**DEEP-LEARNING-BASED-CNN ALGORITHMN DIAGNOSING DIVERSE LUNG DISEASES FROM CHEST X-RAY IMAGES**

**ABSTRACT**

The global public health concern of lung diseases is substantial—due to the rise in morbidity and mortality rates. The emergence of the COVID-19 pandemic in late 2019 has brought even greater urgency for early and accurate diagnosis and management of these diseases. Although chest X-rays play a crucial role in identifying and monitoring these conditions, accurately interpreting the images remains challenging—as the task relies on the expertise and experience of radiologists—making the process time-consuming for large datasets and susceptible to human error when detecting subtle signs of the diseases. Considering the issue, our paper presents a state-of-the-art deep-learning-based CNN algorithm that enables the development of an automated AI tool capable of accurately and independently identifying abnormalities and detecting specific lung diseases.

**Keywords:** Convolution Neural Network (CNN), Chest X-Ray (CXR), Deep-learning (DL), Densely Connected Convolutional Network (DenseNet)

**INTRODUCTION**

Lung diseases are medical conditions that affect the lungs and respiratory system. These conditions develop from various causes such as infections, genetic factors, or environmental factors like smoking, pollution, or chemical exposure. Lung diseases manifest in several types, from acute conditions like pneumonia and bronchitis to chronic conditions such as asthma, lung cancer, and COPD. These diseases often exhibit diverse symptoms, including coughing, shortness of breath, wheezing, chest pain, and fatigue [1], [2]. Consequently, lung diseases have become a substantial cause of morbidity and mortality globally, leading to millions of deaths annually—particularly in low and middle-income countries [3], [4].

The outbreak of the COVID-19 pandemic in late 2019 has emphasized the critical importance of diagnosing and managing lung conditions: not only to prevent infection in individuals with pre-existing lung diseases but also to reduce the risk of severe illness to those already infected [5], [6]. While chest X-rays are a fast, cost-effective, and non-invasive imaging tool that provides valuable and relevant information for diagnosing lung diseases, accurately interpreting the images remains challenging for subtle abnormalities or early-stage diseases. The process relies on the expertise and experience of radiologists, making it expensive, time-consuming, and prone to human errors —resulting in missed or incorrect diagnoses [7]–[10].

In recent years, Artificial Intelligence (AI) has established itself as a dominant and potent technology in medical imaging [11], [12]. By automatically and objectively analyzing images, AI can achieve improved levels of accuracy. Hence, incorporating AI into the analysis of Chest X-ray images can aid in reducing subjectivity interpretation by radiologists [13]. However, earlier studies have suggested that the top traditional machine learning AI algorithms, including support vector machines (SVMs) and decision trees, have certain drawbacks. Specifically, they are subjective due to their dependence on expert domain knowledge and manual feature engineering. Additionally, these techniques are not well-suited for handling large unstructured datasets and can be time-consuming [14], [15].

The capability of Deep learning (DL) to mimic human brain behavior in solving intricate problems—by training artificial neural networks in multiple computational layers: has exhibited immense potential in medical imaging analysis [16]–[18]. As a result, DL has emerged as breathtaking AI innovation in Chest X-ray imaging [19]. With the help of the CNN algorithm, it is now viable to effectively analyze and categorize high-dimensional Chest X-ray images [20]. This algorithm extracts relevant patterns and structures from numerous data, regardless of their variation in qualities—without explicitly feature engineering. Hence, it is fast and achieves accurate results at a low cost [21], [22].

In this study, we showcase an algorithmic tool that utilizes chest X-ray images, employing deep learning convolutional neural networks (CNNs): to diagnose lung diseases and detect abnormalities. The paper is structured as follows: Section I provides background information; Section II outlines the materials used and justifies the proposed methods; Section III presents the experimental setup and results; and Section IV concludes the paper and explores future research opportunities.

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