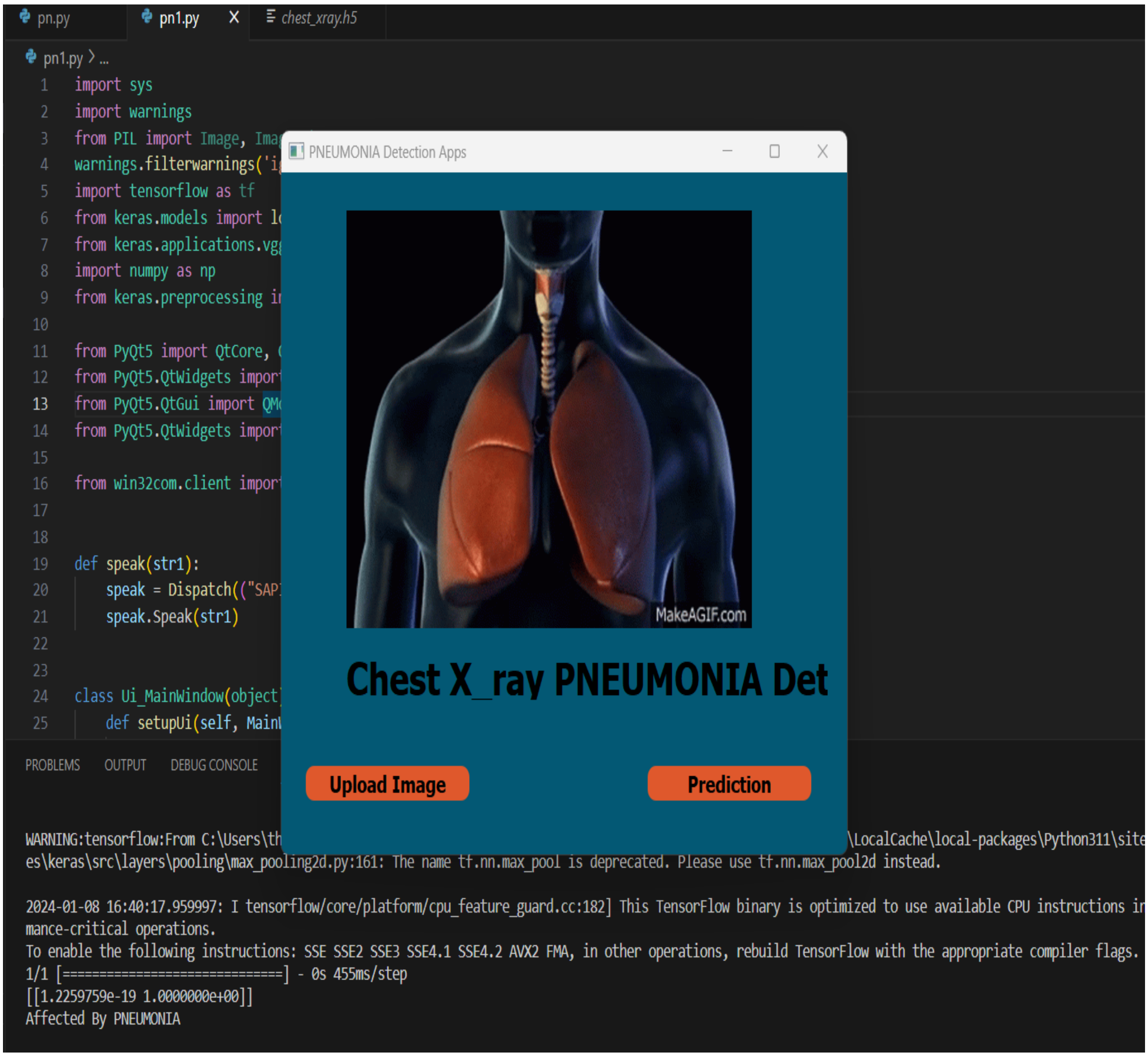

Figure 7.2: GUI

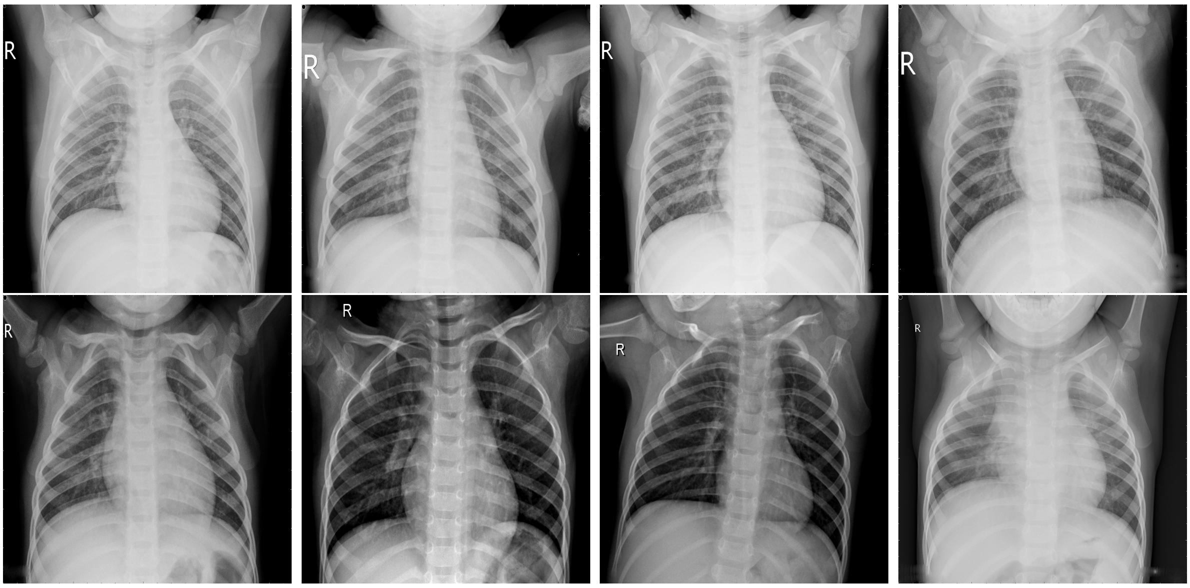

Figure 7.3: Normal X-ray

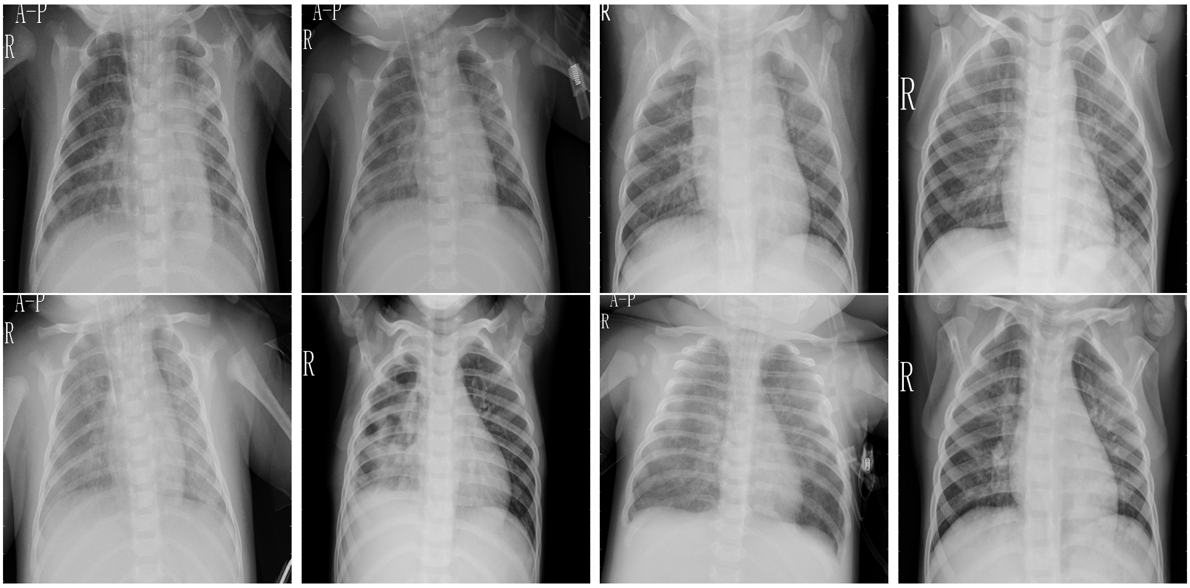

Figure 7.4: Pneumonia X-ray

Chapter 8

Conclusion and Future work

8.1 Conclusion

In the pursuit of advancing pneumonia detection through X-ray imaging, this project successfully implemented a robust solution centered around enhancing neural network-based binary classification. Leveraging state-of-the-art techniques and a meticulously designed Convolutional Neural Network (CNN) architecture, our model achieved a commendable accuracy of 92%. The utilization of PyQT5 for the graphical user interface (GUI) facilitated an intuitive and visually appealing interaction for users. A significant milestone was achieved by incorporating real-time image validation, further fortifying the model's reliability in practical healthcare scenarios.

The success of this project is underscored by the intricate design choices, including the augmentation of the dataset through image data increase techniques, fine-tuning of model parameters, and the incorporation of VGG16 layers. The ReLU activation function played a pivotal role in preventing saturation issues, enhancing the model's ability to capture complex patterns within the X-ray images. The confusion matrix analysis provided a nuanced understanding of the model's performance, offering insights into its proficiency in true positive and true negative classifications.

