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Developing an AI-integrated System for X-ray Imaging to Detect Pneumonia and Fractures Using DL (Deep Learning) Techniques

*Dr. Yousef Qaddoura, **Rahma Mailoud Matouq**[a], **Laila Mailoud Matouq** [b]

a Department of Electrical and Computer Engineering - Libyan Academy for Graduate Studies – Janzour

b Department of Electrical and Computer Engineering - Libyan Academy for Graduate Studies – Janzour

[a] rahmamatouq13@gmail.com
b lailamahmoud9896@gmail.com

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Abstract

This study aims to develop an integrated artificial intelligence system in conjunction with X-ray imaging devices for the accurate and efficient diagnosis of common medical conditions, such as pneumonia and bone fractures. The proposed system leverages advanced deep learning techniques, particularly convolutional neural networks (CNNs), implemented through the Tensor Flow library. In addition, a user-friendly and interactive interface has been designed using Python programming language and the PyQt6 framework, facilitating seamless interaction between healthcare professionals and the AI system. The integration of AI-driven diagnostic capabilities with X-ray imaging is expected to enhance diagnostic precision, reduce human error, and optimize clinical workflow, ultimately contributing to improved patient outcomes and more efficient healthcare delivery.

Keywords:

Artificial Intelligence (AI), X-ray, Deep Learning (DL), Convolutional Neural Networks (CNN), Pneumonia Detection, Fracture Detection, Tensor Flow, PyQt6, ResNet-50, MURA, CheXNet, Image Processing.

Research Objectives

The objectives of this study are as follows:

1. To develop an intelligent AI model capable of accurately diagnosing pneumonia and bone fractures.
2. To integrate the system with medical imaging devices to provide rapid and reliable diagnostic support.
3. To support medical decision-making by offering automated analysis of X-ray images.
4. To provide an easy-to-use diagnostic tool for medical personnel.
5. To enhance diagnostic efficiency using limited medical data resources.

Research Problem

Traditional medical diagnostic systems suffer from several limitations, including:

- Delayed report generation due to complete dependence on manual clinical examination.
- Inconsistent diagnostic accuracy caused by variations in physicians' experience and interpretation.
- Difficulty handling the large volume of imaging data, especially in major hospitals with high patient flow.

Training and Dataset Description

The model was trained using a combination of publicly available datasets, including:

- NIH Chest X-ray Dataset for pneumonia detection

- MURA Dataset for detecting bone fractures
- Advanced preprocessing techniques were applied to improve image quality and enhance the model's performance. These techniques included data augmentation and Contrast Limited Adaptive Histogram Equalization (CLAHE).

Model Performance

1. The proposed system achieved an accuracy of 94% in diagnosing pneumonia and 92% in detecting bone fractures.
2. Superior performance was achieved by employing the CheXNet model architecture, widely recognized for its high efficiency in medical image classification.
3. To further enhance performance, the model utilized ResNet-50 with optimized Dropout layers, increasing diagnostic sensitivity to 93% and specificity to 95%.

Clinical Impact

The results demonstrate the system's potential to support clinicians in making faster and more informed decisions, especially in emergency cases where early detection is critical.

System Architecture

The proposed system consists of three main units:

1 .Image Preprocessing Unit

- Converting images into grayscale format.
- Applying normalization and CLAHE techniques to enhance contrast.

2 .Deep Learning Model Unit

- Building the model using the ResNet-50 architecture with a dropout rate of 0.5.
- Training the model using the Adam optimizer with a learning rate of 0.0001.

3 .User Interface Unit

Designing a graphical interface using PyQt6, allowing users to upload images, view model results, and export diagnostic reports.

Data Sources

The system uses the NIH Chest X-ray Dataset, which includes 5,856 images.

Introduction

Pneumonia represents a serious global public health challenge, posing significant risks of severe illness and mortality across diverse populations. This respiratory infection is defined by the inflammation of the air sacs in one or both lungs, a condition that, if not diagnosed and treated promptly, can lead to dangerous complications and long-term health consequences. Pneumonia, along with other lower respiratory tract infections, remains one of the leading causes of death worldwide, reflecting its persistent threat despite medical advances. The burden is particularly heavy among vulnerable groups, including children under the age of five and older adults who aged 65 and above, who face heightened susceptibility to infection and severe outcomes. Each year, millions of individuals were affected, leading to substantial strain on healthcare systems, prolonged hospitalizations, and considerable economic costs associated with treatment, disability, and loss of productivity. The widespread impact of pneumonia underscores the urgent need for improved diagnostic methods, early detection strategies, and effective clinical interventions to reduce its global burden and improve patient outcomes. **(1)**

