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Thesis:
**An IoT-based deep learning frame work for early
assessment of pneumonia.**

by
Madani Rihab

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Jury:

Presidente	Nadia Iles	ISTA, University of Oran 1
Director	Amine Dahane	ISTA, University of Oran 1
Examiner	Yasmine Ait Si Larbi	ISTA, University of Oran 1

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Abstract

The COVID-19 pandemic has highlighted the importance of remote patient monitoring for the well-being of both patients and healthcare providers. Pneumonia, a leading cause of morbidity and mortality in children, requires prompt diagnosis and treatment due to its impact on the small air sacs in the lungs. Chest X-rays are a common diagnostic tool for detecting pneumonia. This study emphasizes the development of a support tool to assist healthcare professionals in enhancing the accuracy and efficiency of pneumonia diagnosis through advanced deep learning approaches. The best model accuracy of VGGNet of 95.89% confirms that the model is robust however MobileNet can perform well in real-world situations.

Keywords: Pneumonia, Internet of Medical Things (IoMT), Artificial intelligence, Deep learning, Edge computing, Cloud computing.

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Dedication

I dedicate this work to my dear parents, my siblings; Amira, Ayoub, Aymen, Alaa elddine, Hanine, and my first niece Mohamed Firas, and to my dear grandparents.

A special dedication to my roommate BENAOUA Khadidja, for her companionship, moral support, and for putting up with my occasional late-night work sessions.

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List of Abbreviations

IoT	Internet of Things.
IoMT	Internet of Medical Things.
HIoT	Internet of things in healthcare.
TB	Tuberculosis
COPD	Chronic obstructive pulmonary disease
CNN	Conventional Neural Network
SVM	Support Vector Machine
DL	Deep Learning
AI	Artificial Intelligence
MRI	Magnetic Radio Imagery
ECG	electrocardiogram

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General introduction

The integration of the Internet of Things (IoT) into healthcare represents a transformative shift in how medical services are provided and managed. This thesis explores the definition of IoT within the healthcare sector, examining the technologies and architectures that support these systems. Additionally, it highlights the practical applications of IoT in healthcare with a particular focus on pneumonia, a respiratory condition that poses significant health risks worldwide. By understanding the definition, symptoms, risk factors, and diagnostic methods of pneumonia, the research aims to showcase how IoT can enhance healthcare delivery.

Organization of the Thesis

General Introduction: Overview of the integration of IoT in healthcare, Focus on pneumonia as a case study. Chapter 1: Introduction and Motivation, Definition of IoT in healthcare, Examination of IoT technologies and architectures, Practical applications of IoT in healthcare, Detailed study of pneumonia. Chapter 2: Respiratory Illnesses in Deep Learning, Introduction to common respiratory diseases, Overview of deep learning techniques for diagnosing respiratory illnesses, Previous work in the field, Detailed analysis of deep learning models. Chapter 3: Implementation and Results, Development tools used, Detailed description of deep learning models and datasets, Data preprocessing techniques, Training process and performance metrics, Results and comparative analysis of models. Chapter 4: Internship Report, Introduction to the internship setting, Presentation of the hospital and its services, Observations and analyses from different departments, Insights from medical imaging and sterilization methods.

Chapter1 introduction and motivation

1. Introduction

The integration of the Internet of Things (IoT) into healthcare represents a transformative shift in how medical services are provided and managed. This chapter explores the definition of IoT within the healthcare sector, examining the technologies and architectures that support these systems. Additionally, it highlights the practical applications of IoT in healthcare, with a particular focus on pneumonia a respiratory condition that poses significant health risks worldwide. By understanding the definition, symptoms, risk factors, and diagnostic methods of pneumonia.

2. Internet of things in healthcare

2.1 Definition

IoT in healthcare refers to the integration of Internet of Things (IoT) technology into the healthcare sector, enabling real-time monitoring and data collection through connected devices and sensors. This innovative approach enhances patient care by providing remote access to vital health information, facilitating timely interventions and improving overall treatment outcomes[1], [2].

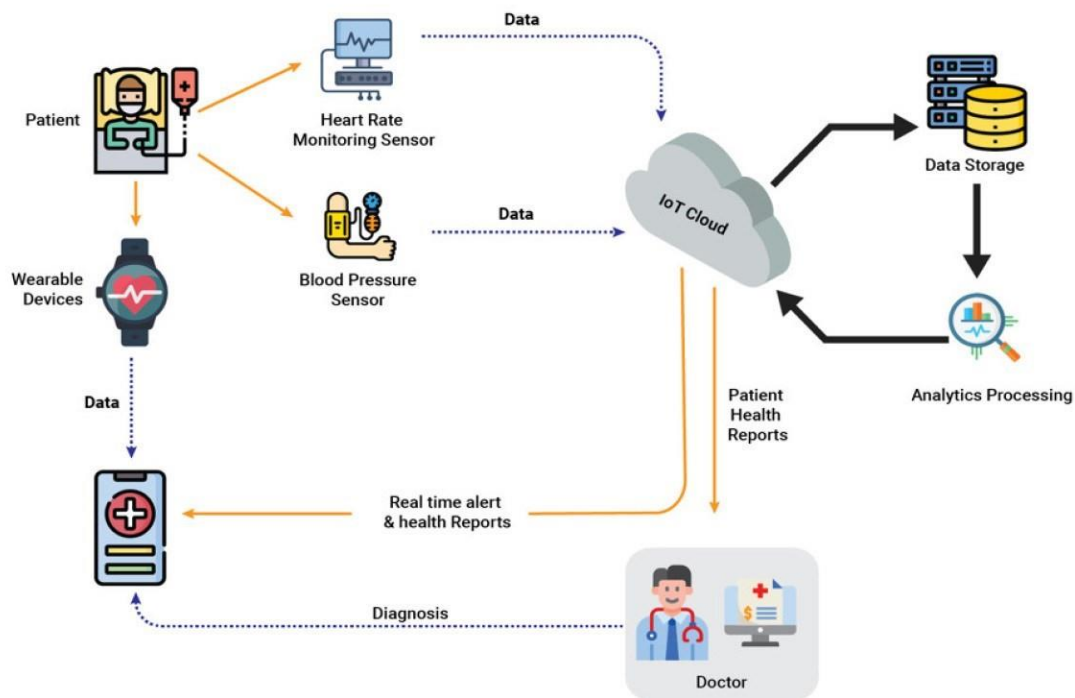


Figure 1: IoT in Healthcare [3].

2.2 Architecture:

The IoT framework in healthcare integrates IoT technology and cloud computing to transmit patient data from sensors and medical devices to healthcare networks. A Healthcare IoT (HIoT) system typically includes components like publishers (sensor networks), brokers (data processors in the cloud), and subscribers (devices for monitoring patient data). This system monitors vital signs like blood pressure, heart rate, and more, providing continuous data to subscribers via devices like smartphones or tablets. The HIoT adapts components into a structured network tailored to healthcare needs, crucial for real-time patient monitoring and treatment [3].

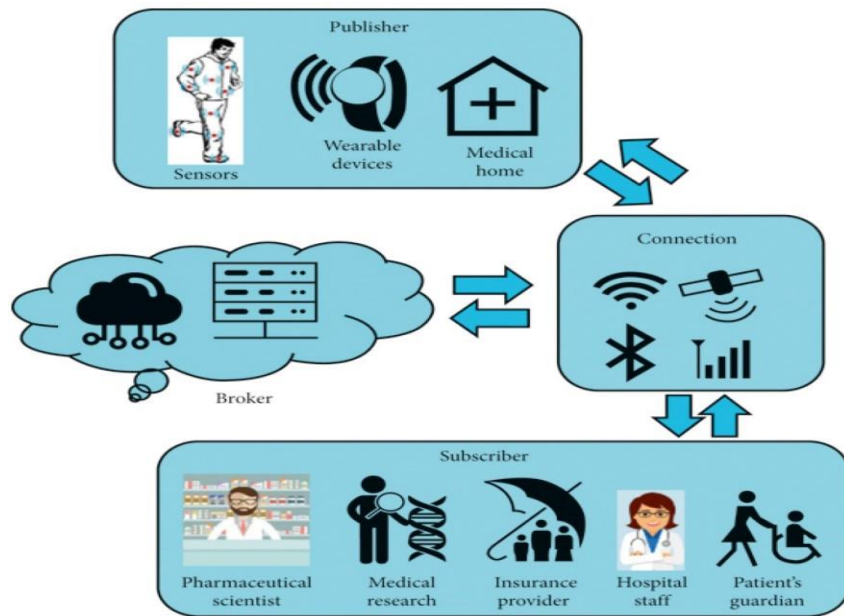


Figure 2: Architecture of an HIoT framework [4].

2.3 Technologies:

2.4.1 Identification Technology:

Designing an HIoT system requires ensuring secure access to patient data from remote sensors. This involves assigning unique identifiers (UIDs) to each authorized node and sensor within the healthcare network. These UIDs facilitate unambiguous data exchange and connection among resources such as hospitals, doctors, and medical devices in a digital environment. Standards like UUID and GUID, developed by the Open Software Foundation, support decentralized and global identification across healthcare networks. However, due to continuous IoT technology upgrades, device UIDs may change over their lifecycle, necessitating mechanisms for updating this information to maintain system integrity and accuracy in healthcare diagnostics. Advanced technologies are crucial for securely managing component identities and efficiently discovering IoT services based on global UUIDs.[3].

2.4.2 Communication technology:

Communication technologies in Healthcare IoT (HIoT) offer a spectrum of options with unique characteristics and applications tailored to the healthcare industry. Bluetooth operating in the 2.4 GHz range, excels in short-range connectivity for wearable health devices, despite limited coverage. Wi-Fi spanning 2.4 to 5.8 GHz, provides high data rates and broad coverage, ideal for data-intensive applications like telemedicine. ZigBee in the 2.4 GHz range supports low-power, short-range communication with a mesh network topology ensuring energy efficiency but with lower data rates. 4G operating across various frequencies delivers high-speed data transfer over long distances suitable for telehealth services but may face power consumption challenges. Each technology's distinct advantages and disadvantages cater to specific healthcare needs, enhancing connectivity, data exchange, and decision making in healthcare IoT applications [4].

2.4.3 Location technology:

Location technology plays a pivotal role in Healthcare IoT systems, enabling real-time tracking and monitoring of patients, medical equipment, and healthcare personnel within medical facilities. Global Positioning System (GPS) and indoor positioning systems (IPS) are commonly used to pinpoint the exact location of assets and individuals in healthcare settings. GPS technology allows for outdoor tracking, while IPS solutions, such as Bluetooth Low Energy (BLE) beacons and Wi-Fi positioning, offer precise indoor localisation capabilities. By leveraging location technology in Healthcare IoT, healthcare providers can enhance patient safety, streamline workflow efficiency, and optimize resource allocation. Real-time tracking of patients and medical equipment facilitates quick response times in emergencies and reduces the risk of equipment loss or misplacement. Additionally, location-based services enable healthcare staff to efficiently navigate hospital premises, locate required resources, and deliver timely care to patients. The integration of location technology in Healthcare IoT systems not only improves operational efficiency but also enhances patient experience and overall quality of care. By leveraging GPS and IPS solutions, healthcare facilities can ensure seamless coordination, effective asset management, and enhanced patient outcomes, ultimately transforming the healthcare delivery landscape [5].

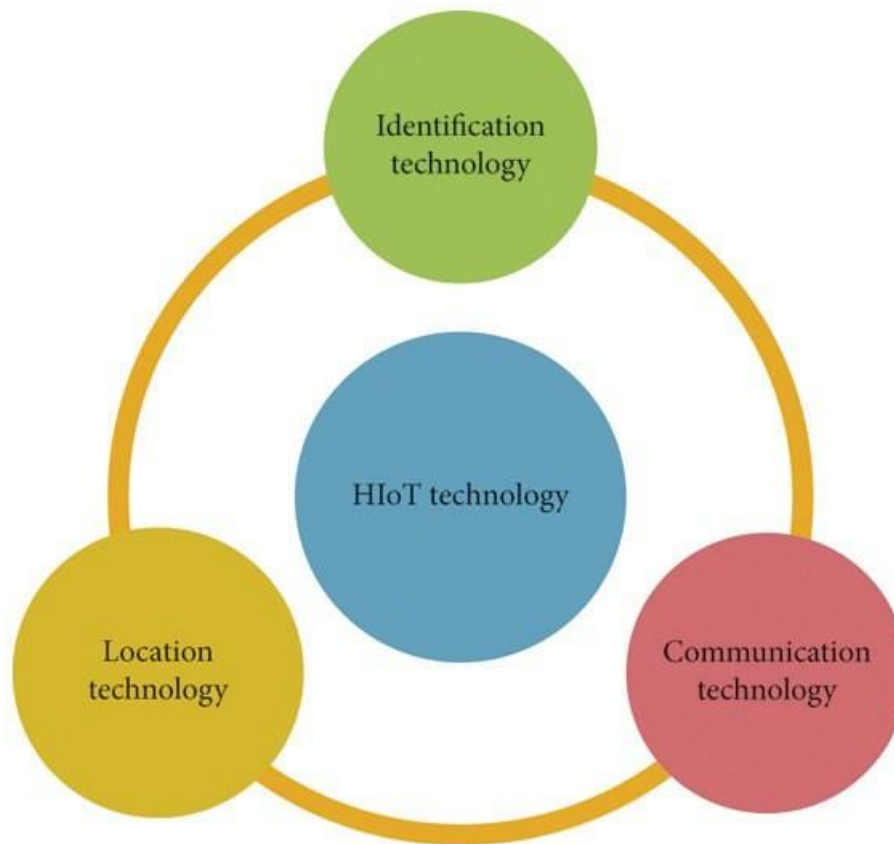


Figure 3: Classification of IoT technology [7].

2.4 Application

In the scope of IoT healthcare applications (HIOT), we find:

2.4.1 Electrocardiogram (ECG) monitoring

is a medical procedure that involves the continuous or periodic recording and analysis of the electrical activity of the heart over a specific period. This monitoring method utilizes electrodes placed on the skin to detect and record the heart's electrical impulses, which are then displayed as a series of waveforms on a monitor or paper printout. ECG monitoring is crucial for diagnosing and monitoring various heart conditions, such as arrhythmias, heart attacks, and other cardiac abnormalities, providing valuable information about the heart's

rhythm, rate, and overall cardiac health status. It allows healthcare providers to assess the heart's function, detect abnormalities, and make informed decisions regarding treatment and management strategies based on the recorded electrical signals[6].