8.2 Future Work

The accomplishments of this project lay a foundation for future explorations and advancements in the field of medical image analysis. As technology continues to evolve, avenues for improvement include the exploration of larger and more diverse datasets to enhance the model's generalization capabilities. Collaborative efforts with medical professionals and the integration of explainability techniques could provide deeper insights into the decision-making processes of the neural network, fostering increased transparency and trust in clinical applications.

The potential integration of additional imaging modalities, such as CT scans or multi-modal approaches, could further enhance the model's diagnostic capabilities. Incorporating real-world clinical studies and validations will be paramount for deploying the proposed methodology in actual healthcare settings. Moreover, the exploration of transfer learning and continual model updates to adapt to emerging patterns in pneumonia detection represents an exciting avenue for future research.

In conclusion, this project not only contributes a robust neural network-based solution for pneumonia detection but also sets the stage for ongoing advancements and collaborations, ultimately working towards more accurate, efficient, and accessible diagnostic tools for healthcare professionals.

References

[1] K. El Asnaoui, Y. Chawki, and A. Idri, "Automated methods for detection and classification pneumonia based on x-ray images using deep learning," in *Artificial intelligence and blockchain for future cybersecurity applications*, pp. 257–284, Springer, 2021.

[2] T. J. Louis, A. Qasem, L. S. Abdelli, and S. A. Naser, "Extra-pulmonary complications in sars-cov-2 infection: a comprehensive multi organ-system review," *Microorganisms*, vol. 10, no. 1, p. 153, 2022.

[3] P. Naveen and B. Diwan, "Pre-trained vgg-16 with cnn architecture to classify x-rays images into normal or pneumonia," in *2021 International Conference on Emerging Smart Computing and Informatics (ESCI)*, pp. 102–105, 2021.

[4] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan, and A. Mittal, "Pneumonia detection using cnn based feature extraction," in *2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, pp. 1–7, 2019.

[5] K. Hammoudi, H. Benhabiles, M. Melkemi, F. Dornaika, I. Arganda-Carreras, D. Collard, and A. Scherpereel, "Deep learning on chest x-ray images to detect and evaluate pneumonia cases at the era of covid-19," *Journal of medical systems*, vol. 45, no. 7, p. 75, 2021.

