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Original Article

Use of CNN with Transfer Learning to Improve the Accuracy of Pneumonia Diagnosis

Orlando Iparraguirre-Villanueva[1], Wilmer Robles-Espiritu[2], María Suxe-Ramírez[3],
Rosalynn Ornella Flores-Castañeda[4]

[1,3]*Facultad de Ingeniería, Universidad Tecnológica del Perú, Lima, Perú.*
[2,4]*Facultad de Ingeniería y Arquitectura, Universidad César Vallejo, Lima, Perú.*

[1]*Corresponding Author : eic-ijepe@honexus.org*

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Abstract - *Pneumonia is a respiratory disease affecting both lungs, causing symptoms such as cough with phlegm or pus, fever, chills and shortness of breath. Different microorganisms, such as bacteria, viruses and fungi, can cause pneumonia. Today, combating pneumonia is challenging for physicians, especially in vulnerable communities and during cold or sudden weather changes. In this work, we explored how Artificial Intelligence can contribute to improving the diagnosis of pneumonia. For this purpose, two Convolutional Neural Network (CNN) models, VGG16 and ResNet50-v2, were evaluated using the transfer learning technique to identify between healthy lungs and those affected by the disease. We worked with a dataset extracted from the Kaggle platform, which included 5216 images for training, 624 for testing and 16 for validation. The results showed that the ResNet50-v2 model obtained better results, reaching an accuracy rate of 90.87% in the test set, standing out for its ability to identify pneumonia cases. These results reinforce the potential of artificial intelligence as a diagnostic support tool. Finally, it can be stated that this work represents a significant advance in using neural networks in medicine. Integrating this technology into public health may not only improve the identification of pneumonia but may also contribute to the development of new efficient healthcare systems.*

Keywords - *Deep Learning, Pneumonia, CNN, Transfer Learning, Diagnosis.*

1. Introduction

Currently, pneumonia is defined as an inflammatory lung pathology characterized by the involvement of the alveoli, resulting in fluid or pus occupancy. The most frequent symptoms include cough, expectoration, fever, chills, and shortness of breath. This condition is triggered by various infectious agents, such as bacteria, viruses and fungi, which manage to lodge in the lung tissue [1]. The clinical severity of pneumonia is very diverse, ranging from mild to life-threatening. This severity is closely related to the type of pathogen involved; the person's age and other health history are determining factors. A higher incidence of complications is observed in children under 5 years of age and geriatric adults [2], 3]. Pneumonia claims more than four million lives worldwide each year, which indicates how dangerous it is if it is not treated in time, which is why it is important to have tools that help to identify this type of pathology early [4]. Currently, in most health centers, the early diagnosis of pneumonia follows the traditional method of using chest X-rays to identify pneumonia, for which the radiologist oversees analyzing the images and confirming whether there is an infection. However,y are useful not only for diagnosis [5] but also for monitoring how the disease evolves in patients with other pulmonary problems [6]. However, access to radiology specialists is scarce in many rural or less developed areas. For example, living in a remote village without sufficient knowledge to interpret an X-ray correctly. That is the big challenge: to ensure that everyone, no matter where they live, has access to an accurate and timely diagnosis [7]. Furthermore, here comes another problem: even when there are specialists, the interpretation of images is not always infallible. It depends a lot on the radiologist's experience and clinical eye [8]. A small error in reading an X-ray can delay treatment and worsen the patient's situation. Therefore, alternatives, such as using artificial intelligence (AI) to support early diagnosis, are being sought in many places. What is certain is that pneumonia remains an enemy, especially for those who do not have access to the necessary resources to combat it in time [9]. The COVID-19 pandemic has left us with many lessons, and one of the most important is the key role that chest X-rays and computed tomography (CT) scans play in diagnosing acute respiratory disease. These tools, used to date, are fundamental for detecting the different types of pneumonia related to coronavirus and other pathogens [10], [11]. However, chest X-ray images are like mirrors that allow us to see what is happening in the lungs. Interpreting them manually can become very tedious [12]. Specialists, particularly in public health centers, are faced with analyzing each one in detail, which not only consumes time but also increases the risk of errors [13]. In this context, one of the biggest challenges is the identification of patterns in the images, such as “ground glass” opacity, which is a common feature in cases of pneumonia [14]. Detecting these signs becomes complex, even more so given the shortage of medical personnel. Images can vary depending on their processing, making it more difficult to diagnose accurately[15]. In this context, new tools are needed to support healthcare professionals in detecting pneumonia and treating other pathologies [16].