2.4.2 Blood pressure monitoring

entails the systematic assessment of the force exerted by the circulating blood against the arterial walls during the cardiac cycle. This essential process facilitates the evaluation of cardiac function and the detection of potential health hazards, notably hypertension. Typically, it encompasses the measurement of systolic and diastolic blood pressure utilizing instruments like sphygmomanometers, thereby furnishing invaluable information regarding an individual's cardiovascular condition and general well-being. Precise blood pressure monitoring serves as a pivotal tool for healthcare practitioners in diagnosing ailments, formulating treatment strategies, and gauging the efficacy of interventions aimed at preserving optimal blood pressure levels and mitigating the incidence of cardiovascular ailments[7].

2.4.3 Temperature Monitoring

refers to the systematic and regular measurement of body temperature to assess a patient's health status. It is a fundamental clinical practice used to detect fever, monitor changes in body temperature, and evaluate the effectiveness of treatments. Healthcare professionals use temperature monitoring to identify infections, inflammatory processes, and other medical conditions that can impact a patient's well-being[8].

2.4.4 Monitoring level glucose

is the process of regularly measuring and tracking the levels of glucose, a type of carbohydrate, in the blood. This monitoring is vital for individuals with diabetes, a chronic disease characterized by abnormal blood glucose levels. Various methods, such as continuous glucose monitors and portable glucose meters, are used to provide instant or periodic readings of glucose levels, enabling individuals to effectively manage glucose levels and make

informed decisions about their health and lifestyle choices. Monitoring glucose levels helps individuals with diabetes maintain healthy metabolic function, prevent complications, and improve overall health outcomes[9]

2.4.5 Oxygen saturation monitoring

is crucial in-patient care. Monitoring oxygen saturation helps understand how oxygen is transported in the blood and utilized by tissues. It aids in assessing the functioning level of vital organs such as the brain, heart, and kidneys. Oxygen saturation monitoring is often performed using a pulse oximeter, a widely used non-invasive device in medical care. As the fifth vital sign, oxygen saturation is an essential measure that guides clinical decisions and can detect levels of hypoxemia even when symptoms are not visible during physical examination[10], [11]

2.4.6 Asthma monitoring

is an important aspect of effective treatment of asthma, a chronic respiratory disease characterized by inflammation and narrowing of the airways. This includes regular assessment of respiratory parameters such as lung function, respiratory rate and oxygen saturation to assess the severity of symptoms and the effectiveness of treatment. By continuously monitoring these indicators, healthcare providers can identify trends, triggers, and early warning signs of asthma exacerbations. This proactive approach allows timely adjustments to medications, lifestyle changes, and personalized treatment strategies to improve asthma control and prevent complications. Continuous monitoring allows patients to actively participate in their own care, identify fluctuations in symptoms, and communicate effectively with their healthcare team, improving asthma management and quality of life[12]

2.4.7 Emotion monitoring

is the systematic and continuous process of assessing, measuring and reflecting on the state of emotion and well-being of an individual in a specific setting. This includes realtime data collection using a variety of methods, including short and long-term surveys based on proven

psychological methods such as the news experiment sample method. The goal of monitoring emotions is to gain insights into an individual's immediate emotions, identify patterns of emotional responses, and ultimately improve the environment to increase well-being and productivity. By leveraging Internet of Things device technologies emotion monitoring systems can enable visualization and analysis of emotions data, facilitating timely adjustments and interventions to support participants' emotional well-being[13]

2.4.8 Medication management

includes a comprehensive approach to the safe and effective use of medications by individuals. It is a systematic process that includes drug evaluation, prescription, dispensing, administration, monitoring and follow-up. This multifaceted strategy is designed to optimize treatment outcomes, minimize medication-related problems, improve patient understanding and compliance, and promote overall health and wellbeing. By integrating different healthcare professionals, technology, and patient education, medication management is designed to ensure that medications are used appropriately to achieve intended clinical goals while minimizing risk and maximizing benefit to the individual [14].

2.4.9 Wheelchair Management

refers to the integration of smart technologies and sensors into wheelchairs to enable continuous health monitoring and improved patient care. This system typically includes sensors for vital signs such as heartbeat, blood pressure, temperature, and step count, which are connected to a central controller. The data collected from these sensors is then transmitted to a cloud platform. By incorporating a joystick for wheelchair navigation and an ultrasonic sensor for obstacle detection, this system enhances the mobility and safety of wheelchair users. The joystick control allows individuals with physical disabilities to operate the wheelchair easily, while the ultrasonic sensor scans for obstacles and automatically stops the wheelchair to prevent collisions[15], [16].

2.4.10 Rehabilitation

Rehabilitation systems include a comprehensive set of interventions and strategies designed to improve and enhance the performance, function, and quality of life for individuals who experience limitations in physical, mental, or social function due to various health conditions, injuries, trauma, or aging. These systems aim to minimize disability, improve independence, and promote overall well-being by providing therapies, treatments, and supportive services tailored to address the specific needs and challenges faced by individuals [17].

2.4.11 Pneumonia monitoring

Pneumonia surveillance entails the structured and ongoing observation of individuals, particularly those at higher risk, to identify, evaluate, and mitigate the onset and advancement of pneumonia-associated complications. This involves gathering and analyzing data on various factors including antibodies, lifestyle, environmental conditions, hospitalization, and ventilator usage to pinpoint vulnerable demographics and gauge the efficacy of preventive measures. The surveillance process strives to curb pneumonia transmission, particularly in hospital settings without ventilators, employing advanced sensor technology and monitoring tactics to track vital indicators like carbon monoxide levels, carbon dioxide concentration, temperature, and humidity [18].

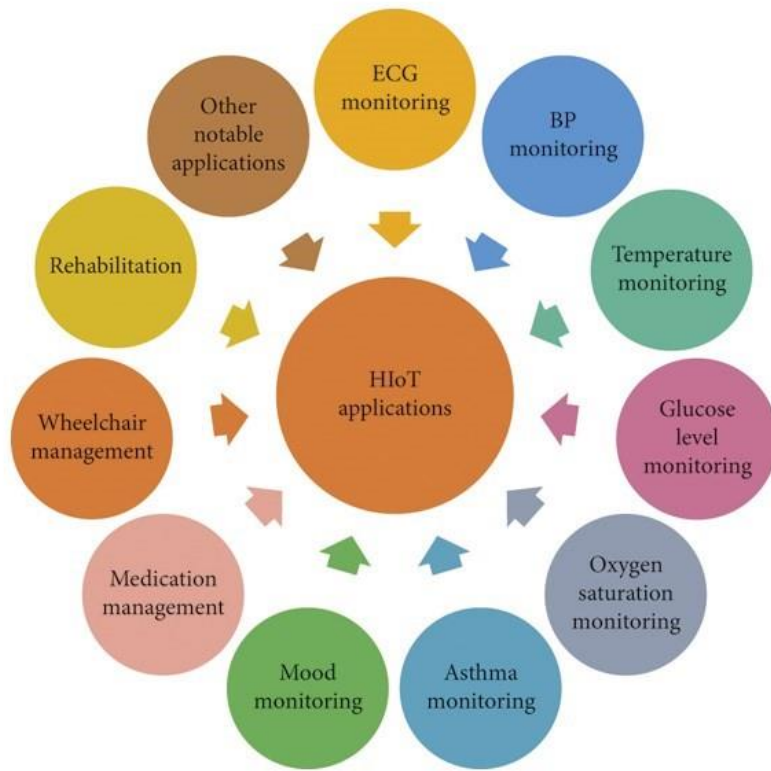


Figure 4: HIoT applications [21].

3. Pneumonia

3.1. Definition

Pneumonia is an infection that affects the lower respiratory tract, specifically the alveolar space, bronchi, and bronchioles. It is caused by the proliferation of microorganisms in these areas along with a response from the body's immune system. The presence of microorganisms without an immune response is known as colonization. Pneumonia is different from other respiratory infections because it occurs at the alveolar level. Different types of pneumonia

can be classified based on microbial causes, host defense, clinical presentation, and other factors [19] .

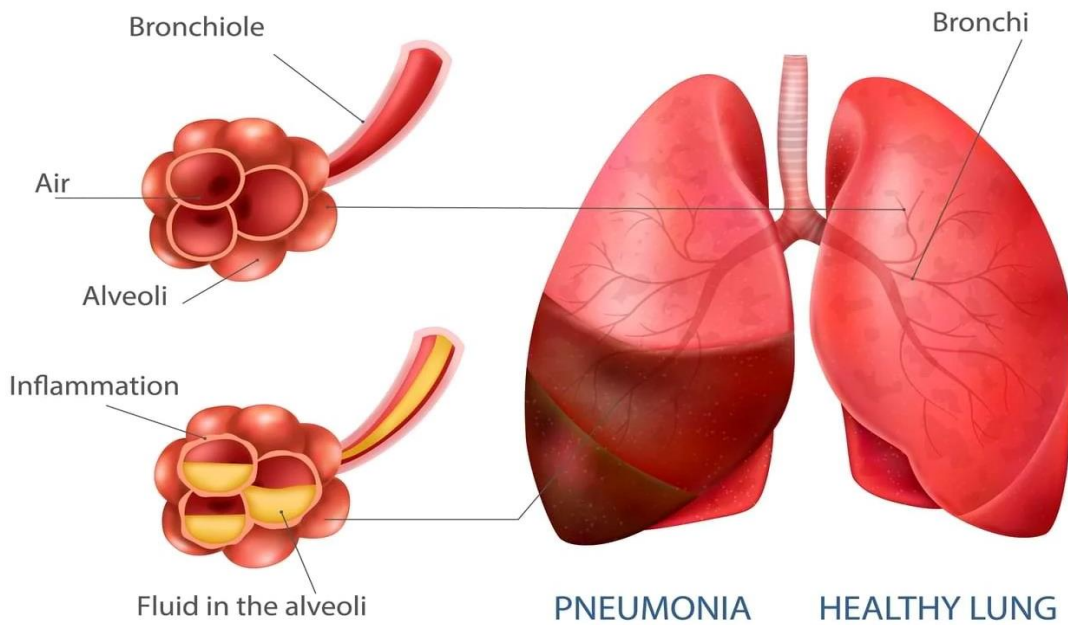


Figure 5: comparison between the inflamed and sane lung [23].

3.2. Symptoms

Pneumonia manifests with a range of symptoms that can vary in severity. The most common signs include a productive cough with phlegm, high fever often accompanied by sweating and chills, and shortness of breath that may worsen with physical activity. Patients might also experience sharp chest pain that intensifies when breathing deeply or coughing. Additional symptoms can include fatigue, weakness, nausea, vomiting, and in some cases, confusion or changes in mental awareness, particularly in older individuals [20].

3.3. Causes and Risk Factors

Babies and older adults (aged over 65) face a heightened risk of developing pneumonia. Individuals with weakened immune systems, such as those with diabetes, kidney issues, or cancer, are also more susceptible. Conditions like asthma, COPD, heart disease, and smoking, along with certain viral infections like influenza, increase the likelihood of pneumonia. Aspiration pneumonia can occur when oral or gastric contents enter the airways, particularly affecting individuals who are bedridden or experience confusion or swallowing difficulties due to conditions like dementia or stroke. Certain medications, including those that reduce stomach acid, may potentially elevate pneumonia risk, although the exact impact remains uncertain.[19]

3.4. Diagnosis and Examination of Pneumonia

the diagnosis of pneumonia begins with a thorough physical examination. The lungs are listened to with a stethoscope to detect any abnormal sounds such as rales or wheezing, which are signs of pneumonia. If pneumonia is suspected, further tests may be ordered:

- A blood test to confirm the infection and try to identify the pathogen involved, even if it's not always possible to identify it precisely.
- Chest X-ray to diagnose pneumonia and assess its extent and location. However, it is not always possible to determine the type of germ responsible.
- Oximetry to measure oxygen levels in the blood, as pneumonia can lead to oxygen depletion.
- Sputum examination to analyze a sample of fluid from the lungs and try to determine the cause of the infection. Additional tests, such as a chest X-ray or pleural fluid analysis, may also be necessary, especially for the elderly, hospitalized or those with severe symptoms. [21],[22].

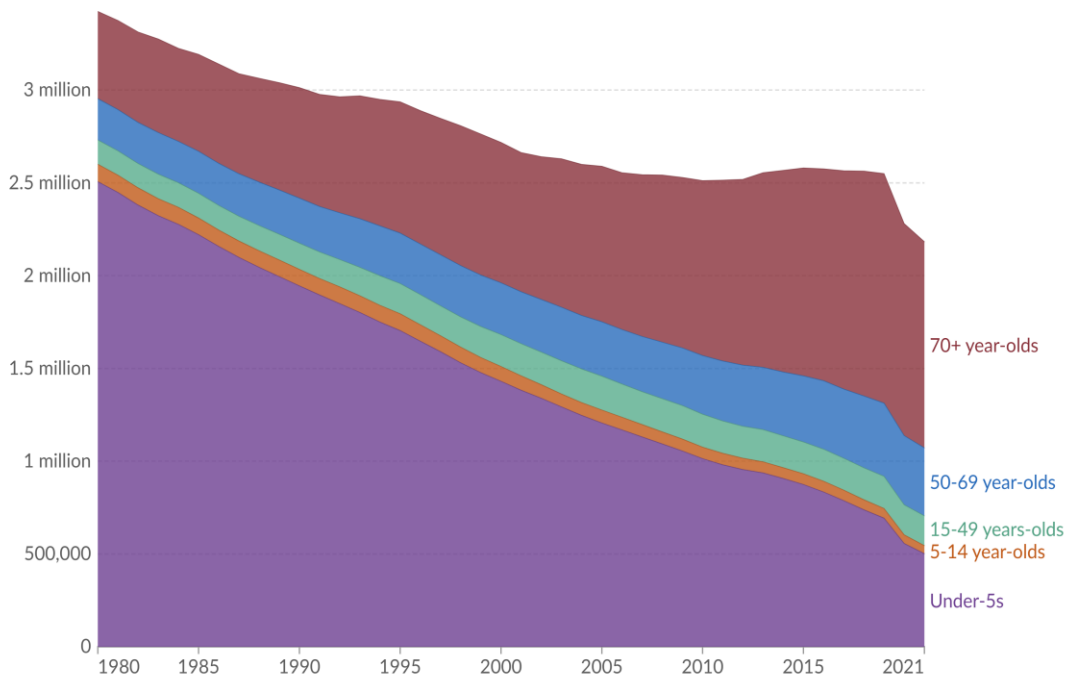


Figure 6 :deaths from pneumonia by age, world,1980 to 2021[23].

3.5 Pneumonia Stats

3.5.1 Burden of pneumonia

As shown in figure (6), the global annual deaths from pneumonia and other lower respiratory infections have significantly decreased across all age groups. The most substantial decline is observed in children under 5, with deaths dropping from over 1.5 million to under 500,000. Similarly, notable reductions are seen in adults aged 50-69 and those over 70, from approximately 1 million and 1.5 million respectively, to below 500,000 [23].

