Deep Learning-Based Pneumonia Detection Using Chest X-Ray Images

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***Abstract*—Pneumonia is a serious respiratory infection that affects the lungs, often caused by bacteria or environmental factors, leading to fluid accumulation in the alveoli. Accurate diagnosis of pneumonia is crucial for effective treatment, and it typically involves methods such as physical exams, chest X-rays, ultrasounds, and lung biopsies. However, misdiagnosis and delayed treatment can lead to severe complications. This research explores the use of deep learning techniques, particularly Convolutional Neural Networks (CNNs), to enhance pneumonia detection. By analyzing chest X-ray images, the study develops a CNN model that classifies patients as either suffering from pneumonia or not. A dataset consisting of 20,000 high-resolution chest X-ray images (224x224) was used, with a batch size of 32 for model training. The CNN model achieved a 95% accuracy rate, demonstrating its potential for diagnosing pneumonia effectively. The model is capable of distinguishing between various types of pneumonia, including bacterial, viral, and COVID-19, solely based on chest X-ray images, showcasing its accuracy in medical diagnostics.**

Keywords—Pneumonia Detection, Adaptive Deep Learning, Deep Convolutional Neural Network Architecture

I. INTRODUCTION

Pneumonia is an inflammatory condition of the lung parenchyma caused by a variety of factors including bacterial infections, immune responses, environmental influences, and certain medications. Pneumonia can be classified in different ways: (1) Based on its pathogenesis, pneumonia is categorized as infectious or non-infectious, with infectious pneumonia being the most common. This includes bacterial, viral, and fungal pneumonias, as well as aspiration pneumonia and radiation-induced pneumonia. Non-infectious types include immune-related and radiation-induced pneumonia. . (2) Pneumonia can also be classified as community-acquired pneumonia (CAP), hospital- acquired pneumonia (HAP), and ventilator-associated pneumonia (VAP), with CAP being the most widespread. HAP is particularly difficult to treat due to its association with antibiotic resistance. Globally, pneumonia is responsible for over 800,000 childhood deaths annually and affects over 1,400 children per 100,000. According to the Global Burden of Disease Study, pneumonia was the second leading cause of death due to pulmonary infections in 2013. In Europe, pneumococcal disease affected 35% of hospitalized patients, with a global prevalence of 27.3%. A report from the Johns Hopkins Bloomberg School of Public Health indicated that India had the highest mortality rate from pneumonia, accounting for nearly 297,000 child deaths under five in 2015. Furthermore, pneumonia remains the leading cause of death in children under five. Although pneumonia-related mortality declines with age, its incidence increases in older adults, particularly those over sixty-five. The high mortality rate among infants has spurred calls for improved detection methods. Advancements in medical imaging, such as chest X-rays, computed tomography (CT), and magnetic resonance imaging (MRI), have improved diagnostic accuracy for pulmonary diseases. Chest X-rays, however, remain the most affordable and accessible option, though their interpretation can be difficult, even for experienced radiologists, due to overlapping symptoms with other diseases, like lung cancer.

Traditional diagnostic methods are often slow and inconsistent, which makes early detection challenging. In response, this study proposes using a Convolutional Neural Network (CNN) to automatically detect pneumonia from chest X-rays. The model achieves an impressive accuracy rate of 96.07% with an AUC of 0.9911. The paper is structured as follows: Section 2 covers perspectives on medical image processing; Section 3 provides an overview of CNN architectures; Section 4 outlines the materials, methods, and training procedures; Section 5 presents experimental results; and Section 6 concludes the study.

II. RELATED WORKS

[1] The identification of COVID-19 from X-ray images presents several challenges. One of the primary obstacles is the limited availability of X-ray images due to the recent onset of the pandemic, which has resulted in insufficient datasets for widespread use by researchers. Additionally, there is a need for advanced technologies to enable rapid identification and deep understanding of viral infections through X-ray images, which could provide insights into the severity of the infection. Based on current technology and the challenges encountered, it is concluded that transfer learning is a feasible approach for this task. This method involves training deep neural networks on pneumonia-related X-ray images that

[2] Show infection in one or both lungs caused by bacteria, viruses, or fungi. These infections lead to inflammation in the alveoli, causing difficulty in breathing due to the accumulation of pus or fluid. Transfer learning enables models to be trained on existing pneumonia datasets and then adapted for new, fast-spreading infectious diseases such as COVID-19. This method addresses the issue of building a reliable model with a small, unexamined dataset containing unknown characteristics.