Currently, the use of artificial intelligence (AI), specifically the application of Deep Learning (DL), through CNN, is experiencing significant growth in various sectors, with the medical sector being one of the most benefited [17]. DL technology has been consolidated in the development of computer-assisted diagnostic systems, which are of great help to professionals in the detection of pathologies [18]. Thanks to this technology, it is possible to identify subtle patterns in images that otherwise may go unnoticed, even to the human eye. In addition to DL, the transfer learning technique has meant a great advance in this field, in which this technique takes advantage of pre-trained CNNs, in this case, the VGG16 and ResNet50V2 architectures, which allows significant savings in time and resources, since the architecture is not trained from scratch.

The ability to detect patterns and take advantage of the pre-existing knowledge of pre-trained CNNs has represented a significant advance in this field [19], [20]. This study compares two CNN models, VGG16 and ResNet50V2, to identify pneumonia from medical images. To achieve this, we rely on advanced transfer learning techniques, which allow us to leverage the knowledge these models already must apply to a specific problem: classifying radiographs and determining whether there is evidence of pneumonia. The research aims to train these models with a data set of radiographic images. To do this, we had to manage incomplete data and apply data augmentation techniques to ensure that the models learned as well as possible. We then evaluated their performance using specialized metrics, such as accuracy, recall and F1-score, to see which performed better.

2. Literature Review

Numerous studies have investigated pneumonia diagnosis using deep learning, including transfer learning techniques. For example, in [21], ‘ResNetFed’, a CNN adapted to Federated Learning, was introduced to detect COVID-19 pneumonia. With 1411 chest X-rays, including 658 COVID-19 cases, it achieved an accuracy of 82.82%, outperforming local ResNet50 and showing greater efficiency and privacy in diagnoses with less data. In [22], ‘LWSNet’, an advanced CNN, classified chest X-rays into COVID-19, common pneumonia, and standard categories, achieving an accuracy of 98.54%, highlighting its efficiency and accuracy in diagnosing pneumonia. On the other hand, in [23], a CNN was applied to classify 8071 chest X-rays, distinguishing viral or bacterial pneumonia from healthy cases. With data augmentation, the model achieved 97% accuracy in detecting lung disease.

Similarly, the study [24] focused on the diagnosis of pneumonia and COVID-19 using chest X-rays. For this, they employed a completely new deep-learning architecture in addition to the well-known CNN models such as VGG16, ResNet50 and Inceptionv3. To ensure that the interpretation of the radiographs was as objective as possible, they optimized the key hyper-parameters of the system using a randomized search.

Also, in [25], they presented a pneumonia detection model combining enhanced versions of RetinaNet and Mask R-CNN with ResNet-50 and ResNet-101. Tested on 26,684 chest X-rays, the model achieved a recall of 0.813 and a mAP of 0.2283, demonstrating its effectiveness in X-ray diagnosis. On the other hand, in [26], the XAI-ICP model was developed, which uses deep convolutional neural networks (DCNN) for pneumonia classification, achieving an accuracy of 92.14%, improved to 93.29% with transfer learning. This AI model stands out for its transparency and adaptability.

In [27], a CNN such as VGG16 differentiated bacterial and viral pneumonia in chest X-rays, achieving an AUC of 0.97 against normal cases and 0.91 between bacterial and viral, showing high efficiency in low-contrast images. In turn, in [28], a CNN (ResNet-50) with an optimization algorithm (ASSOA) was implemented to classify pneumonia in chest X-rays, reaching accuracies of 99.26% and 99.7% in Kaggle and GitHub datasets. ASSOA proved to be more efficient than other algorithms. On the other hand, CNN models, including VGG16 and MobileNetV2, were evaluated in [29] to detect SARS-CoV-2 in chest X-rays, reaching an accuracy of up to 100%. A test with VGG16 showed 91% accuracy in classifying COVID-19, pneumonia, and normal cases, highlighting the effectiveness of CNN in medical diagnosis.