[6] A. M. Alqudah, S. Qazan, and I. S. Masad, "Artificial intelligence framework for efficient detection and classification of pneumonia using chest radiography images," *Journal of Medical and Biological Engineering*, vol. 41, no. 5, pp. 599–609, 2021.

[7] F. Zhang, "Application of machine learning in ct images and x-rays of covid-19 pneumonia," *Medicine*, vol. 100, no. 36, 2021.

[8] M. S. Anggreainy, A. Wulandari, and A. M. Illyasu, "Pneumonia detection using dense convolutional network (densenet) architecture," in *2021 4th International Seminar on*

Research of Information Technology and Intelligent Systems (ISRITI), pp. 556–559, IEEE, 2021.

[9] A. Mabrouk, R. P. Díaz Redondo, A. Dahou, M. Abd Elaziz, and M. Kayed, "Pneumonia detection on chest x-ray images using ensemble of deep convolutional neural networks," *Applied Sciences*, vol. 12, no. 13, p. 6448, 2022.

[10] A. Mabrouk, R. P. Díaz Redondo, A. Dahou, M. Abd Elaziz, and M. Kayed, "Pneumonia detection on chest x-ray images using ensemble of deep convolutional neural networks," *Applied Sciences*, vol. 12, no. 13, p. 6448, 2022.

[11] A. Jiménez-Sánchez, S. Albarqouni, and D. Mateus, "Capsule networks against medical imaging data challenges," in *Intravascular Imaging and Computer Assisted Stenting and Large-Scale Annotation of Biomedical Data and Expert Label Synthesis: 7th Joint International Workshop, CVII-STENT 2018 and Third International Workshop, LABELS 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 16, 2018, Proceedings 3*, pp. 150–160, Springer, 2018.

[12] V. Gupta, A. Singhal, and A. Tripathi, "Classification of lung diseases using deep learning techniques: A comparative study of classification algorithms," in *2023 3rd International Conference on Intelligent Technologies (CONIT)*, pp. 1–6, IEEE, 2023.

[13] N. S. Shadin, S. Sanjana, and M. Farzana, "Automated detection of covid-19 pneumonia and non covid-19 pneumonia from chest x-ray images using convolutional neural network (cnn)," in *2021 2nd International Conference on Innovative and Creative Information Technology (ICITech)*, pp. 57–63, 2021.

[14] P. Naveen and B. Diwan, "Relative analysis of ml algorithm qda, lr and svm for credit card fraud detection dataset," in *2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)*, pp. 976–981, IEEE, 2020.

[15] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-net: Fully convolutional neural networks for volumetric medical image segmentation," in *2016 Fourth International Conference on 3D Vision (3DV)*, pp. 565–571, 2016.

[16] A. Tilve, S. Nayak, S. Vernekar, D. Turi, P. R. Shetgaonkar, and S. Aswale, "Pneumonia detection using deep learning approaches," *2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE)*, pp. 1–8, 2020.

[17] A. Sharma, K. Guleria, and N. Goyal, "Prediction of diabetes disease using machine learning model," in *International Conference on Communication, Computing and Electronics Systems: Proceedings of ICCCES 2020*, pp. 683–692, Springer, 2021.

[18] E. Çallı, E. Sogancioglu, B. van Ginneken, K. G. van Leeuwen, and K. Murphy, "Deep learning for chest x-ray analysis: A survey," *Medical Image Analysis*, vol. 72, p. 102125, 2021.

[19] A. Shelke, M. Inamdar, V. Shah, A. Tiwari, A. Hussain, T. Chafekar, and N. Mehendale, "Chest x-ray classification using deep learning for automated covid-19 screening," *SN computer science*, vol. 2, no. 4, p. 300, 2021.