3.5.2 Geographic Distribution of Pneumonia Mortality

The map below shows the annual death rate from pneumonia, per 100,000 people in the population. The death rates are age-standardized, which helps make comparisons between populations of different age structures. As shown in figure (7) The difference between death rates in different world regions is very large. The death rate from pneumonia is highest in sub-Saharan Africa and South East Asia, and much lower in Europe and North America.

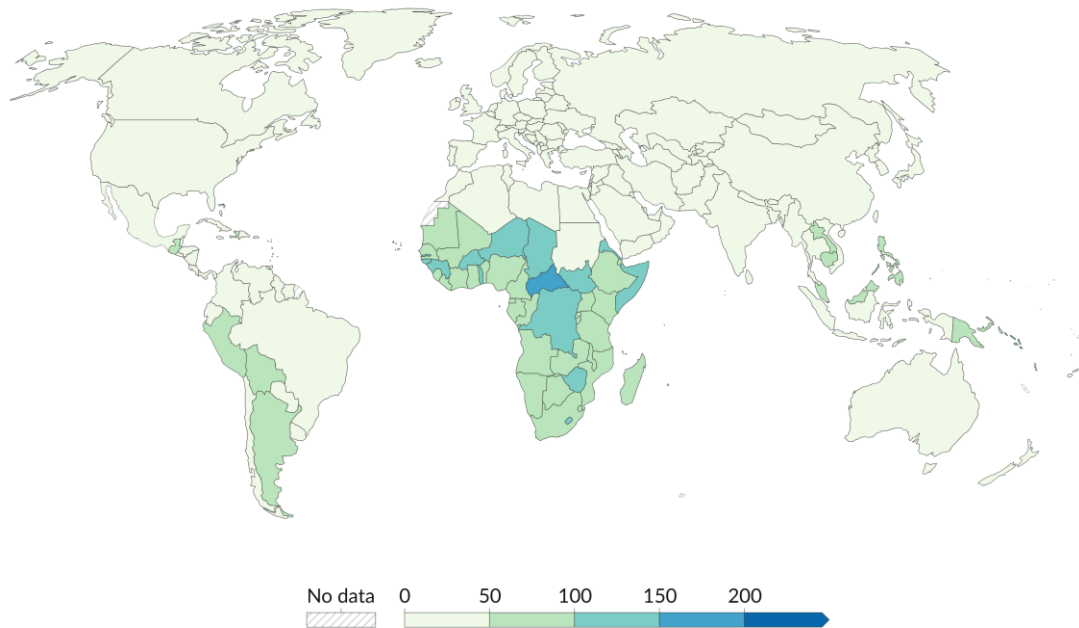


Figure 7: Map of death rate of pneumonia ,2021 [23].

4. Conclusion

In conclusion, the adoption of IoT technologies in healthcare offers significant potential for improving patient care and streamlining medical operations. By exploring the definition, symptoms, risk factors, and diagnostic methods of pneumonia, this chapter has shown how IoT can be effectively used to monitor, diagnose, and treat this condition. The integration of advanced technology and healthcare through IoT paves the way for more accurate diagnoses, timely interventions, and better health outcomes, highlighting the promising future of IoT in the medical field.

Chapter 2: Respiratory illnesses in deep learning

1. Introduction

Deep learning is revolutionizing many fields, including healthcare. This chapter introduces the basics of deep learning and how it applies to common lung diseases. We'll start by explaining the main concepts of deep learning, then discuss common lung conditions like asthma, Bronchitis, chronic obstructive pulmonary disease (COPD), Lung cancer, tuberculosis, and pneumonia. Additionally, we'll look at previous studies that have used deep learning to diagnose and treat these diseases. By understanding the theoretical and practical aspects of deep learning in this context, we aim to highlight its potential to transform lung healthcare.

2. Common Respiratory Diseases

2.1 Asthma

Asthma is a chronic inflammatory disorder of the airways resulting in, variable airflow bronchial obstruction which is potentially reversible with appropriate therapy or spontaneously. It is typically characterized by episodic attacks of breathlessness, cough, and wheezing.[24]

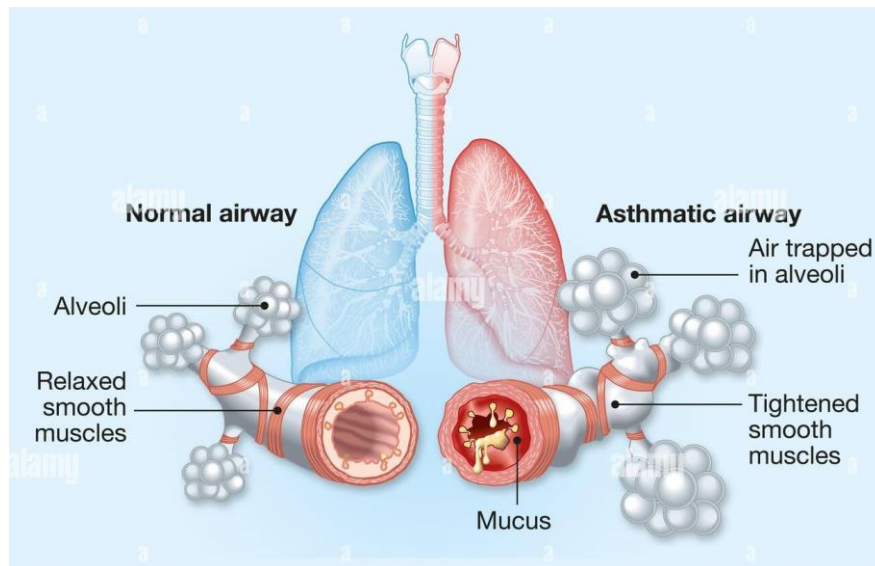


Figure 8 : Differences Between Healthy and Asthmatic Airways [25].

2.2 Bronchitis

Bronchitis is an inflammation of the bronchial tubes, the airways that carry air into your lungs, leading to symptoms such as persistent coughing, mucus production, and difficulty breathing. It can be acute, often caused by a viral infection such as the common cold or flu, usually lasting a few days to weeks, or chronic, lasting months and recurring over years, often caused by long-term irritants such as smoking [26].

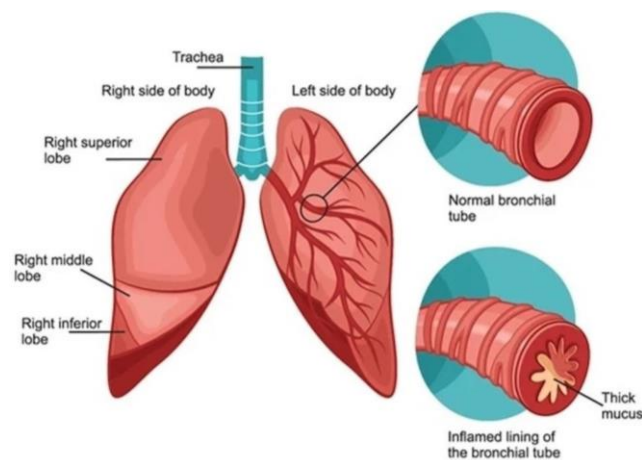


Figure 9 : Comparison of Healthy and Inflamed Bronchi in Bronchitis [27].

2.3 COPD

Chronic obstructive pulmonary disease (COPD) is a chronic inflammatory lung disease that causes obstructed airflow from the lungs. Symptoms include breathing difficulty, cough, mucus (sputum) production and wheezing. It's typically caused by long-term exposure to irritating gases or particulate matter, most often from cigarette smoke. People with COPD are at increased risk of developing heart disease, lung cancer and a variety of other conditions [28].

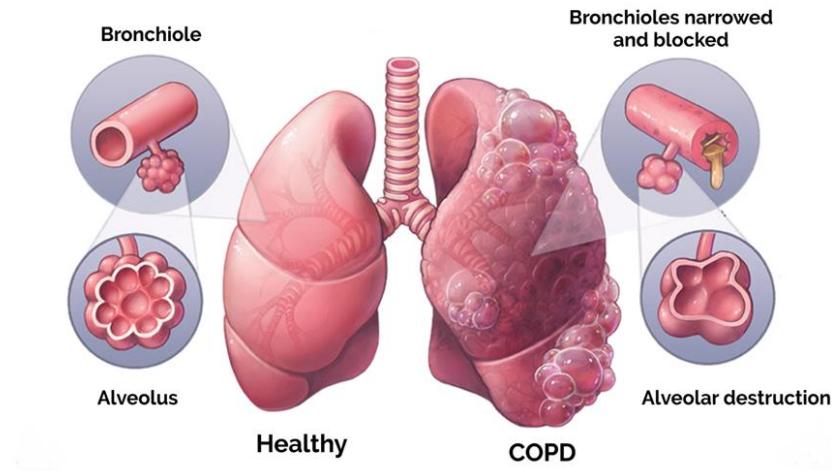


Figure 10: Alveolar and Bronchiolar Changes in Chronic Obstructive Pulmonary Disease[29].

2.4 Lung cancer

Lung cancer is a type of cancer that starts when abnormal cells grow in an uncontrolled way in the lungs. It is a serious health issue that can cause severe harm and death. Symptoms of lung cancer include a cough that does not go away, chest pain and shortness of breath [30].

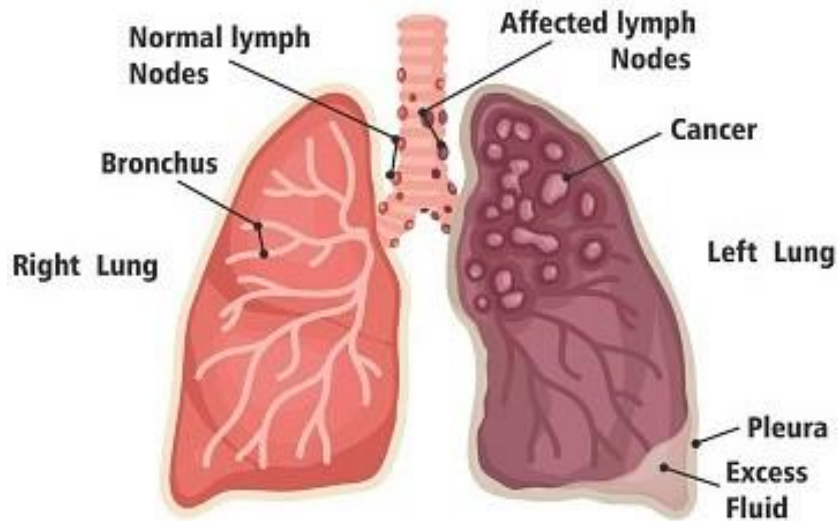


Figure 11: comparison between healthy lung and cancer lung [31].

2.5 Tuberculosis

TB is an airborne bacterial infection caused by *Mycobacterium tuberculosis*, which can affect any part of the body but most commonly the lungs. *Mycobacterium tuberculosis* is released into the air as droplet nuclei from coughing, sneezing, shouting, or singing by individuals with pulmonary or laryngeal TB. Transmission occurs through inhalation of these droplet nuclei, which pass through the mouth or nasal cavities, the upper respiratory tract, bronchi, and finally reach the alveoli of the lungs [32].

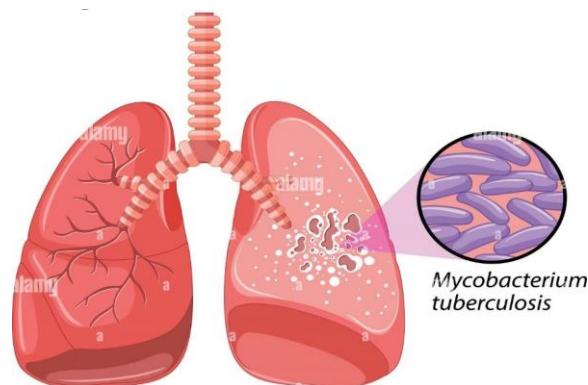


Figure 12 : Schematic Representation of the Progression of Tuberculosis in the Lungs [33].

2.6 Pneumonia

Pneumonia is an infectious disease caused by viruses, germs, fungi, and bacteria. It inflames the lungs' air sacs, which can be extremely hazardous and life-intimidated if not identified at the early stages. The lung infection then affects the pulmonary alveoli, which rapidly deteriorates the health conditions of a person. generally affects people of all ages and is more dangerous for smokers, alcoholics, recent surgical patients, asthma, viral infected, and people with frail immune system. It is considered a harmful disease that may lead to death worldwide [34].

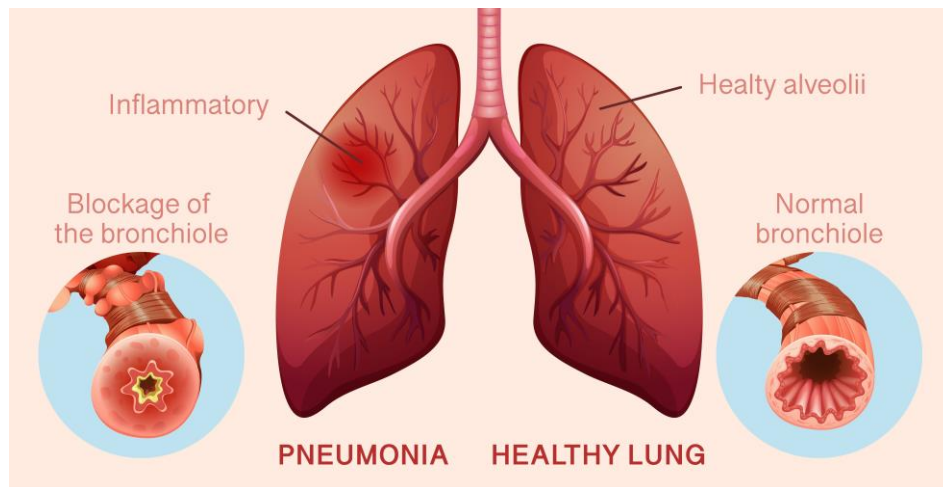


Figure 13: Comparison of Healthy Lungs and Lungs Affected by Pneumonia.