In a similar study [30], they used Deep Learning to analyze chest X-rays to detect pneumonia in children. The researchers combined convolutional neural networks (CNNs), transfer learning and an ensemble approach (several models working together). The results were impressive: they achieved 93% accuracy with transfer learning and 92% accuracy with the ensemble approach, clearly outperforming CNN alone, which scored 89%. Interestingly, the ensemble approach proved to be the most effective in all metrics evaluated, making it a solid choice for this type of task. On the other hand, in [31], they used a Multiscale Convolutional Neural Network (MS-CNN) to examine 6,650 Chest X-rays (CXR) and detect seven different lung diseases. The model achieved a very significant accuracy of 96.05%, but what made the difference was the integration of explainable artificial intelligence (XAI). This technology improves accuracy and helps us understand how the model reaches its conclusions, which is crucial for gaining physicians' confidence and advancing the diagnosis of lung diseases through X-rays. Table 1 summarises the main findings, limitations and gaps in the literature review.

Table 1. Findings, limitations and shortcomings in the research reviewed

Ref.	Findings (Models, Accuracy and Dataset)	Gaps, Deficiencies, Limitations Identified
[22]	They used a deep neural network model (from Xception to ResNet50v2) to detect COVID-19 and pneumonia. They achieved high accuracy rates.	Yes, the pressure was high. However, concatenated models generally require more computational resources.
[23]	They used ResNetFed for pneumonia detection, emphasizing data privacy. Achieved 82% accuracy	Although it addresses data privacy, the accuracy obtained is moderate compared to other models. In addition, adaptability for multiple types of pneumonia is not emphasized.
[24]	Proposed a hybrid deep learning model to detect COVID-19.	Generalization to other types of pneumonia or the performance of models with higher variability of data sets could be limited.
[25]	Concatenated Xception and ResNet50v2 for COVID-19 detection.	The complexity of the model may limit direct applicability to pneumonia classification.
[26]	They used CNN to classify chest X-rays to detect pneumonia. Achieved accuracy of 97%.	Although high accuracy was obtained, the approach is limited to differentiating viral and bacterial pneumonia. It does not address distinctions with healthy lungs.
[27]	Implemented a hybrid deep learning model with transfer learning to detect pediatric pneumonia. Achieved 93% accuracy.	The approach is only for pediatric pneumonia, indicating that it cannot be generalized to adult populations. Other pre-trained models for balance and adaptability have also not been explored.
[28]	Trained a lightweight neural network for COVID-19 diagnosis.	The use of lightweight models may not deepen the capabilities of more robust models such as VGG16 or ResNet50V2.
[29]	Analyzed models such as VGG16, ResNet50 and InceptionV3 were used to diagnose pneumonia and COVID-19.	We do not comprehensively evaluate the adaptability and balance between overfitting and generalization of general pneumonia diagnostic models.
[30]	They used a data set with 26,000 images. They achieved a recall of 81% and mAP of 0.228 with ResNet-50/ResNet-101.	The metrics are different from the classification metrics, and their focus is object detection.
[31]	They trained the DCNN XAI-ICP model to classify pneumonia. Achieving 92% accuracy, 93% improved with transfer learning.	Although the accuracy is good, it is not the highest of the reviewed works. The work could not focus solely on comparing multiple architectures to identify the optimal balance between accuracy and adaptivity.

3. Methodology

In this section, we describe our research methodology in two parts. The first part focuses on the detailed presentation of the deep learning architectures. Here, we explain the CNNs developed specifically for this study and the transfer learning models VGG16 and ResNet50V2, chosen for their proven effectiveness in medical image processing and analysis. In the second part, we detail the technical implementation of the models in our study. For data collection and preparation, standardized protocols in chest X-ray digitization and advanced preprocessing techniques, such as normalization and contrast adjustment, were applied to optimize the images for deep learning analysis. A specific CNN was developed, and transfer learning models such as VGG16 and ResNet50V2 were used. After rigorous evaluation, the most efficient model was selected to perform predictions on new chest radiographic images, demonstrating its applicability in diagnosing pneumonia. Figure 1 shows the CNN architecture.