[20] R. H. Abiyev, M. K. S. Ma'aitaH, *et al.*, "Deep convolutional neural networks for chest diseases detection," *Journal of healthcare engineering*, vol. 2018, 2018.

[21] A. Khatri, R. Jain, H. Vashista, N. Mittal, P. Ranjan, and R. Janardhanan, "Pneumonia identification in chest x-ray images using emd," in *Trends in Communication, Cloud, and Big Data: Proceedings of 3rd National Conference on CCB, 2018*, pp. 87–98, Springer, 2020.

[22] Y. Wu, X. Qin, Y. Pan, and C. Yuan, "Convolution neural network based transfer learning for classification of flowers," in *2018 IEEE 3rd international conference on signal and image processing (ICSIP)*, pp. 562–566, IEEE, 2018.

[23] P. Mooney, "Chest x-ray images (pneumonia)."

[24] S. Sharma and K. Guleria, "A deep learning based model for the detection of pneumonia from chest x-ray images using vgg-16 and neural networks," *Procedia Computer Science*, vol. 218, pp. 357–366, 2023.

[25] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-net: Fully convolutional neural networks for volumetric medical image segmentation," in *2016 fourth international conference on 3D vision (3DV)*, pp. 565–571, Ieee, 2016.

Appendix

Listing 8.1: main.py

```python
import warnings
warnings.filterwarnings('ignore')
from keras.models import load_model
import tensorflow as tf
from tensorflow import keras
from keras.layers import Input, Lambda, Dense, Flatten
from keras.models import Model
from keras.applications.vgg16 import VGG16, preprocess_input
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator
import numpy as np
from glob import glob

# IMAGE_SIZE = [224, 224]  # Use this line if you want to define
   a custom image size
IMAGE_SIZE = (224, 224)    # Use this line for a tuple

train_path = 'C:/Users/theja/Downloads/datasets-20240102T020101Z-
001/datasets/chest_xray/train'
test_path = 'C:/Users/theja/Downloads/datasets-20240102T020101Z-
001/datasets/chest_xray/test'

vgg = VGG16(input_shape=IMAGE_SIZE + (3,), weights='imagenet',
   include_top=False)

for layer in vgg.layers:
    layer.trainable = False

folders =
   glob('C:/Users/theja/Downloads/datasets-20240102T020101Z-
001/datasets/chest_xray/train/*')
x = Flatten()(vgg.output)
prediction = Dense(len(folders), activation='softmax')(x)
model = Model(inputs=vgg.input, outputs=prediction)
```

```
model.summary()

model.compile(
    loss='categorical_crossentropy',
    optimizer='adam',
    metrics=['accuracy']
)

train_datagen = ImageDataGenerator(rescale=1./255,
                                   shear_range=0.2,
                                   zoom_range=0.2,
                                   horizontal_flip=True
                                   )
test_datagen = ImageDataGenerator(rescale=1./255)

training_set = train_datagen.flow_from_directory(train_path,
                                                 target_size=IMAGE_SIZE,
                                                 batch_size=10,
                                                 class_mode='categorical')
test_set = test_datagen.flow_from_directory(test_path,
                                            target_size=IMAGE_SIZE,
                                            batch_size=10,
                                            class_mode='categorical')

r = model.fit_generator(
    training_set,
    validation_data=test_set,
    epochs=1,
    steps_per_epoch=len(training_set),
    validation_steps=len(test_set)
)

model.save('chest_xray.h5')

# Load the model for prediction
model = load_model('chest_xray.h5')
```

```
# Example prediction on a single image
img =
   image.load_img('C:/Users/theja/Downloads/datasets-20240102T020101Z-
001/datasets/chest_xray/train/PNEUMONIA/person9_bacteria_38.jpeg',
                     target_size=IMAGE_SIZE)
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
img_data = preprocess_input(x)
classes = model.predict(img_data)

result = classes[0][0]

if result > 0.5:
    print("Result is Normal")
else:
    print("Affected by pneumonia")
```