Pneumonia remains the leading infectious cause of death among children worldwide, surpassing other major illnesses such as diarrhea and malaria in both severity and fatality. Each year, millions of children are affected by this largely preventable and treatable disease, highlighting a persistent gap in global healthcare access and early intervention efforts. The high mortality rate among young children underscores the urgent need for comprehensive strategies focused on prevention, rapid detection, and timely medical treatment. Despite advancements in medical care and the increasing availability of effective vaccines, pneumonia continues to pose a critical global health challenge. These ongoing difficulties reflect disparities in healthcare resources, limited access to vaccination programs in underserved regions, and delays in diagnosis and treatment, all of which contribute to the sustained threat pneumonia presents to children worldwide. **(2)**

The disproportionately high fatality rates observed among vulnerable populations emphasize the serious challenges posed by delayed diagnosis and inadequate treatment, underscoring the urgent need for more effective and timely clinical strategies. Early and accurate identification of pneumonia is essential to improving patient survival, particularly through the use of reliable diagnostic tools such as chest X-rays, lung ultrasounds, and molecular testing methods. These advanced diagnostic approaches enable healthcare professionals to detect the disease at earlier stages, differentiate it from other respiratory conditions, and initiate targeted therapeutic interventions without delay. By facilitating rapid and precise clinical decision-making, such methods significantly enhance the effectiveness of treatment, reduce the risk of complications, and ultimately improve patient outcomes. This highlights the vital role of accessible and efficient diagnostic systems in strengthening healthcare responses and safeguarding high-risk groups. **(3)**

In this research, we focus on examining recent advancements in the use of deep learning (DL) techniques for the automated detection of pneumonia and bone fractures in X-ray (CXR) images, with particular relevance to the development of our proposed AI-integrated diagnostic system. While early studies between 2012 and 2016 primarily relied on traditional machine learning approaches, significant breakthroughs in deep learning—especially following the landmark success of CNN architectures in the 2012 ImageNet competition—have driven a rapid shift toward more robust, scalable, and accurate diagnostic models. Therefore, this review concentrates mainly on studies published from 2016 onward, with a stronger emphasis on research conducted between 2020 and 2023 to better reflect the current state of the art in medical imaging and AI-based detection. To ensure comprehensive coverage, relevant literature was retrieved from leading scientific databases, including IEEE Xplore, SpringerLink, Science Direct, and the ACM Digital Library. The collected studies were critically reviewed and analyzed in order to highlight methodological trends, dataset characteristics, model architectures, performance benchmarks, and existing gaps. This focused analysis provides a solid scientific foundation for the development and justification of the integrated AI diagnostic framework proposed in this study.To support the development of the proposed AI-integrated system for detecting pneumonia and bone fractures in X-ray images, a comprehensive literature search was conducted to identify recent and relevant deep learning–based studies. **(4)**

The search began with an exploratory scan on Google Scholar using broad phrases such as "pneumonia detection in X-ray using deep learning," "fracture detection in X-ray using deep learning," and "COVID-19 detection in CXR using deep learning," which helped establish an initial understanding of key research trends. From these preliminary findings, a refined set of keywords—such as "pneumonia," "fracture," "chest X-ray," "CXR," "deep learning," "convolutional neural network," and "CNN"—was developed based on their frequent appearance in highly cited and methodologically significant publications. To ensure credibility and comprehensive coverage, the literature search was then expanded to four major scientific databases: IEEE Xplore, ScienceDirect, SpringerLink, and the ACM Digital Library. A structured search query combining Boolean operators was applied as follows: "pneumonia" OR "fracture" AND ("CXR" OR "chest X-ray" OR "radiograph") AND ("deep learning" OR "CNN" OR "convolutional neural network"). Additional filters were used to refine the results, limiting the search to peer-reviewed research articles within the fields of computer science, biomedical engineering, and medical imaging. This systematic search strategy generated a large number of relevant studies, with the number of retrieved items from each database summarized in Table 1.

Table 1 Number of search items returned by the research databases.

Electronic Research Database	Search Results (Number of Items)
IEEE Xplore	304
ScienceDirect	160
SpringerLink	240
ACM Digital Library	85

(Source : Raheel Siddiqi, Sameena Javaid , (2024) , Deep Learning for Pneumonia Detection in Chest X-ray Images: A Comprehensive Survey , 10(8):176 , P. 4**)**

In total, 789 research items were initially retrieved from the four selected databases, after which a rigorous filtering process was applied using clearly defined inclusion and exclusion criteria to ensure the relevance and scientific quality of the studies incorporated into this research. Eligible studies were required to be empirical, peer-reviewed publications focused on the use of deep learning techniques for detecting pneumonia or fractures in X-ray images, and published between 2020 and 2023. Studies were excluded if they were review papers, non–peer-reviewed, short publications under five pages, book chapters, duplicates, or papers written in languages other than English. Additional exclusion criteria removed scientifically unsound studies—defined as those lacking clear objectives, insufficient methodological detail, inadequate evaluation, unclear limitations, or publication in low-impact venues—as well as papers focusing solely on other chest diseases, traditional machine learning approaches, or non–X-ray imaging modalities such as CT or ultrasound. This rigorous selection strategy ensured that only high-quality and methodologically robust research contributed to the foundation of the proposed AI-integrated diagnostic system. **(5)**