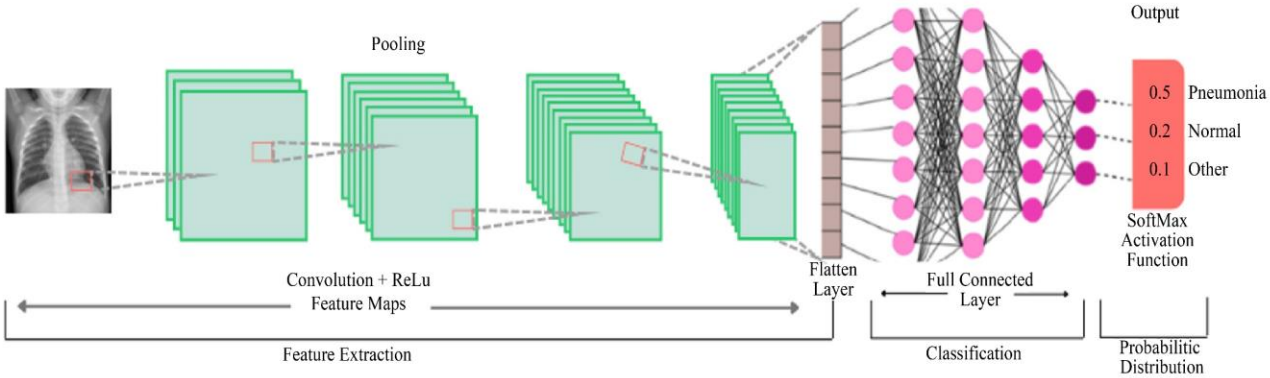


Fig. 1 Architecture of how our convolutional neural network works

3.1. CNN and Transfer Learning

Convolutional Neural Networks: They are a key algorithm in Deep Learning, recognized for their effectiveness in modeling various data [32]. CNNs use convolution layers and kernels to extract features from images, create feature maps, and apply non-linear activation functions to learn complex patterns [33]. In turn, CNNs, by efficiently processing spatial data such as images, employ fewer parameters than densely connected networks, gaining relevance in Deep Learning, particularly in computer vision, due to their local perception and fewer required parameters [34]. T formally defined convolution operation is central to CNNs [35]. In formal terms, this is expressed from Equation (1).

$$h(t) = \int_{-\infty}^{\infty} f(t-\tau)g(\tau)\ d\tau \tag{1}$$

The above operation can also be represented by an asterisk and is expressed by Equation (2).

$$h(t) = (f * g)(t) \tag{2}$$

Convolution shows how one function affects another, similar but different from cross-correlation, with properties such as commutativity. In deep learning, these differences are usually secondary. The definition of convolution is extended for discrete and finite signals. Thus, given two discrete signals, f[k]" and "g[k], where k belongs to the integers, the operation of convolution is stated in Equation (3).

$$h[k] = \sum_n f[k-n]g[n] \tag{3}$$

Finally, the convolution operation can also be applied similarly to multidimensional signals. For example, the convolution between two discrete and finite two-dimensional signals, such as I[i,j] and K[i,j], can be represented in Equation (4).