3. Previous Work

Albuquerque et al. [35] developed a real-time IoT system for pneumonia detection in children by evaluating 6,000 CXR images from the Guangzhou Women and Children's Medical Center. They applied transfer learning with CNNs and classic classifiers, achieving an accuracy of 96.47% using the VGG19 CNN and SVM RBF classifier. This research showcases the potential of utilizing large and diverse datasets for accurate and efficient pneumonia diagnosis in pediatric radiology. Nahiduzzaman et al.[36] introduced a novel

method for pneumonia classification using a hybrid CNN-PCA model. The research focused on enhancing accuracy in pneumonia diagnosis through advanced machine learning techniques. By utilizing a dataset from the Guangzhou Women and Children's Medical Centre, the study achieved impressive accuracy rates of 98.32% for multiclass classification and 99.83% for binary classification. Ahmed et al.[37] proposed a novel IoT-based deep learning framework for early Covid-19 assessment, utilizing Faster R-CNN with ResNet-101 on chest X-ray images. The study employed a dataset comprising approximately 4000 Covid-19 positive and 7000 non-Covid-19 negative samples collected from Kaggle RSNA Pneumonia detection datasets and Covid-19 databases. The framework achieved a high detection accuracy of 98%, showcasing its potential to support medical professionals in the early assessment of Covid-19 cases. Norva et al.[38] explored pulmonary tuberculosis detection through deep learning convolutional neural networks, focusing on various preprocessing techniques and a hybrid method combining computer-aided detection and CNN. Using the Shenzhen Hospital X-ray Kit and Montgomery Data Set, which contains normal and abnormal X-ray images that depict the manifestations of tuberculosis. Achieve 92.54% accuracy. Varshni et al.[39] developed a novel deep learning framework for detecting pneumonia in chest X-rays. Utilizing the diverse Open dataset of chest radiographs, the study aimed to enhance diagnostic accuracy and efficiency. The proposed approach combined DenseNet-169 as a feature extractor with an SVM classifier optimized for hyperparameters, achieving a notable of 80,02%. These results demonstrate significant promise for automated pneumonia detection from medical images. Ishtiaque et al. [40] developed a cost-effective and energy-efficient patient monitoring system that gathers vital signs like ECG, heart rate, SpO2, and body temperature, transmitting them to doctors online. The system also employs a GSM module to send alert messages to local healthcare providers during critical situations.

Reference	year	Objective	Machine algorithms	IoT system	Performance
[35]	2021	Detection of pneumonia in children using chest X-ray (CXR)	CNN and transfer learning combined with classic classifiers	Yes	Accuracy:96.47%
[36]	2021	Multivariant Pneumonia Classification using Hybrid CNN-PCA Based Feature Extraction Using Extreme Learning Machine	CNN-PCA Based Feature Extraction Using Extreme Learning Machine	No	98.32% for multi class classification for binary classification 99.83%
[37]	2021	develop an IoT-based deep learning framework for early assessment of Covid-19 through X-Ray image analysis, aiming to assist medical experts and contribute to pandemic control.	CNN (faster - RCNN) with ResNet-101	Yes	Accuracy: 98%
[38]	2019	Develop a deep learning framework utilizing convolutional neural networks for early detection of pulmonary tuberculosis in chest X-ray images	CNN hybrid method	No	92.54%
[39]	2019	Develop an algorithm for detecting thoracic diseases, specifically pneumonia, using frontal chest X-ray images. The goal was to improve healthcare services by providing early diagnosis of pneumonia in remote areas with limited access to	Pre-trained CNN models (ResNet-50, DenseNet-121, DenseNet-169) as feature extractors with SVM classifier	No	80,02%

		radiologists.			
[40]	2021	Develop a low-cost patient monitoring system with arrhythmia and pneumonia detection	2D CNN algorithm for arrhythmia For pneumonia Deeper Dense Net architecture	Yes	94% accuracy in arrhythmia detection and 98.97% accuracy in pneumonia detection

Table 1 :Difference between the previous work .

4. Deep Learning Techniques for Respiratory Illnesses

4.1 Overview of Deep Learning

Deep learning is a type of machine learning and artificial intelligence that involves using artificial neural networks with multiple layers to process data and create computational models. It is known for its ability to learn from data and has been successful in various classification and regression challenges [41].

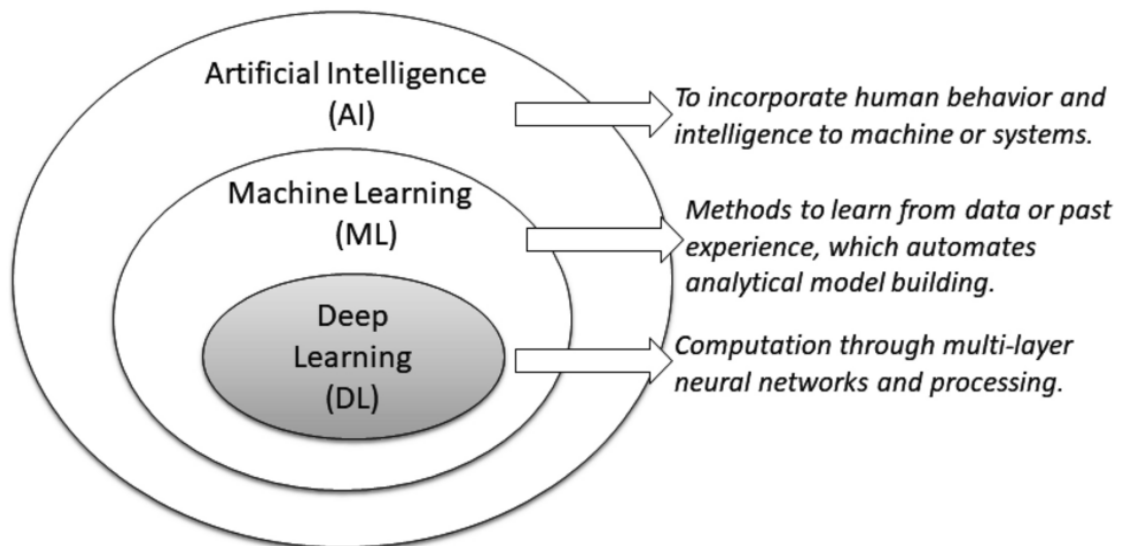


Figure 14: Hierarchy of AI [41].

4.2 Deep Learning Models:

4.2.1 Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNN) are a type of deep learning algorithm particularly suited for image processing. Inspired by the human visual system, CNNs can automatically extract relevant features from visual data, such as images or videos.

A Convolutional Neural Network (CNN) processes an image by passing it through several layers, each playing a specific role in extracting visual features. Here is a detailed description of the process:

4.2.2. Convolutional Layers

Convolutional layers are at the heart of CNNs. They apply filters (or kernels) to the input image to detect simple patterns like edges and textures. Each filter slides over the image, performing a convolution operation to create a feature map. This operation highlights important features from the original image.

4.2.3 Pooling Layers

Pooling layers, often called subsampling or subsampling layers, reduce the size of the feature maps while retaining essential information. The most common method is max-pooling, which selects the maximum value within each sub-region of the feature map. This reduction decreases computational load and helps make the network more robust to variations and distortions in the images.

4.2.4 Fully Connected Layers

After several convolutional and pooling layers, the feature maps are flattened into a 1D vector. This vector is then passed through fully connected (Dense) layers for final

classification. These layers are similar to those in traditional neural networks and allow combining the extracted features to predict the class of the image .

4.2.5 Learning and Optimization

The network learns by adjusting the weights of the filters and fully connected layers through a process called backpropagation. The error between the network's predictions and the true labels is calculated and propagated back through the network to adjust the weights. Optimization algorithms, such as gradient descent, are used to minimize this error [42].

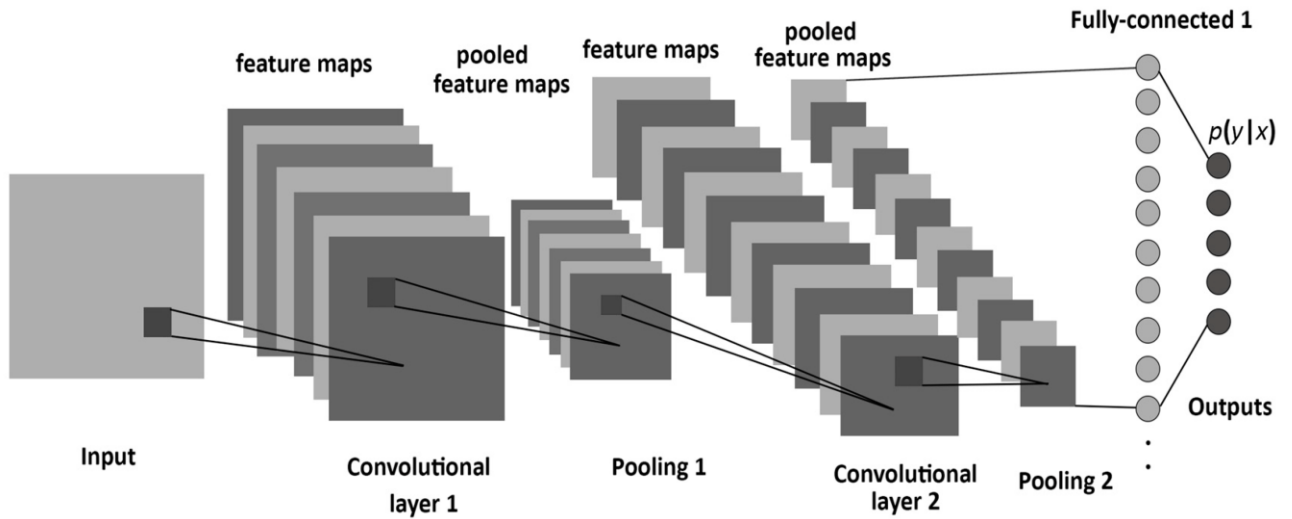


Figure 15 : Convolutional Neural Networks [42].

4.2.2 Recurrent Neural Networks (RNNs):

A recurrent neural network (RNN) is a type of neural network used for modeling sequential data. Derived from feedforward networks, RNNs exhibit behavior similar to human brain functions. In simple terms, recurrent neural networks make predictions in sequential data that other algorithms cannot achieve [43].

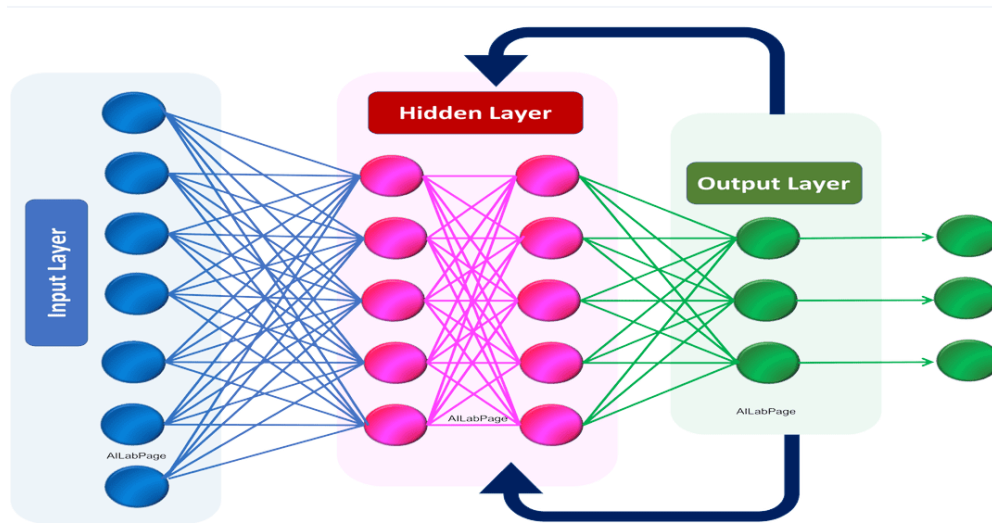


Figure 16 : Recurrent neural networks [44].

4.3 Tools and Frameworks:

In the rapidly evolving field of deep learning, specialized tools and frameworks are essential for model development and enhancement. This section will cover key components utilized in this domain.

4.3.1 TensorFlow:

TensorFlow is an open-source library developed by Google. It's widely used for numerical computations, statistical analysis, and large-scale deep learning. It allows developers to create dataflow graphs, where nodes represent mathematical operations, and connections define how data moves through the graph. TensorFlow is versatile, suitable for both research and development [45].

4.3.2 Keras:

Keras is a high-level neural networks API written in Python, designed to simplify the creation and training of deep learning models. It offers a user-friendly interface for building and

experimenting with neural network architectures, suitable for both beginners and experts [46].

4.3.3 PyTorch

PyTorch is another popular open-source deep learning framework developed by Facebook's AI Research lab (FAIR). It emphasizes dynamic computation graphs, which researchers and practitioners appreciate for their flexibility in customizing neural network components. PyTorch is widely utilized in natural language processing (NLP) and computer vision tasks[46].

4.3.4 OpenCV

OpenCV (Open-Source Computer Vision Library) is the largest open-source computer vision library. While not exclusively for deep learning, it provides essential tools for image and video processing, including feature extraction, object detection, and image manipulation. Many deep learning projects integrate OpenCV for pre-processing and post-processing tasks [45].

4.3.5 MXNet

MXNet is a flexible deep learning framework that supports both symbolic and imperative programming. It's efficient for training large-scale neural networks and has bindings for various programming languages. MXNet is used in research, industry, and production systems [45].

5. Conclusion

In conclusion, deep learning is a powerful tool for advancing the diagnosis and treatment of lung diseases. This chapter has covered the basic principles of deep learning, discussed common lung conditions, and reviewed important previous research in this field. By examining various deep learning techniques used in lung diseases, we have shown their potential to improve diagnostic accuracy, predict disease progression, and personalize

treatment plans. As deep learning continues to advance, its use in lung healthcare will gradually become essential, offering promising opportunities to enhance patient care and improve outcomes.

Chapter3: Implementation and results

1. Introduction

This chapter provides a comprehensive account of the practical implementation of various deep learning models and presents the corresponding findings. It focuses on the configuration of the development environment, the specific deep learning architectures employed, the dataset utilized, and the preprocessing techniques applied. this chapter aims to elucidate the methodologies adopted and the results obtained in this study.

2. Development tools

The development environment plays a crucial role in the successful implementation and implementation of deep learning models. The following tools and devices were used:

2.1 . Hardware

- Processor: Intel(R) Core (TM) i7-7600U CPU @ 2.80GHz 2.90 GHz.
- Installed RAM: 8.00 GB.
- System Type: 64-bit Operating System, x64-based processor.
- Operating System: Windows 11 Professional.
- System SKU: LENOVO_MT_20HG_BU_Think_FM_ThinkPad T470s.
- Computer Brand: Lenovo ThinkPad T470s.

2.2 . Software Environment

2.2.1 Anaconda

Anaconda Navigator is a desktop graphical user interface (GUI) included in Anaconda Distribution that allows you to launch applications and manage conda packages, environments, and channels without using command line interface (CLI) commands. It is available for Windows, macOS, and Linux [47].



Figure 17: Logo anaconda [47].