[3] Deep Convolutional Neural Networks (CNNs) generally perform better when trained with large datasets compared to smaller ones. Despite the global presence of COVID-19, publicly available chest X-ray images of infected patients are scarce. To address this, a new dataset of COVID-19 chest X-ray images was curated, while standard pneumonia and normal X-ray images were used from public sources. This study utilizes robust deep learning techniques, focusing on the ResNet- 50 CNN architecture to classify chest X-ray images into categories of affected or unaffected by pneumonia. The model was trained on over 1,500 high-resolution chest X-ray images (224x224) with batch sizes of 32 and 64 for optimal performance. Using the Adam optimizer with a learning rate of 1e-4, the model underwent 500 epochs of training to refine its ability to distinguish pneumonia from other lung conditions. The ResNet-50 model achieved an accuracy of 80%, demonstrating its potential in clinical pneumonia detection.

[4] In this paper, the authors employ an ensemble method to classify chest X-rays into three categories: COVID-19, pneumonia, and normal. Each X-ray image is processed through a classification layer to determine its category. This method combines multiple models to improve classification accuracy.

[5] The X-ray dataset is initially divided into training and test sets during the preprocessing phase. Image normalization and data augmentation are performed to strengthen model training. In the second phase, the model is trained to classify X-rays into two categories: consolidation and non-consolidation. Cross-validation using k-fold techniques ensures the reliability of the model. The final phase integrates explainable AI to enhance model interpretability, using heatmaps to visualize the areas of interest in the X-rays and assess the model's robustness.

[6] This paper presents a method using an ensemble of RetinaNet and Mask R-CNN models to identify pneumonia regions in chest X-rays. Pneumonia areas are detected based on their dimensions and aspect ratios. Given that pneumonia typically occupies a small section of the X-ray image, the models employ Feature Pyramid Networks (FPN) to extract multi- scale features, improving detection accuracy. FPNs combine low-resolution, semantically rich features with high-resolution, weaker features, enhancing the model's ability to detect pneumonia regions. Additionally, residual networks are used as the backbone to counteract the degradation problem and enable the development of deeper architectures for better performance.

III. BACKGROUND

Machine learning (ML) algorithms have steadily gained the interest of researchers over the last few years. This type of method can make full use of the massive ability to create computer calculators in image processing with pre-determined algorithm stages. Traditional machine learning methods for dividing jobs, on the other hand, necessitate the use of manual design algorithms or the manual setting of output layers to separate images. In response to the aforementioned situation, LeCun et al. [7] Offered a CNN approach, which can automatically extract features with the use of constantly stacking features and exit that the included photos may not be in any class. The shallow networks are very deep and concentrate on the image's low-level features. CNN the model increasingly exposes advanced features as the number of network layers increases. CNN learns the distinctions between different images by combining and evaluating these priority features, and it uses a back-propagation technique to update and record learned parameters. CNN's concept is to use a specific convolution kernel to filter a prior picture or map component to build the next layer map element, as well as merge functions like merging functions to minimize feature map scale and mitigation to count. The created component is then given the non-line activation function.

A mapping to improve the model's simulation capabilities .The most common integration tasks include mid and high integration. The plural of integration denotes that the element sent to the integration layer is split into many regions, with each sub-region having a different size in terms of horizontal and vertical steps. The sole distinction between high and medium integration is a lower region where the aggregation rate yields the average of each sub-region. ReLU (Rectified Linear Units) and Sigmoid are two common activation events.

Image elements are automatically extracted using segmentation and a continual accumulation of convolutional processes, integration functions, indirect opening functions, and other completely integrated layers. Then, by evaluating these derived characteristics, it is possible to extract pneumonia from the photos processed by the model. The model's general capacity is increased by fully utilising pixel-level image information. The most prominent neural framework has been proposed in past few decades for in-depth learning development, such as AlexNet [8] and VGGNet [9]. However, when the number of layers in the network increase, Instead of learning the numerous productive features, the neural network will be modified to particular parts of the training image, which makes the model similar to the capacity declines and creates congestion. The remaining communication framework was proposed to overcome the problem of network depth. Since then, neural networks have advanced, garnered a lot of attention and research, and have formed the foundation for a lot of occupations. We also looked at the efficiency of residual connections in our reduced CNN architecture with only a few layers in this study.