$$H[i,j] = \sum_m \sum_n I[i-m, j-n]K[m,n] \tag{4}$$

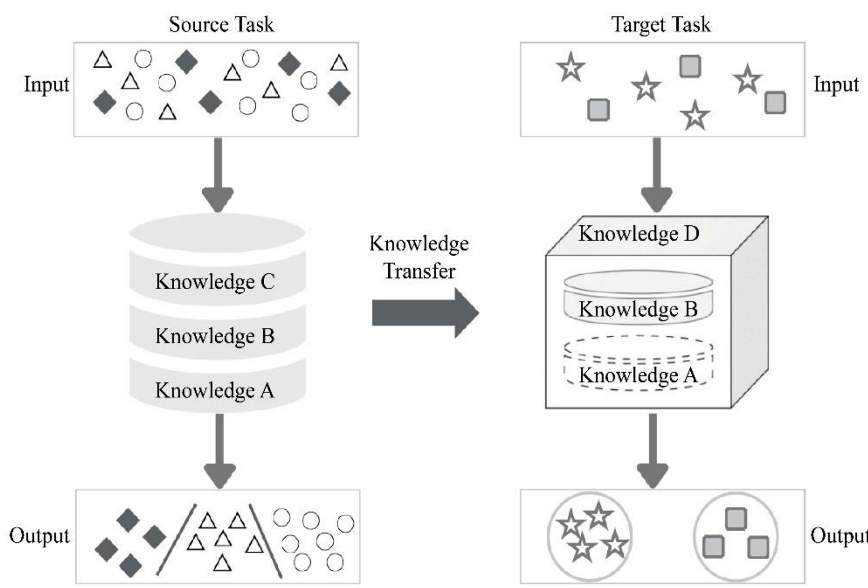


Fig. 2 This graphical representation allows us to understand how the model learns from what it already knows

Transfer Learning: A technique in which knowledge acquired from a source task is applied to a target task to improve model efficiency, using common architecture and initial training with general datasets, followed by task-specific adaptation and tuning the model to the task of interest [36]. It is also described as the efficient use of pre-trained models in one task to facilitate and improve learning in another similar task within deep neural networks [37]. Transfer learning techniques allow us to leverage the knowledge of models already trained on a new task. This technique is useful, especially when the new task does not have sufficient training data[38]. The knowledge transfers intrinsic to transfer learning evidence its ability to mitigate the scarcity of labeled data, a critical resource in training deep learning models. A graphical representation of transfer learning is presented in Figure 2.

As shown in Figure 2, knowledge A and B acquired in a source task can be transferred to a target task. The combination of knowledge A and B and knowledge D in the new model allows the target task to be completed efficiently.

3.2. Specific CNN Models Applied to Transfer Learning

The selection of appropriate CNN architecture is crucial in transfer learning. Pre-trained models such as VGG16 and ResNet50V2 stand out for their image classification efficiency and adaptability to related tasks. Pre-trained datasets such as ImageNet these models are ideal for new data-limited applications. In the following, we will detail the architectures of VGG16 and ResNet50V2, focusing on their design and role in deep learning.

3.2.1. VGG16

Developed by the Visual Geometry Group at Oxford University, VGG16, or VGGNet, is a pre-trained CNN model that has marked an important milestone in the field of CNN, especially recognized for its effectiveness in computer vision tasks [39]. This model uses weights modeled from large datasets to execute specific tasks and is characterized by a 16-layer architecture, which includes 13 convolutional and 5 max-pooling layers, ending in 3 fully connected layers [40]. In turn, VGG16 uses transfer learning with a pre-trained ImageNet configuration, which enhances its ability to classify various visual features, extending its utility in computer vision [41]. Figure 3 illustrates the VGG16 model, a convolutional network that processes images through 13 convolutional (blue) and 5 max-pooling (orange) layers, progressively extracting essential features. In the end, three dense layers (green) synthesize these features to classify the image, with an output layer determining the category by sigmoid or SoftMax activation.

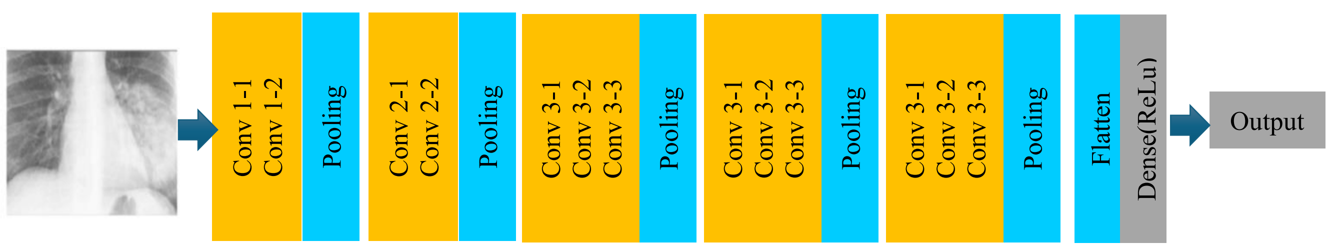


Fig. 3 VGG16 Model

3.2.2. ResNet50V2

This represents an advanced CNN architecture that focuses on complex computer vision tasks, including efficient and accurate image classification. The integrated residual blocks are key to training deeper networks, overcoming the problem of vanishing gradients, and enabling more detailed learning of visual features [42]. This version significantly modifies and improves the ResNet50 model. This version is different and performs better than the original version, working with images like ImageNet. This was achieved by refining the different communication components that process the information[43]. In addition, ResNet50V2 excels in several computer vision applications due to its 50-layer architecture and pre-training on ImageNet.