2.2.2 Jupiter Notebook

Jupyter Notebook is an open-source web application that came into existence in 2015. Previously called IPython Notebook, the tool is an interactive computing environment that allows developers to showcase their work and interact with other project members.

The name Jupiter is a combination of Julia, Python, and R, but the tool is not limited to these languages. The Jupiter Notebook environment supports more than 50 different programming languages, allowing users to create interactive documents called notebooks. These documents can contain computer code, comments, math equations, graphics, or multimedia content [48].



Figure 18:Logo jupyter.

3. Deep Learning Models Used

To evaluate the effectiveness of various deep learning models, we implemented four well known architectures: AlexNet, MobileNet, VGGNet, and ResNet.

3.1 AlexNet

AlexNet is a CNN architecture introduced by Alex Krizhevsky and his colleagues in 2012.

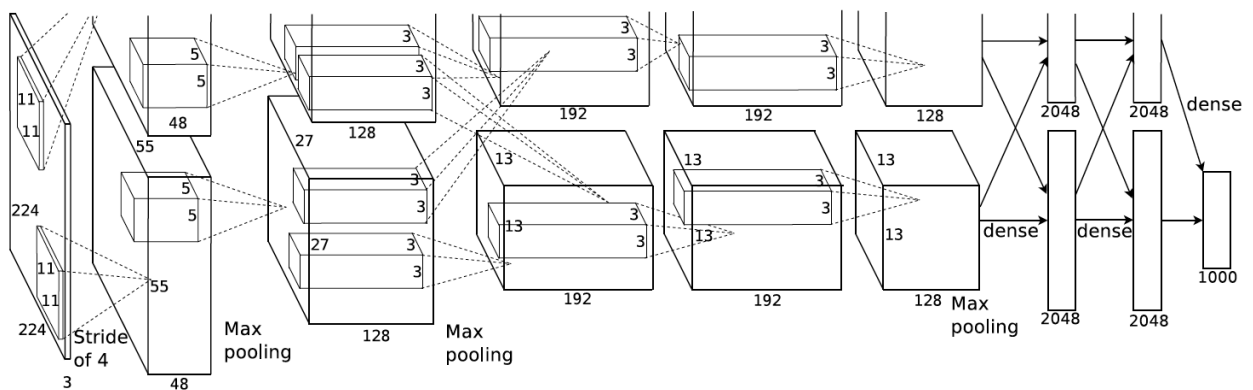


Figure 19: Architecture AlexNet [49].

It won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012. AlexNet consists of five convolutional layers followed by three fully connected layers and uses techniques such as local response normalization and dropout to enhance performance and reduce overfitting [49].

We used the AlexNet model from the official GitHub repository to train our models, as mentioned in [50]. This model, built with Tensorflow and keras, has layers that extract features and classify images. First, the network processes input images through layers that reduce the image size while capturing important features. Then, adaptive average pooling ensures the output size is consistent. The classification part includes fully connected layers with dropout to prevent overfitting and ReLU activations to introduce non-linearity, which together produce class predictions. The forward method manages these steps, making the network capable of classifying images.

3.2 VGGNet

VGGNet, proposed by Simonyan and Zisserman in 2014, is known for its simplicity and efficiency. The architecture consists of several stacked 3x3 convolution layers, followed by Fully connected layers. VGGNet is available in different variants, such as VGG16 and VGG19, indicating the number of weighted layers in the network [51].

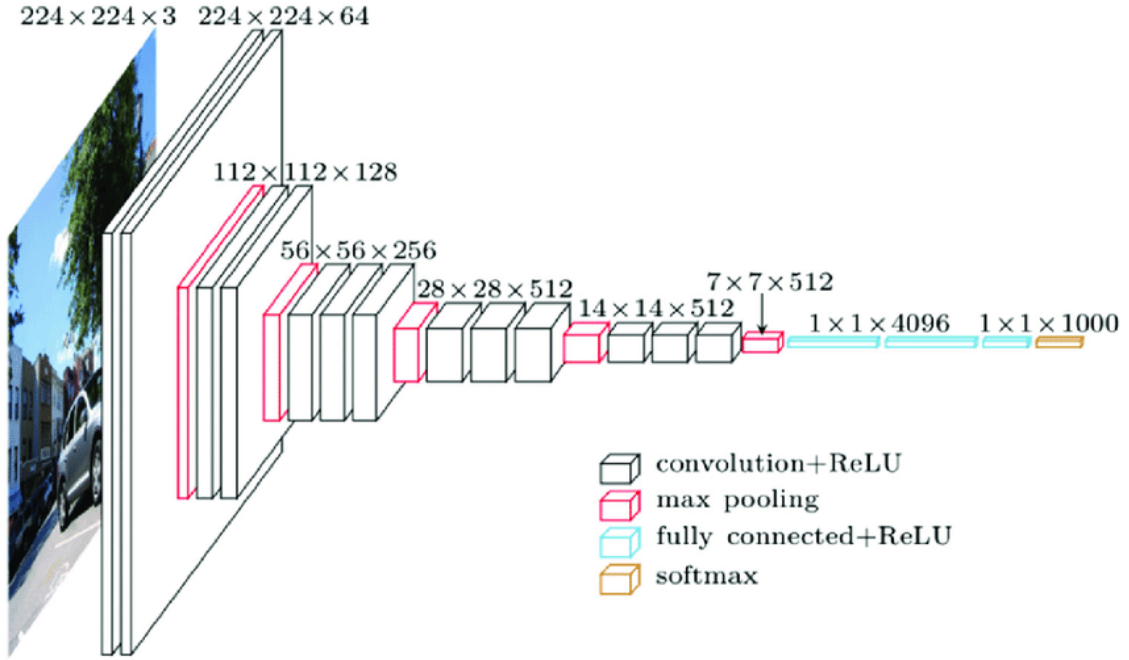


Figure 20:Architecture VGGNet [51].

We employ the VGG16 implementation from the official GitHub repository for training the models, as referenced [52]. The code constructs the VGG16 neural network using TensorFlow library for training our models. This setup defines a neural network model based on the VGG16 architecture. The model starts by collecting and combining image paths from the training and validation directories. These images are split into an 80:20 ratio for training and validation. We then create new directories to store the balanced datasets, ensuring an even distribution of images. Data augmentation techniques, such as rotation, width shift, height shift, and zoom, are applied to the training images using the TensorFlow ImageDataGenerator. The pre-trained VGG16 model, with its layers frozen to retain learned weights, serves as the base. Custom layers, including dense and dropout layers, are added for regularization and further processing. The model is compiled using the Adam optimizer and binary cross-entropy loss function, with accuracy as the primary evaluation metric.

3.3 ResNet (Residual Network)

ResNet, introduced by Kaiming He and his colleagues in 2015, is a CNN architecture that incorporates "residual blocks" allowing information to pass through direct connections between layers. This approach solves the gradient degradation problem in very deep networks, enabling the training of much deeper networks without loss of accuracy [53].

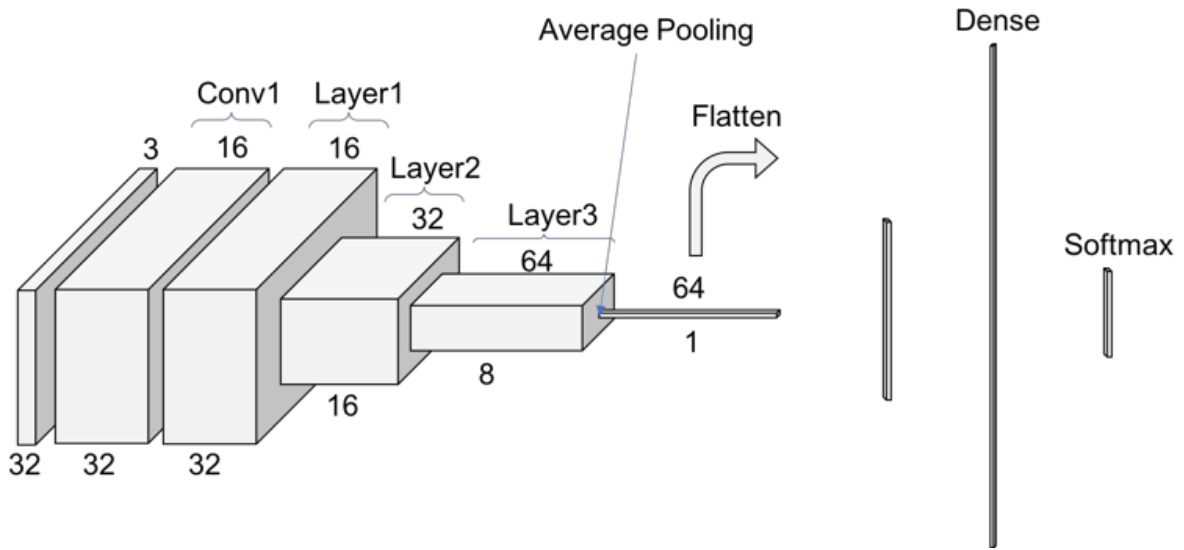


Figure 21 : Architecture ResNet [53].

we employ the ResNet 50 implementation from the official GitHub repository for training the models, as referenced [54]. The ResNet-50 model defines a neural network architecture based on the ResNet framework. It starts with a convolutional layer and a batch normalization layer to capture initial features and stabilize the learning process. The network is structured with four main layers, constructed using the 'make layer' function, which systematically builds each layer with a specific bottleneck block type and a designated number of blocks. These layers progressively increase the depth of the features while reducing spatial dimensions through strided convolutions. Following these layers, the model employs an average pooling layer to spatially condense the features. Finally, a fully connected layer interprets these features to produce the classification output. The 'ResNet50' function configures this model

with the specific arrangement of bottleneck blocks typical of ResNet-50, achieving a robust and efficient architecture for image classification.

3.2 MobileNet

MobileNet is a neural network developed by Google in 2017 to work efficiently on mobile and embedded devices. It uses a technique called depthwise separable convolutions, which breaks the standard convolution process into two simpler steps: one that processes each channel separately and another that combines the results. This approach reduces the number of calculations needed, making MobileNet faster and more energy-efficient than traditional neural networks. Additionally, MobileNet can be customized by adjusting the width and resolution settings, allowing it to balance accuracy and speed according to the specific needs of an application [55].

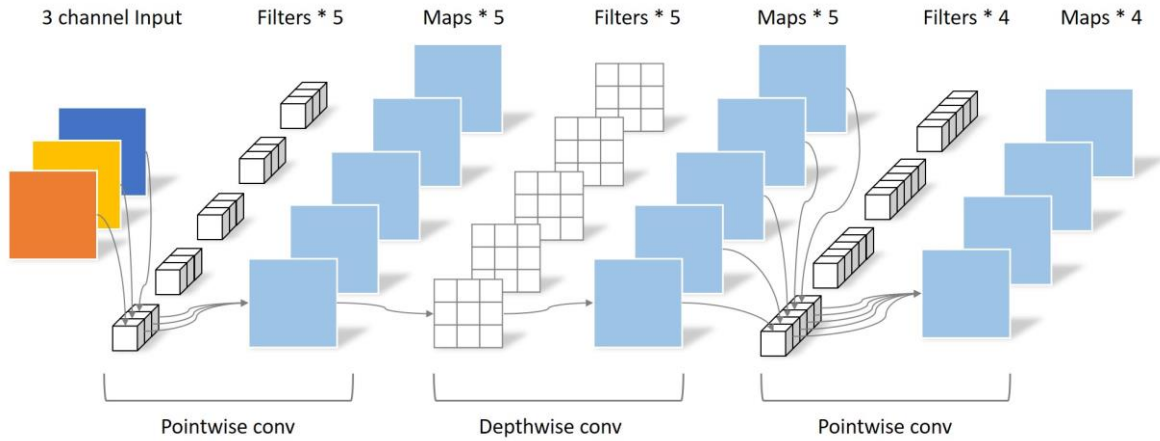


Figure 22: Architecture MobileNet [56].

We employ the MobileNetV2 implementation from Kaggle for training the models, as referenced[57]. The code constructs the MobileNetV2 neural network Using Keras library. The model setup begins by loading the MobileNetV2 with pretrained weights from ImageNet, excluding the top classification layer to adapt it for the current binary

classification task. The initial layers of the network, which include convolutional and batch normalization layers, are frozen to preserve the learned features and stabilize the training process. The core of the network is a series of depth wise separable convolutional layers that efficiently increase the feature complexity while maintaining computational efficiency. The network then applies a global average pooling layer to spatially condense the features, followed by a dense layer with ReLU activation to further process the features. A dropout layer is incorporated to reduce overfitting. Finally, a fully connected layer with a sigmoid activation function translates these features into binary classification outputs. This architecture strikes a balance between performance and efficiency, making it suitable for deployment in resource-constrained environments.

4. Dataset used

The dataset is structured into three main directories: test, train, and validation for each image category, Pneumonia and Normal. It comprises 5,863 X-ray images in JPEG format, with 4,273 images labeled as Pneumonia and 1,583 images labeled as Normal. The chest X-ray images were sourced from Guangzhou Women and Children's Medical Center in Guangzhou. The dataset was published on January 6, 2018 [58]. Below, I display two examples from the dataset: one from the "Normal" category and one from the "Pneumonia" category.

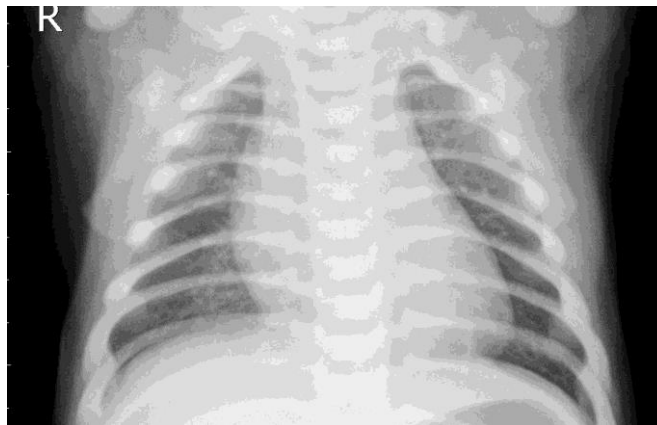


Figure 23: Example of a Normal Chest X-ray.