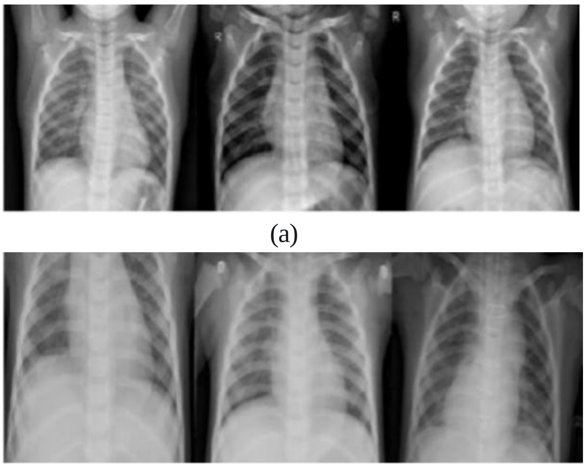
IV. MATERIALS AND METHODS

4.1 Data

The proposed database, which will be used to test the model's performance, comprises a total of 5863 X- ray pictures via Kaggle.

Dr. Paul Mooney created a Kaggle contest in 2017 to classify viral and bacterial pneumonia. It differs from the other datasets since it contains 5,863 paediatric photos. We're talking about the updated version of this dataset.[6]

The database is further divided into three folders (train, test, and val) with subfolders for each image category (Pneumonia / Normal). Figure 1 shows a few instances of common and pneumonia photos that have been scaled to a static size. Due to the low amount of exposure in patients, chest X-ray images always show symptoms of limited brightness, and chest X-ray images always have black, white, and grey pants. The lungs are on both sides of the thoracic cavity, and the lung area is plainly visible on an X-ray since it is virtually black. The heart, which is situated between the lungs, appears practically as white as X-rays can go through it entirely. Because bones are comprised of protein and are exceedingly dense, X-rays cannot pass through them, leaving the bones virtually white. Furthermore, the bones have distinct edges.



(a)

(b)

Fig. 1. Examples from the dataset. (a) normal cases, (b) pneumonia cases

4.2 Data Preprocessing

Table 1 lists the tactics employed throughout this article. Rescale is a value that we will multiply the data by before any other processing in our investigation. Our original photos had RGB coefficients ranging from 0 to 255, but values like this would be too high for our models to handle (given a typical learning rate), so we scale them down by a factor of 1./255. shear range is used to apply shearing transformations at random. When there are no assumptions of horizontal asymmetry, zoom range is used to randomly zoom inside photographs, and horizontal flip is used to randomly flip half of the images horizontally (e.g. real-world pictures)

Data pre-processing techniques used in this study

Rescale	1./255
Zoom Range	0.2
Shear Range	0.2
Horizontal_Flip	True

Table 1

4.3 Proposed Network

In this study, we designed a VGG-based CNN model to extract the features of chest X-ray images and use those features to detect if a patient suffers from pneumonia. In Our CNN Architecture, We started with a lower filter setting of 32 and worked our way up layer by layer. A layer of Conv2D was used to build the model, followed by a layer of MaxPooling. An odd number, such as 3x3, is desirable for kernel size.

The activation functions Tanh, ReLU, and others can be employed, but ReLU is the most popular. input shape accepts the width and height of an image, with the last dimension serving as a colour channel. After that, we flattened the input and added ANN layers.

$$S(x) = \frac{1}{1+e^{-x}}$$

f(x)=max(0,x)

S(x) = Sigmoid f(x) = ReLU

For the last layers (ANN Layers), I used a softmax activation function and defined units as the total number of classes. For binary classification, I used a sigmoid and set the unit to 1.

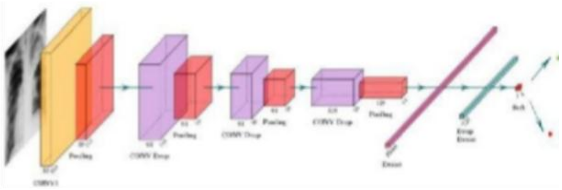


Fig 2. Details of proposed DL model.

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