3.3. Advanced CNN Implementation with Transfer Learning

Understanding the Thoracic X-ray dataset: In the initial phase of our research, a detailed analysis of the thoracic X-ray dataset obtained from a well-known repository in Kaggle was carried out. This dataset consists of 5216 training, 624 tests, and 16 validation images, divided into 4273 images of lungs with pneumonia and 1583 of normal lungs. To choose the dataset, we considered certain criteria, such as image diversity, which is very important for our study. A balanced dataset is important to avoid biases and ensure the models learn to recognize pneumonia more accurately. To prepare and analyze the dataset, we used different Python tools and specific libraries for image and data processing, such as the Numpy and Pandas libraries, which helped us to manage the information. In contrast, the OpenCV library was used for image processing. This preliminary phase is essential for the data to be ready before entering a neural network.

The tensorFlow library is one of the most widely used for training DL models. We chose to use this library to implement the VGG16 and ResNet50-v2 architectures since it offers advanced features for training and evaluating the models. In addition, data augmentation and normalization techniques were applied to optimize the data better. These strategies are important to improve the model’s ability to identify imperceptible patterns in the radiographs, specifically when identifying between healthy lungs and those with pneumonia. Figure 4 shows the flow from image processing to final classification. The steps in the flow are quite clear. First, the images go through preprocessing to ensure they are in the best condition before being analyzed.

Next, the two models, VGG16 and ResNet50-v2, extract key features from the images, and then these features are sent to the dense layer classifier, which includes dropout, to avoid over-fitting. Finally, the SoftMax activation accurately and objectively decides whether the image shows signs of pneumonia.