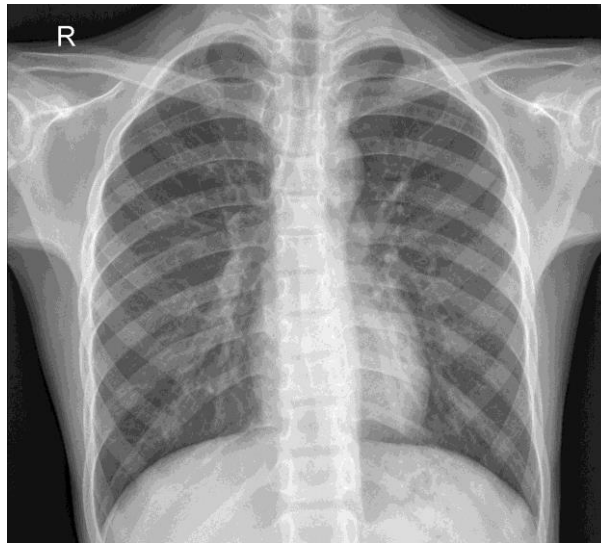


Figure 24: Example of a Pneumonia Chest X-ray.

5. Data Preprocessing

5.1 Data augmentation

Data Augmentation is a technique in machine learning and deep learning used to increase the diversity and size of a training dataset by creating modified versions of existing data samples. This is achieved through transformations such as rotation, translation, flipping, zooming, and adding noise. Data augmentation helps improve the generalization ability of models, making them more robust to variations in data and reducing the risk of overfitting by allowing the model to learn from a more varied set of training examples.

5.2 Image Resizing

Image resizing is a critical preprocessing step where the dimensions of an image are adjusted to fit the input size required by the neural network. This resizing ensures that the image maintains its essential features without distortion, which is achieved by preserving the aspect ratio or using various interpolation methods like nearest neighbor. By standardizing the input image dimensions, resizing enhances the efficiency of the model training and inference processes, ensuring that the neural network can accurately recognize and learn from the

images. This step is vital for achieving consistent and reliable performance in tasks such as image classification, object detection, and segmentation.

6. Training process

The training process for the pneumonia detection model begins with the careful preparation of the dataset. Initially, the dataset contains an imbalance with more pneumonia cases than normal cases. This is visualized by plotting the distribution of the labels, showing a significant disparity between the two classes. This imbalance is clearly seen in the initial bar plot, which highlights the disproportionate number of images in each class. Such an imbalance can lead to biased model training, where the model may become more attuned to identifying pneumonia at the expense of normal cases.

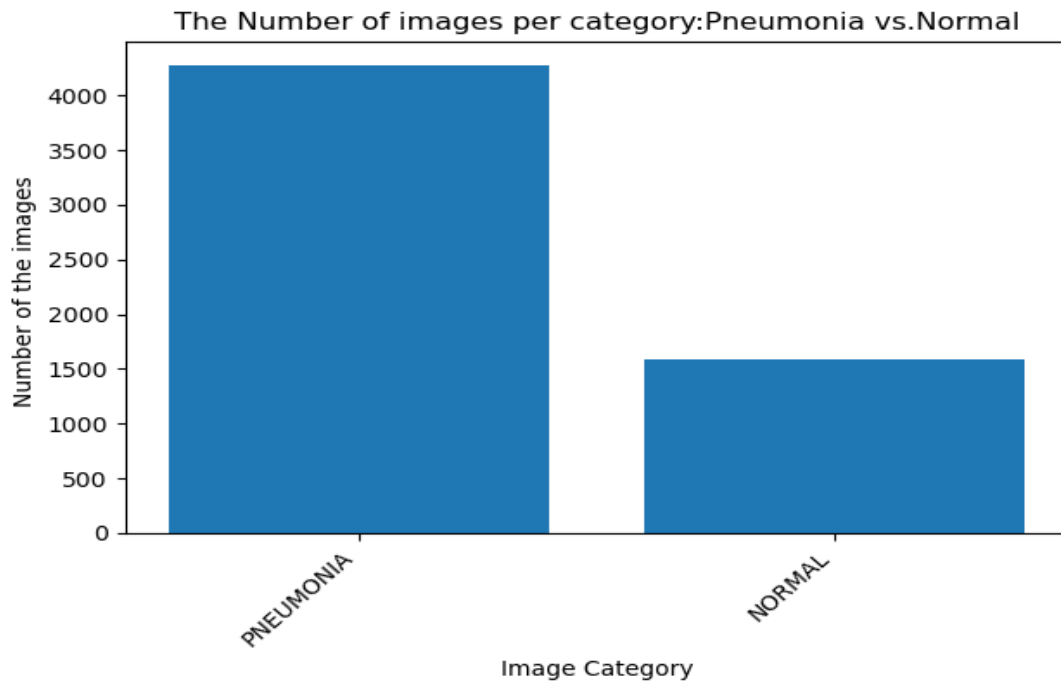


Figure 25: Before Balancing the Dataset.

To address this imbalance, the majority class (PNEUMONIA) is downsampled to match the number of samples in the minority class (NORMAL), resulting in an equal representation of 1583 images for each class. This balanced dataset is then visualized using another bar plot, demonstrating an equal distribution of both labels, which ensures that the model receives a fair representation of both conditions during training.

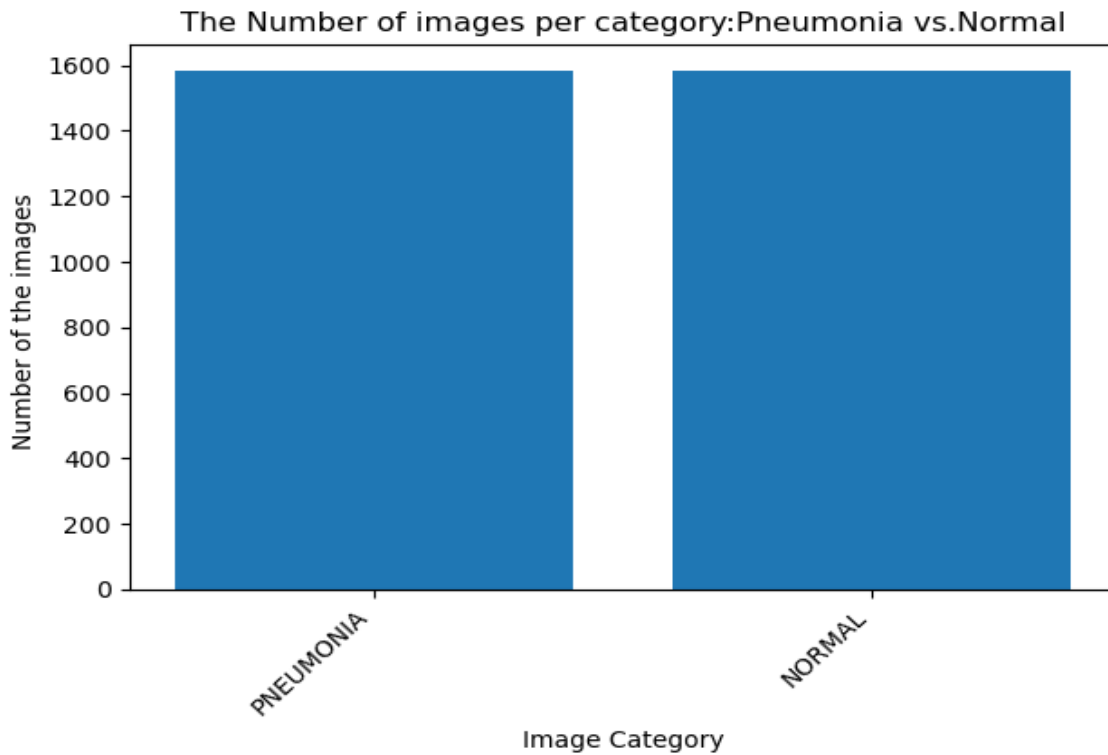


Figure 26: After Balancing the Dataset.

With the balanced dataset, the model is trained over 50 epochs with a batch size of 80. During each epoch, the model processes batches of images, performing forward passes, calculating the loss using the CrossEntropyLoss function, and updating the model's parameters through backpropagation with the Adam optimizer. The training process monitors the accuracy of predictions by comparing the predicted labels with the actual labels,

providing feedback on the model's performance. Early stopping is implemented using the Early Stopping function, which monitors validation accuracy (Val accuracy) and halts training if no improvement is observed for 15 consecutive epochs. After each epoch, the model's performance is evaluated on the validation set to ensure it generalizes well to unseen data. Essential metrics such as accuracy, precision, recall, and F1 score are computed to assess the model's effectiveness. This rigorous training process, combined with careful data preparation and continuous performance evaluation, ensures the development of a robust and accurate pneumonia detection model.

7. Performance Metrics

Accuracy, precision, recall, and F1-score were the four most commonly used validation performance metrics used to evaluate the performance of DL models. They are calculated as follows:

- **Accuracy:** reports the proportion of properly categorized samples to all other samples in the testing set.

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

- **Precision:** reports the percentage of samples properly categorized for all TP and FP in the testing set.

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

- **Recall:** reports the ratio of TP samples to the total number of TP and FN samples is known as recall.

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

- **The F1-score:** reports the Harmonic Mean between Precision and Recall.

$$\text{F1-score} = \frac{(2 * TP)}{(2 * TP + FP + FN)}$$

- **True Positive (TP):** represents the number of abnormal samples correctly classified as exacerbation (correct detection).
- **False Positive (FP):** represents the number of normal samples wrongly classified as attacks (incorrect detection).
- **True Negative (TN):** represents the number of normal samples wrongly classified (correct detection).
- **False Negative (FN):** represents the number of abnormal samples wrongly classified as attacks (incorrect detection).

8. Results

8.1 AlexNet

The figure [27] above illustrates the training and validation accuracy of the pneumonia detection model over the course of 26 epochs. Initially, the training accuracy rapidly increases, indicating quick learning from the training data. However, the validation accuracy exhibits significant fluctuations in the first 10 epochs, even dropping to around 0.5, suggesting early struggles in generalization. As training progresses, the training accuracy

stabilizes around 0.9, but the validation accuracy remains volatile, reflecting potential overfitting. After epoch 15, the validation accuracy stabilizes and trends upward, nearing the high training accuracy levels, indicating improved generalization.

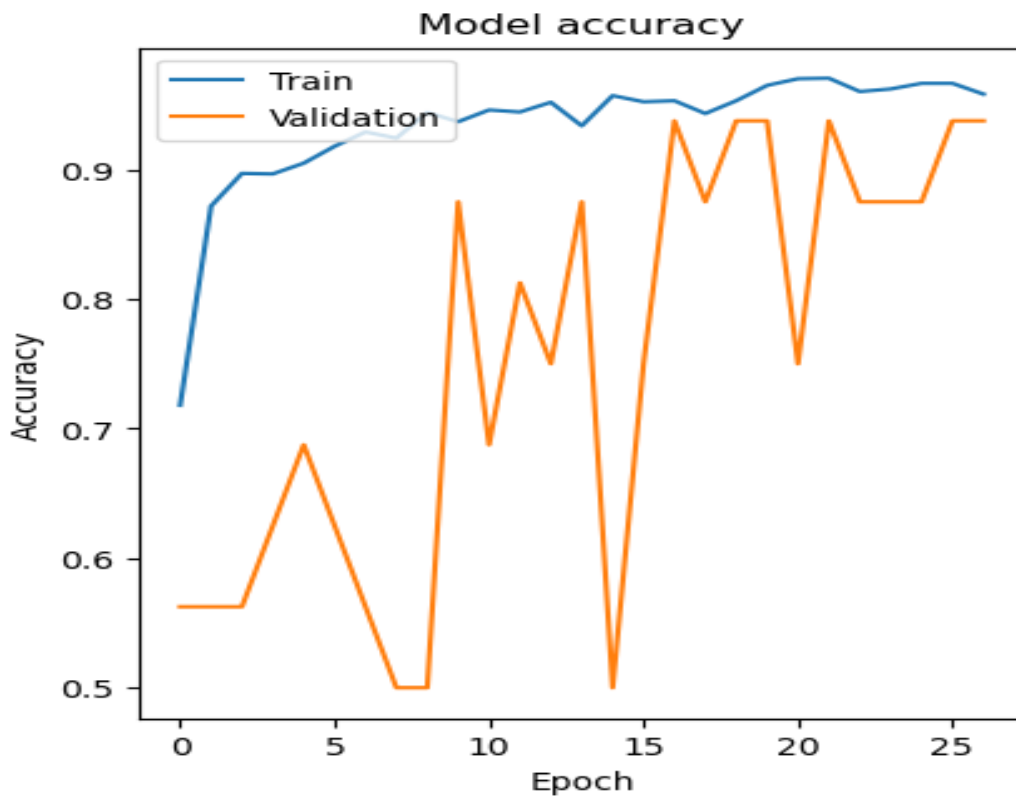


Figure 28: AlexNet Accuracy.

The plot highlights signs of overfitting during the mid-phase, but the implementation of early stopping, which halts training if no improvement in validation accuracy is observed for 15 consecutive epochs, mitigates this issue. The overall trend of increasing validation accuracy towards the end demonstrates the model's ability to generalize better, achieving a balance between fitting the training data and maintaining generalization capability.

The table [2] presents the performance metrics for the pneumonia detection model, evaluating its accuracy, precision, recall, and F1 score. The training accuracy stands at 97.27%, indicating the model's exceptional performance on the training data and its strong generalization capability. The validation accuracy, slightly lower at 93.75%, still signifies robust performance, confirming the model's ability to generalize well without overfitting to the training data. The test accuracy, at 94%, shows that the model maintains good performance on unseen test data. The model demonstrates a precision of 97.82%, meaning it is highly accurate when predicting pneumonia cases, with very few false positives, ensuring reliability in identifying actual pneumonia cases. With a recall rate of 89.40%, the model correctly identifies the majority of pneumonia cases, although there is still a small percentage of false negatives, suggesting some room for improvement in capturing all positive cases. The F1 score, which balances precision and recall, is 93.42%, reflecting the model's overall effectiveness and indicating a good balance between correctly identifying pneumonia cases and minimizing false positives and false negatives.

Table 2: Performance Metrics of AlexNet.

Train	97.27 %
validation	93.75%
Test	94 %
Precision	97.82 %
F1 Score	93.42 %
Recall	89.40 %

8.2 VGGNet

The figure above illustrates the training and validation accuracy of the pneumonia detection model over the course of 16 epochs. Initially, both the training and validation accuracies exhibit fluctuations, indicating early instability in the model's performance. The training accuracy, represented by the blue line, consistently remains high, staying above 0.97, demonstrating quick learning from the training data. However, the validation accuracy, shown by the orange line, exhibits significant fluctuations in the early epochs, suggesting initial struggles with generalization.