Chest X-ray (CXR)

The X-ray beam is divergent and acts as a point source. In a posterior-anterior (PA) chest X-ray, the beam passes through the thorax from the back (posterior) while the X-ray plate is placed in front of the patient. This positioning is considered the most optimal for chest imaging because the patient is usually standing. Since the heart is located anteriorly in the thorax, its size is minimally magnified in this view. In contrast, during an anterior-posterior (AP) chest X-ray, the beam enters from the front (anterior), and the plate is placed behind the patient, who is often semi-erect in bed. In this case, the anterior position of the heart leads to apparent enlargement, making it unreliable to assess the cardiothoracic ratio (calculated as the maximum cardiac diameter divided by the maximum thoracic diameter) or the true heart size. AP films are typically used for patients who are critically ill and unable to stand, as they provide an accessible alternative for chest imaging. **(6)**

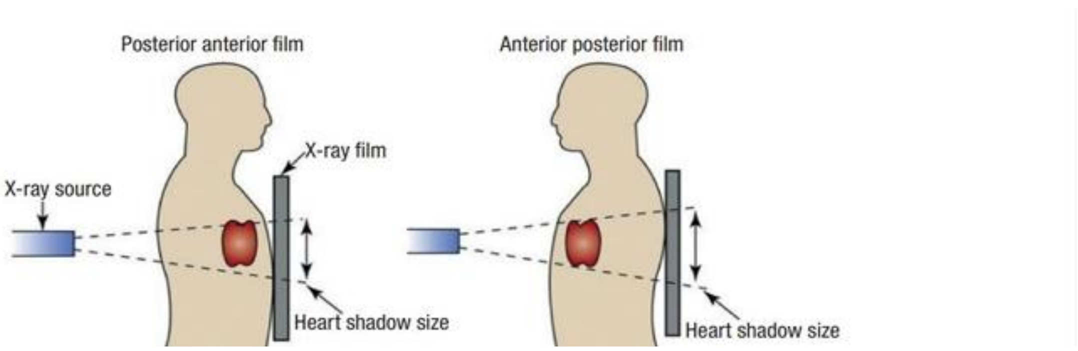

Figure 1 Because the heart is an anterior structure in the thorax, the heart size is minimally magnified in a posterior anterior film in comparison to an anterior posterior film

(source : Dr Taranpal Bansa , Dr Richard Beese , (2019), *Interpreting a chest X-ray* , https://www.magonlinelibrary.com)

The Silhouette Sign

The silhouette sign refers to the interface between air-filled spaces and soft tissues, and it serves as a key marker for identifying thoracic structures on a standard chest X-ray. Pathological changes can obscure this normally sharp air–soft tissue boundary. The specific location where the clear interface is lost can help localize the most likely site of the underlying pathology. **(7)**

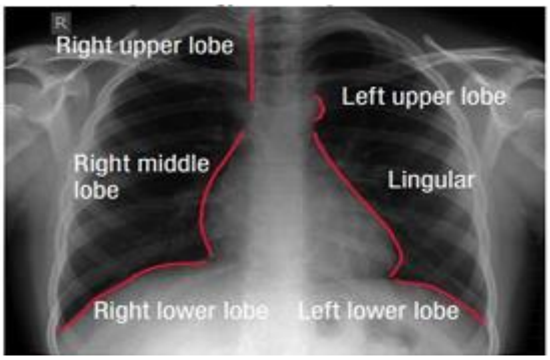

Figure 2 The probable location of pathology may be determined by the location of the silhouette sign's loss (red)

Lungs: Comparing the right and left lungs is essential for assessing opacities, lung borders, and lung volumes. Opacifications may appear on one or both sides, and any loss of definition of the lung borders may indicate underlying pathology. Lung volumes should also be evaluated, as visualization of more than seven ribs can suggest either inadequate inspiration or hyperinflation

Mediastinum: The mediastinum, located centrally between the lungs, is often difficult to distinguish due to its soft tissue density. It may shift toward or away from a diseased side, and its width can be increased in certain pathological conditions. **(7)**

Heart: The heart appears as a soft-tissue density structure and normally occupies less than half of the thoracic width (cardiothoracic ratio). Cardiomegaly is suspected if this ratio exceeds 50%, although such assessment should not be based solely on an anterior-posterior (AP) film. Accurate evaluation requires tracing the borders of both the right and left heart to exclude underlying pathology.

Hemidiaphragms: The contours of the right hemidiaphragm should be clearly defined, ensuring proper assessment of diaphragmatic position and shape. **(7)**

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