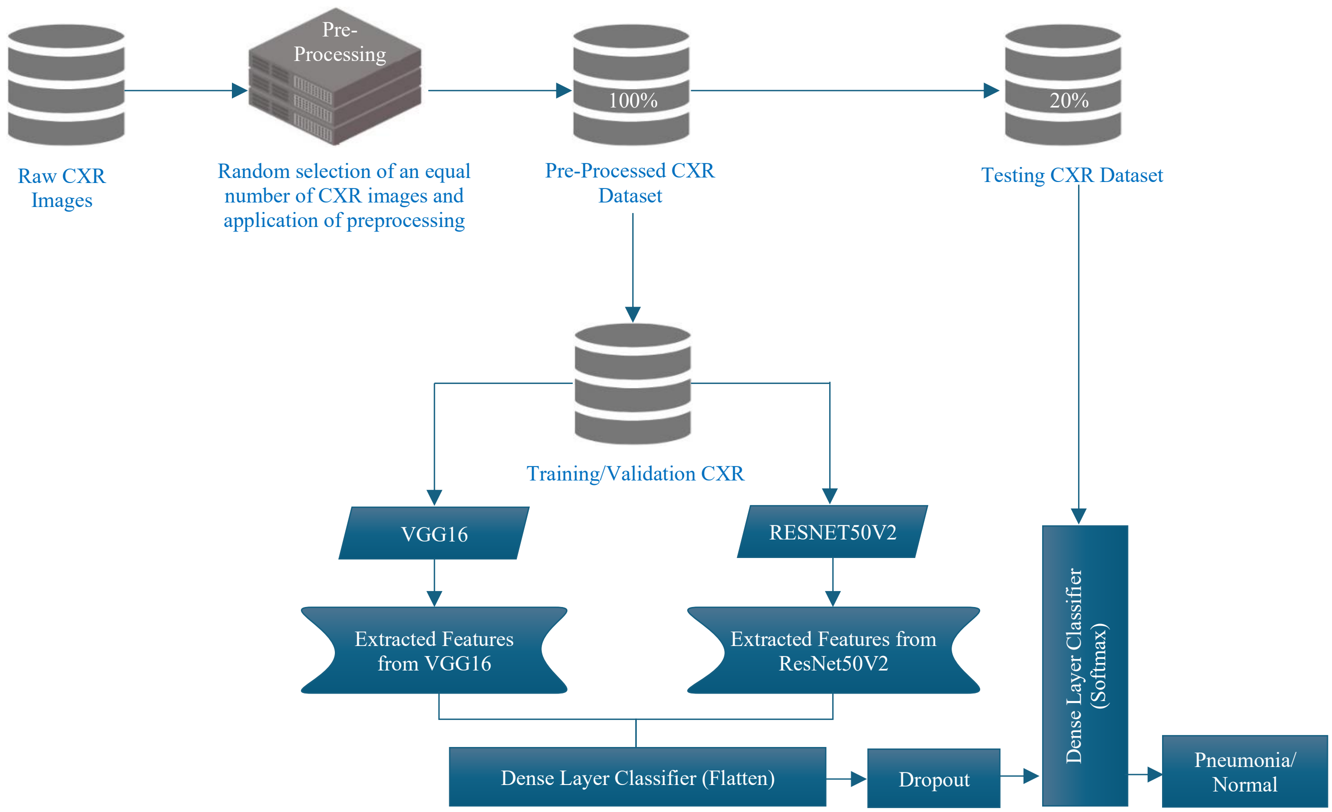


Fig. 4 Chest X-ray diagnostic pipeline using deep learning

3.3.1. Exploratory Data Analysis (EDA)

The EDA is a fundamental phase in medical diagnosis based on images and DL. This phase helps us better understand the data set, allowing us to identify key features that differentiate healthy lungs and those with pathologies.

In this phase, a detailed evaluation of the radiographic images was carried out, and the most relevant anatomical and pathological features were organized and highlighted. A series of transformations applied to the chest radiographic data set can be seen in Figure 5. The images labeled as figure 5(a) and 5(d) served as a starting point, and from there, the image processing techniques were applied to highlight details, which at first glance go unnoticed. For example, in Figure 5(e) and 5(h), morphological erosion was used, a technique that reduces the intensity of the pixels in the brightest areas. This allows for the highlighting of the edges and linear structures, which is useful for detecting variations in the texture of lung tissue that may indicate the presence of a pathology. In Figure 5(i) to 5(l), the opposite operation, morphologic dilation, was applied. This technique expands the areas of greater intensity, reconstructing the regions of clinical interest that may have been reduced during erosion. The alternation between erosion and dilation is key to optimizing the representation of lung structures, preparing them for a more accurate automatic analysis. Next, in Figure 5(m) to 5(p), the effectiveness of Canny edge detection is appreciated.

This is a refined method that helps to highlight anatomical contours within lung tissue, which is often quite complex. The algorithm, through calculating the intensity gradient and applying optimal thresholds, for this case, 80 and 100, manages to emphasize important transitions in the images.

This captures important details and helps reduce unnecessary noise, facilitating a cleaner computational analysis. An important element is the conversion from HSV to RGB, which helps to improve the visual interpretation of radiographic images, which is important for computerized systems. This final phase highlights the texture and details of the lungs and facilitates diagnosis by either a physician or a computer system.