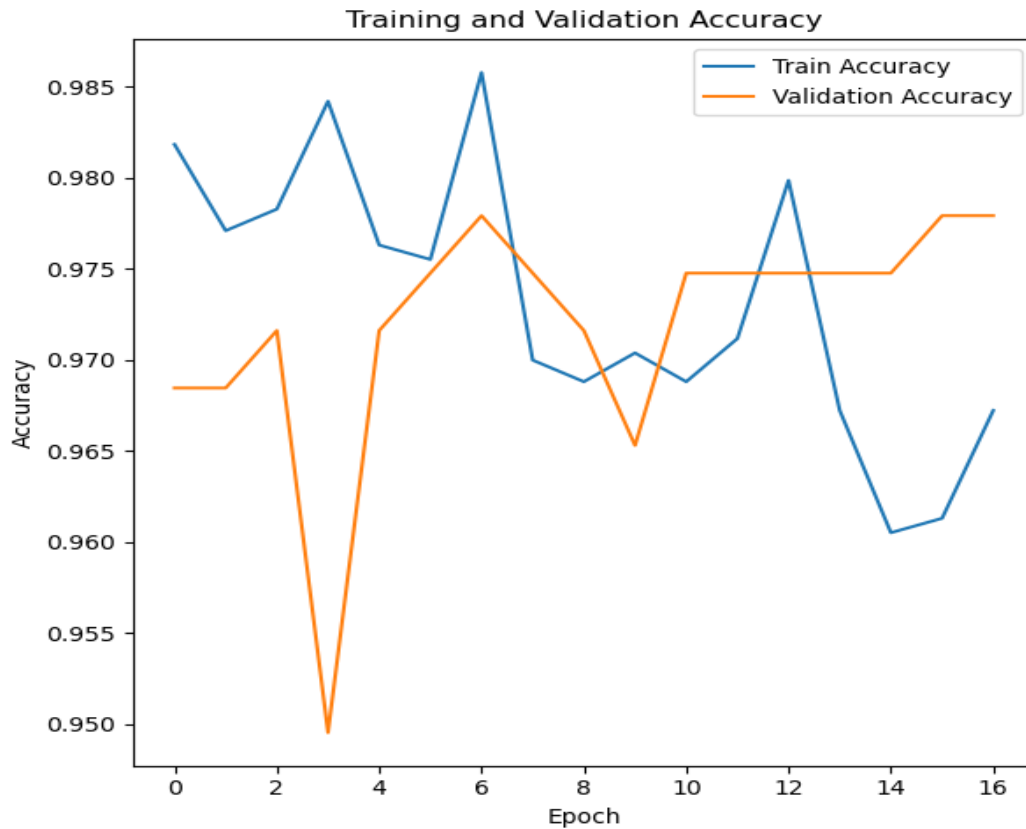


Figure 29: VGGNet Accuracy.

As training progresses, both accuracies experience notable variability, reflecting the model's adjustments and improvements in its generalization capability. During the mid-epochs, the validation accuracy begins to stabilize and trends upward, nearing the high training accuracy levels. By the later epochs, the validation accuracy stabilizes around 0.975, closely aligning with the training accuracy, which indicates that the model achieves better generalization without overfitting. The table 3 presents the performance metrics for VGGNet model. The training accuracy of 98.45% indicates that the model has learned the training data well, and the validation accuracy of 97.79% shows that it can generalize well to new data, avoiding overfitting. The test accuracy of 95.89% confirms that the model is robust and can perform well in real-world situations. With a precision of 93.71%, the model minimizes false positives, meaning it rarely misclassifies non-pneumonia cases as pneumonia. The very high recall of 98.03% shows that the model detects almost all true pneumonia cases, which is crucial for medical diagnostics. The F1 score of 95.82% balances precision and recall, highlighting the model's reliable performance.

Table 3: Performance Metrics of VGGNet.

test	95.89%
Train	98.45%
validation	97.79%
Precision	93.71 %
Recall	98.03 %
F1 Score	95.82 %

8.3 ResNet

The figure 30 above shows the progression of training and validation accuracy for the pneumonia detection model over the epochs. Initially, the training accuracy starts at around 55% and steadily increases to about 79.49% by the end of the training. The validation accuracy, on the other hand, shows more significant fluctuations at the beginning but generally remains higher than the training accuracy, reaching a peak of 89.27% by the end. This trend indicates that the model is gradually learning to predict well on new data. The initial fluctuations in validation accuracy may suggest challenges in generalization at early stages, but as training progresses, the model's performance becomes more stable and converges to high levels of accuracy for both training and validation.

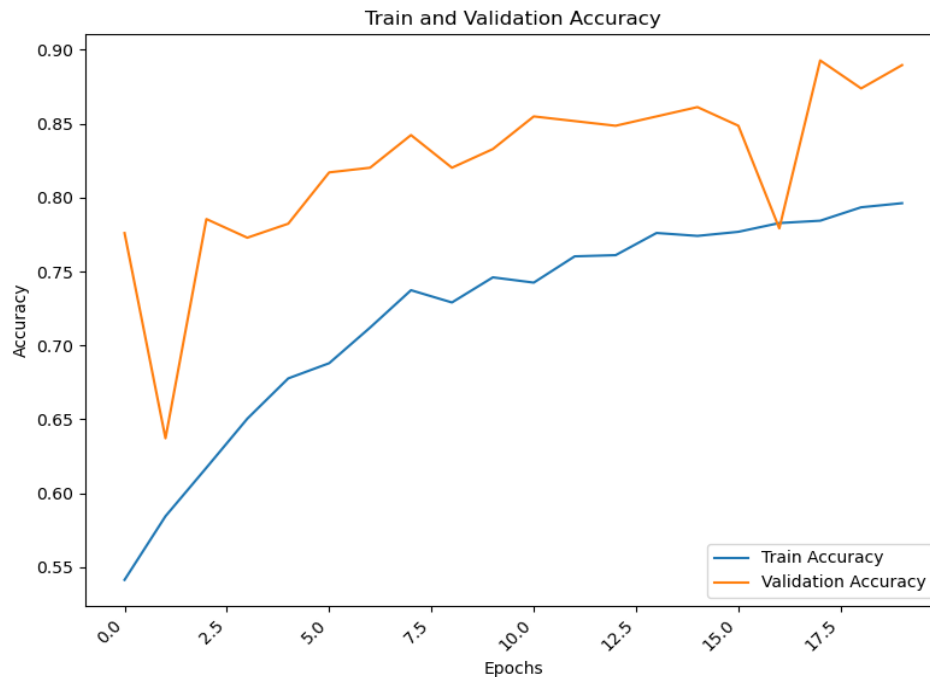


Figure 30: ResNet Accuracy.

These results demonstrate a continuous improvement in the model's performance, indicating good generalization capability while avoiding overfitting. The table 4 presents the performance metrics of the model, showing a test accuracy of 85.48%, which indicates that the model performs well when exposed to unseen data. The training accuracy of 79.49% suggests that the model has learned effectively from the training data, though there is room for improvement. The validation accuracy of 89.27% is higher than the training accuracy, indicating that the model generalizes well to new data without overfitting. The precision of 87.58% reflects the model's ability to correctly identify positive cases, while the high recall of 98.33% demonstrates the model's effectiveness in capturing almost all true positive cases. The F1 score of 88.44% balances both precision and recall, providing a comprehensive measure of the model's performance.

Table 4: Performance Metrics of ResNet

test	85.48%
Train	79.49%
validation	89.27%
Precision	87.58 %
Recall	98.33 %
F1 Score	88.44 %

8.4 MobileNet

The figure above shows the progression of training and validation accuracy for the pneumonia detection model over the epochs. Initially, the training accuracy starts at around 82% and rapidly increases, stabilizing at approximately 98.45% by the end of the training. The validation accuracy, on the other hand, shows more significant fluctuations but generally follows an upward trend, reaching a peak of 97.79%. Despite the variability in validation accuracy, it consistently remains high, indicating the model's effective learning and strong performance on new data. The close alignment between the training and validation accuracies suggests that the model is generalizing well and avoiding overfitting. This continuous improvement and high accuracy levels for both training and validation sets demonstrate the model's robust capability in accurately detecting pneumonia.

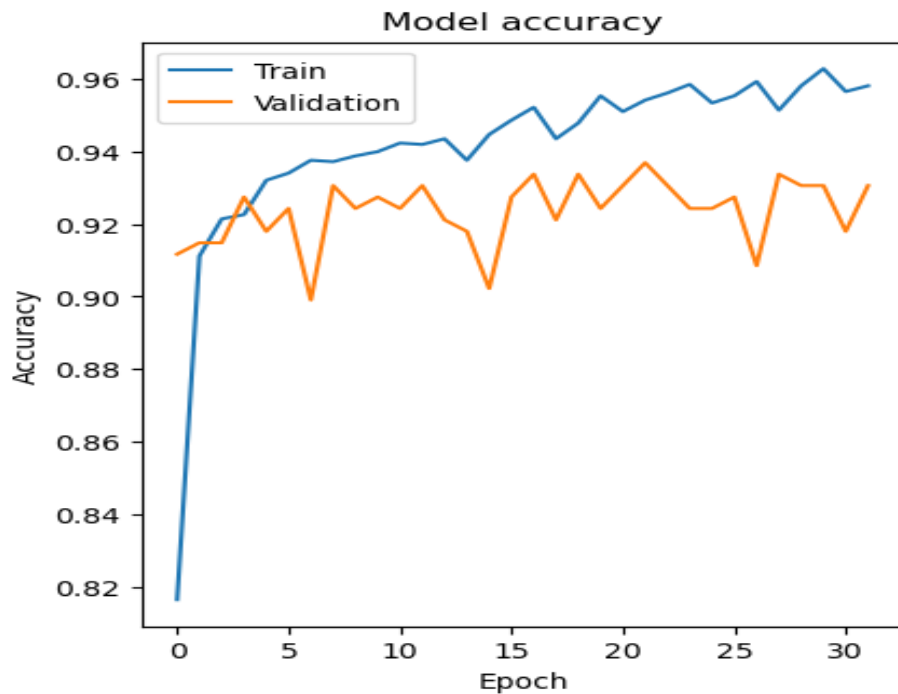


Figure 31: MobileNet Accuracy.

The table [5] presents the performance metrics of the MobileNet architecture for the pneumonia detection model. The test accuracy of 94.63% indicates that the model performs exceptionally well on unseen data, showcasing its strong generalization capability. The training accuracy of 97.10% suggests that the model has effectively learned from the training data, achieving a high level of performance. The validation accuracy of 93.96% is close to the test accuracy, indicating that the model maintains its performance during the training process without significant overfitting. The precision of 95% reflects the model's ability to correctly identify positive pneumonia cases out of all positive predictions, while the recall of 95% demonstrates the model's effectiveness in capturing almost all true positive cases. The F1 score of 95%, which balances both precision and recall, provides a comprehensive measure of the model's performance.

Table 5: Performance Metrics of MobileNet.

test	94.63%
Train	97.10%
validation	93.96%
Precision	95 %
Recall	95 %
F1 Score	95%

8.5 Comparative Analysis of Deep Learning Architectures

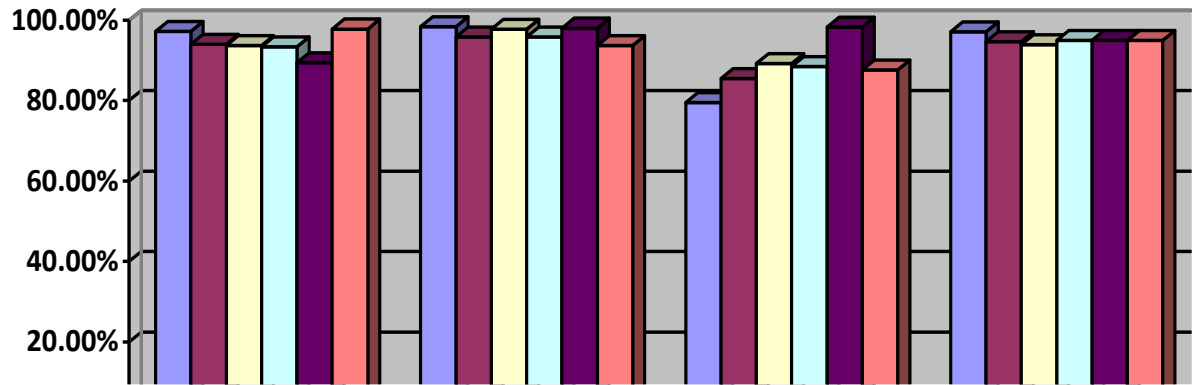


Figure 32: Performance Comparison of Different Architectures.

After analyzing the results, it is evident that VGGNet outperforms the other architectures in this study. It achieves the highest training accuracy of 98.45% and impressive test and validation accuracies of 95.89% and 97.79%, respectively. VGGNet also boasts a high F1 score of 95.82% and recall of 98.03%, indicating that the model is highly effective and reliable in predicting pneumonia cases while maintaining a good balance between precision (93.71%) and recall. AlexNet also demonstrates strong performance with a high training accuracy of 97.27%, and test and validation accuracies of 94% and 93.75%, respectively. Its F1 score of 93.42% and precision of 97.82% highlight its capability to correctly identify positive cases. However, its recall is slightly lower at 89.40%, suggesting it misses some true positives. ResNet, on the other hand, achieves a training accuracy of 79.49%, which is significantly lower than the other architectures, potentially indicating underfitting. Despite this, its test and validation accuracies are 85.48% and 89.27%, respectively. ResNet's F1 score is 88.44%, with a very high recall of 98.33% but a lower precision of 87.58%, indicating it captures almost all true positives but includes more false positives. MobileNet offers a balanced performance with a training accuracy of

97.10%, test accuracy of 94.63%, and validation accuracy of 93.96%. MobileNet's F1 score, recall, and precision are all at 95%, suggesting a well-rounded performance with a good balance between precision and recall. Considering the overall performance, VGGNet emerges as the best architecture for pneumonia detection in this study. It consistently achieves high accuracy and demonstrates reliable performance across multiple evaluation metrics. In conclusion, based on the provided metrics, VGGNet appears to be the most suitable choice for this study.

9. Conclusion

In this chapter, we explored the implementation and evaluation of deep learning models AlexNet, VGGNet, ResNet, and MobileNet for pneumonia detection using chest X-ray images. Each architecture was assessed based on training accuracy, validation accuracy, precision, recall, and F1 score. VGGNet emerged as the top-performing architecture, demonstrating high accuracy and robust generalization capabilities across evaluation metrics. These findings underscore the potential of deep learning in enhancing diagnostic processes for pneumonia, highlighting VGGNet's effectiveness in this medical imaging task. Future research could focus on further optimizing these models and exploring their deployment in clinical settings to support accurate and timely healthcare interventions.

Chapter 4: Internship Report

1.Introduction

As part of my medical studies, I had the opportunity to do an internship at the 240-bed hospital in Kharouba, Mostaganem. Although for confidentiality reasons I could not collect specific patient data that was the purpose in the first place, I was able to closely observe and analyze the organization and various departments of this major healthcare facility. This report therefore, presents an overview of the services and activities of this major hospital in the wilaya of Mostaganem.

2.Presentation of the hospital:

The 240-bed hospital in Mostaganem which was launched in 2007, is one of the major projects in the MOSTAGANEM Wilaya. With a capacity of 240 beds, the hospital was put into operation and now everything is back in order thanks to the intervention of the Wali, who has followed the work on this structure since its installation, as it has reached 100 per cent completion. This new hospital will be a very important asset for the population, and it will be converted into a university hospital centre (CHU), as declared by the Minister of Health during his visit to Mostaganem on 22.09.2020. This health structure comprises a number of departments and pavilions, including a surgery department with 6 surgical blocks, a radiotherapy department, a forensic medicine department and a medical and surgical

emergency pavilion equipped with a landing strip for rescue helicopters, which will be used in cases of absolute emergency [59].



Figure 33 : Unit Hospital Dr. Bensmaine Boumediene Kharouba,Chu De Mostaganem [59].

2.1 Hospital services:

The hospital where I completed my internship has three main activity hubs. Each of these hubs includes several specialized departments, the detailed list of which is as follows:

2.1.1. Block A:

Pharmacy: is a store where medicinal drugs are dispensed and sold.

Forensic Medicine Department: deals with the examination and diagnosis of individuals who have been injured by or have died due to external or unnatural causes (such as poisoning, assault, suicide, etc.).

ENT Department: (ear, nose, and throat) doctors, also known as otolaryngologists, specialize in diagnosing and treating conditions related to the head, neck, ears, nose, and throat.

Orthopaedics and Traumatology Department: focuses on diseases and conditions affecting the musculoskeletal system (bones, muscles, joints, ligaments, tendons). Traumatology deals with complex fractures, non-unions, and mal-unions.

Neurosurgery Department: involves surgery of the nervous system, including the brain, spinal cord, spinal column, and peripheral nerves.

General Surgery Department: encompasses a wide range of surgical procedures involving various organs and systems. General surgeons perform surgeries related to the abdomen, digestive tract, skin, and more.

Nephrology Department: Nephrology focuses on the diagnosis and treatment of kidney-related conditions, including kidney diseases, kidney stones, and renal function disorders.

Neurology Department: Neurology deals with disorders of the nervous system (excluding surgical interventions). Neurologists diagnose and manage conditions like epilepsy, stroke, and multiple sclerosis.

2.1.2. Block B

Medical imaging department: The medical imaging department is responsible for performing various diagnostic imaging procedures, such as X-rays, CT scans, MRI, ultrasound, and nuclear medicine scans.

Sterilisation unit: A sterilization unit is a facility equipped to ensure the cleanliness and safety of medical instruments and equipment

Anatomical Pathology Department: The anatomical pathology department (also known as anatomic pathology) focuses on diagnosing diseases by examining tissues and organs under a microscope.

Laboratory: A laboratory is a facility where scientific experiments, tests, and investigations are conducted.

Haemodialysis unit: The haemodialysis unit provides life-saving treatment for patients with kidney failure.

Functional operations: Functional operations refer to medical procedures or interventions that restore or improve the function of specific organs or systems in the body. Examples include joint replacements, organ transplants, and corrective surgeries.

Operating theatres: Operating theatres (also known as operating rooms) are specialized rooms in hospitals where surgical procedures are performed.

Intensive care unit: The intensive care unit is a specialized ward where critically ill patients receive close monitoring, advanced life support, and specialized medical treatment.

2.1.3. Block C:

Reception: Reception refers to the area in a hotel, office, or establishment where guests and visitors are greeted and dealt with.

Cardiology department: The cardiology department focuses on the prevention, diagnosis, and treatment of heart and cardiovascular disease

Pneumology department: Pneumology deals with diseases of the respiratory system, including the lungs, trachea, and bronchi.

Gastrology department: Gastroenterology focuses on the health of the digestive system, including the esophagus, stomach, intestines, liver, and pancreas

Internal medicine department: Internal medicine (or general internal medicine) specializes in preventing, diagnosing, and treating internal diseases in adults.

3. Medical Equipment Maintenance and Clinical Observations in a Hospital Setting

As part of the maintenance team I worked with, we conducted daily checks on all the specialized medical equipment in the hospital, including the x-ray machines, MRI scanner, and other critical technologies. The maintenance department played a vital role in ensuring this equipment remained in proper working order to support patient care. In addition to the hands-on maintenance tasks, the department was also responsible for liaising with suppliers to procure the necessary replacement parts and new equipment for the hospital. This involved

carefully evaluating options to identify the most cost-effective solutions that still met the required performance and safety specifications. By managing these procurement processes, the maintenance team helped the hospital maximize the value of its capital investments in medical technology while maintaining a fully functional fleet of diagnostic and treatment devices. In addition to the hands-on maintenance work, the hospital also had a dedicated team responsible for the daily diagnostics and monitoring of the medical equipment. This specialized team had the knowledge and access required to closely examine the various parameters and settings of the devices, many of which could only be modified by authorized technicians from the original equipment manufacturers. Using specialized ID cards provided by the manufacturers, this diagnostics team was able to delve deeper into the internal workings of the medical technologies, ensuring they were operating within the appropriate specifications and thresholds. By conducting these regular checks and adjustments, the diagnostics team played a crucial role in maintaining the optimal performance and safety of the hospital's critical medical equipment. This proactive approach to monitoring the Equipment's health helped to prevent unexpected malfunctions and breakdowns, thereby supporting the uninterrupted delivery of patient care. During my internship, I had the privilege of observing several essential medical services within the hospital setting. These departments play critical roles in patient care, diagnosis, and treatment. In the subsequent sections, I will delve into the specifics of each service, highlighting their functions and significance. And as my primary interest lies in respiratory health, the pneumology department captured my attention.

3.1. Insights from the Medical Imaging Department

During my clinical rotation in the medical imaging department, I had the opportunity to witness the seamless integration of cutting-edge technologies in patient care. The department primarily utilized four essential imaging modalities:

3.1.1 Radiography (X-rays):

Radiography remains a fundamental tool for diagnosing skeletal and soft tissue abnormalities. The radiology team expertly positioned patients and captured X-ray images, revealing fractures, dislocations, and other skeletal pathologies. The speed and accessibility of X-rays impressed me, especially in emergency cases.



Figure 34: X-ray Radiography[60].

3.1.2. Computed Tomography (CT) Scans:

CT scans provided detailed cross-sectional images of various body structures. The radiologists meticulously adjusted scan parameters to visualize organs, blood vessels, and tumors. The rapid acquisition and high-resolution images allowed for precise anatomical localization and disease characterization [61].



Figure 35:CT scan.

3.1.3. Magnetic Resonance Imaging (MRI):

MRI, a non-invasive technique, fascinated me with its ability to capture exquisite soft tissue details. The powerful magnetic fields and radiofrequency pulses generated multi-planar images of the brain, spine, joints, and abdominal organs. Radiologists interpreted these images to diagnose conditions like tumors, inflammation, and vascular anomalies.



Figure 36:MRI

During my recent clinical rotation, I had the valuable opportunity to spend time in the pneumonia ward, where I was able to observe the circumstances and suffering of the patients firsthand, as well as learn about the process of making diagnoses. Concurrently, I also worked closely with the maintenance team, gaining insights into the upkeep and repair of the hospital's MRI scanner, which had been experiencing technical difficulties. The MRI machine requires a specialized, climate-controlled environment due to its reliance on helium, an expensive coolant that must be maintained at a low temperature. The primary issue stemmed from a malfunction in the compressor responsible for cooling the MRI system, which in turn had its own dedicated cooling mechanism. Further investigation revealed that the root cause of the breakdown was the buildup of mineral deposits from polluted water, which had compromised the compressor's cooling functions. This hands-on experience allowed me to develop a deeper understanding of not only patient care in the pneumonia ward, but also the crucial role of medical equipment maintenance in supporting effective healthcare delivery. Observing the systematic troubleshooting and repair process for the MRI

scanner was particularly enlightening, as it highlighted the importance of proactive maintenance and the complex interplay of various subsystems within advanced medical technologies.

3.1.4. Ultrasound (Sonography):

Ultrasound, often performed by sonographers, played a crucial role in assessing dynamic processes. By emitting sound waves and analyzing their reflections, ultrasound provided real-time images of organs, blood flow, and fetal development. Its safety, lack of ionizing radiation, and versatility made it indispensable[62].



Figure 37: Ultrasound [63].

3.2. Comparative Analysis of Sterilization Methods in the Sterilization Department

During my internship in the sterilization department, I had the opportunity to explore different techniques employed for effective pathogen elimination. Notably, three key methods stood out:

3.2.1. Autoclave

Autoclaves utilize heat and pressurized steam to achieve sterilization. The combination of high temperature and pressure effectively eradicates microorganisms, including bacteria and spores. Autoclaves are commonly used in medical and laboratory settings for sterilizing various materials such as surgical instruments, laboratory equipment, and liquid media.



Figure 38: Autoclave[64].

3.2.2. Thick-Walled Autoclave (Autoclave de Paise) :

The thick-walled autoclave, designed for robust materials, offers enhanced durability and safety. It ensures thorough sterilization even for items with complex shapes or dense structures. This specialized autoclave is particularly useful for heat-resistant instruments and heavy-duty equipment. In health care facilities, ensuring the sterility of medical instruments is crucial. Steam sterilization, commonly performed using autoclaves, stands as a key defense

against microbial contamination. Utilizing steam under pressure, this method effectively sterilizes a wide array of medical tools and supplies.

3.2.3. UV Sterilizer (Armoire UV):

UV sterilizers employ ultraviolet (UV) light to deactivate microorganisms by damaging their DNA and RNA. Unlike autoclaves, UV sterilization is chemical-free and residue-free. These devices are commonly used for air, water, and surface sterilization in settings such as water treatment plants, hospitals, and food processing facilities.



Figure 39: Armoire UV [65].

The hospital also had a dedicated sterilization cabinet that played a vital role in maintaining the cleanliness and sterility of essential medical equipment and materials. This specialized cabinet featured two distinct sides - one where the items to be sterilized were placed, and another where the now-sterile items could be retrieved after the sterilization process was complete. This two-sided design helped to prevent cross-contamination by physically

separating the dirt and clean sides of the sterilization workflow. In addition to the sterilization cabinet, the hospital also maintained a dedicated storage cabinet specifically for housing the sterilized materials. This allowed the hospital to keep a stock of sanitized equipment and supplies readily available for immediate use; while ensuring they remained in a controlled, sterile environment until needed. The careful management of this sterilization infrastructure was critical to upholding the highest standards of infection control and patient safety throughout the hospital.

3.4. Insight of common machines in blocks

3.4.1. ECG Machine (Electrocardiogram Machine):

The ECG machine records the electrical activity of the heart. It does so by placing electrodes on the skin, which detect the heart's electrical impulses. These impulses are then graphically represented as waves on an ECG tracing. ECGs are essential for diagnosing various heart conditions, such as arrhythmias, myocardial infarctions (heart attacks), and other abnormalities.



Figure 40:ECG machine [66].

The hospital's electrocardiograph (ECG) machine had also been experiencing some technical issues, though the problem was not as severe as the MRI breakdown. In this case, the root cause was simply the buildup of dust and dirt within the internal components of the ECG device. As part of my maintenance duties, I was able to perform a thorough cleaning of the ECG, which resolved the functional problems and restored the machine to its proper working condition. Additionally, the maintenance team had identified instances where certain components within their medical equipment had been subjected to excessive force or strain during routine use, leading to premature wear and eventual malfunctions. Addressing these types of usage-related issues was an important aspect of the team's preventive maintenance protocols, as they worked to extend the operational lifespans of the hospital's valuable diagnostic tools and technologies.

3.4.2. Mobile Scanner (Portable Imaging Device):

A mobile scanner refers to a portable imaging device used to visualize internal body structures. Common types include:

- **Ultrasound Scanners:** Use sound waves to create real-time images of organs, blood vessels, and tissues.
- **MRI (Magnetic Resonance Imaging) Scanners:** Utilize strong magnetic fields and radio waves to produce detailed cross-sectional images. These scanners aid in diagnosing conditions ranging from soft tissue injuries to tumors.

3.4.3. Pimp Syringe (Contrast Injection Syringe)

A pimp syringe (likely a typo; perhaps you meant "pinch syringe" or "contrast injection syringe") is used during medical imaging procedures. It delivers contrast agents (such as iodine-based solutions) into blood vessels or body cavities. These agents enhance visibility in X-rays, CT scans, or angiography [67].



Figure 41: pump syringe [68]

Another piece of medical equipment I had the opportunity to work on during my maintenance rotation was the hospital's syringe pump. These automated syringe devices are designed to accurately deliver precise doses of medication or fluids to patients at specified time intervals, providing a controlled and consistent method of administration. As part of my maintenance duties, I was able to service and maintain one of these syringe pumps, ensuring it remained in proper working order to support the critical care needs of patients. This hands-on experience allowed me to develop a deeper understanding of the technical inner workings of these specialized medical devices, as well as the importance of rigorous preventive maintenance to keep them functioning reliably. By incorporating regular checks, calibrations, and cleaning of the syringe pump's components, the maintenance team played a vital role in upholding patient safety and the overall quality of care delivered within the hospital.

3.4.4. Sialitic

The Surgical Shadowless Lamp is a medical device with a lighting system used in operating rooms. The Surgical Shadowless Lamp is a specialized medical lighting device that is used in hospital operating rooms to provide illumination during surgical procedures.



Figure 42: Sialitic

4.Conclusion:

Through this internship, I was able to understand the functioning of a large Algerian public hospital, equipped with modern facilities and offering comprehensive medical care to the local population. The diversity of services, specialized departments and activities carried out allowed me to acquire valuable practical knowledge that will enrich my training as a future physician. This experience also made me aware of the importance of public health facilities in providing healthcare coverage to a region. I will remember from this internship the rigor of the work provided by the entire healthcare staff to ensure quality care for patients.

General conclusion

In this master thesis, we explored the implementation and evaluation of deep learning models AlexNet, VGGNet, ResNet, and MobileNet for pneumonia detection using chest X-ray images. Each architecture was assessed based on training accuracy, validation accuracy, precision, recall, and F1 score. VGGNet emerged as the top-performing architecture, demonstrating high accuracy and robust generalization capabilities across evaluation metrics. These findings underscore the potential of deep learning in enhancing diagnostic processes for pneumonia, highlighting VGGNet's effectiveness in this medical imaging task. Future research could focus on further optimizing these models and exploring their deployment in clinical settings to support accurate and timely healthcare interventions.

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