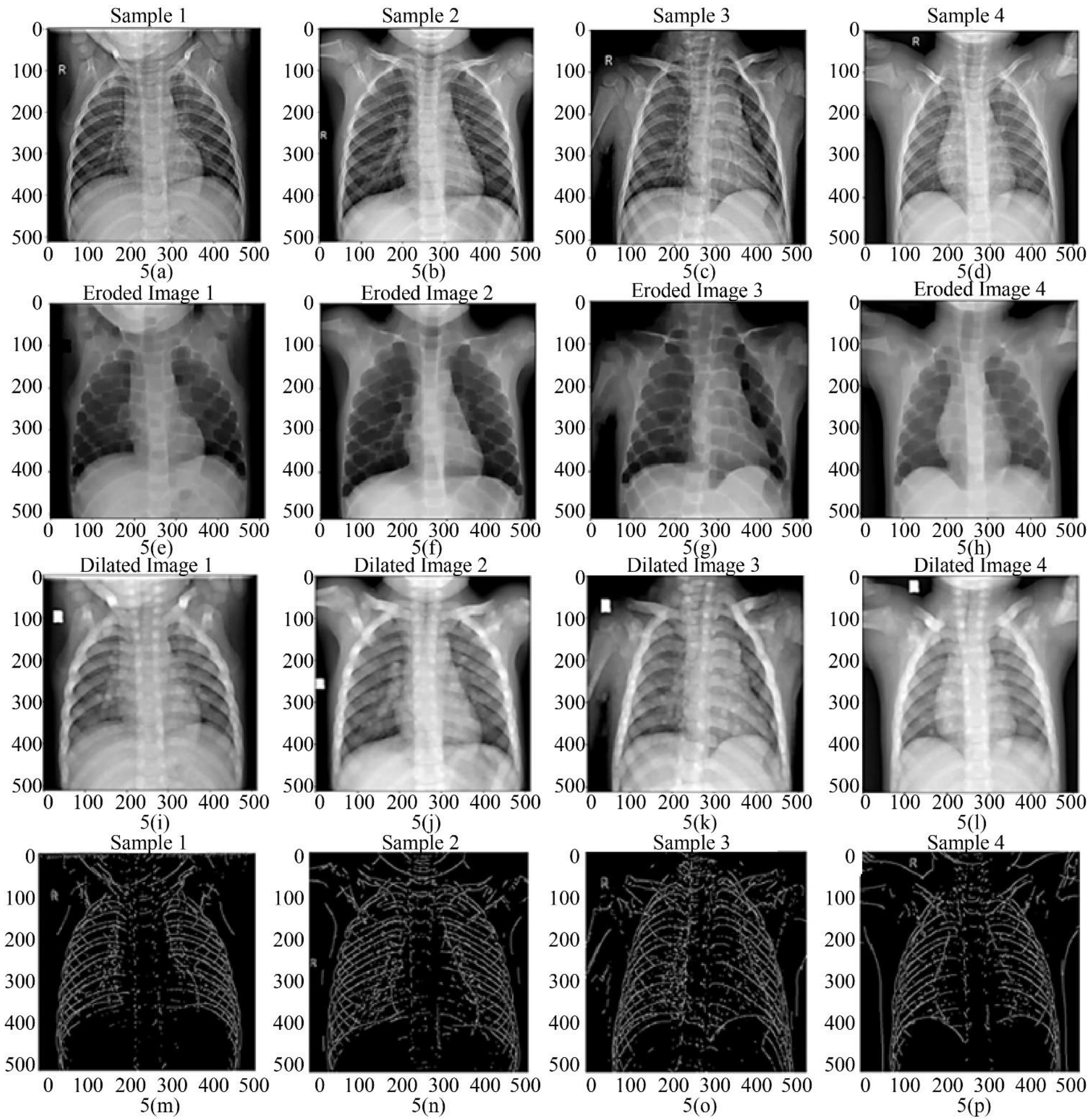


Fig. 5 Visual Enhancement and Edge Detection in Thoracic Radiography Analysis, 5(a)-5(d) Original chest X-ray images depicting standard presentations of thoracic anatomy, 5(e)-5(h) Images after morphological erosion highlighting linear structures and edges by reducing the brightness scale of prominent regions, 5(i)-5(l) Images following morphological dilation to emphasize areas of clinical interest, potentially understated post-erosion, and 5(m)-5(p) presents the results of the application of the Canny edge detection algorithm, delineating anatomical contours with a focus on detecting patterns indicative of lung pathology

3.3.2. Deep Learning Models

Deep learning models To classify chest X-rays, CNN models were developed to distinguish between healthy and diseased lungs. The dataset used is divided into 5216 images for training, 624 for testing and 16 for validation, distributed in two classes. Sequential CNN architectures with convolution layers, maximum clustering and dropout regularization were designed to minimize overfitting. Data augmentation techniques were applied to make the model learn better and more efficiently. This included inverting, rotating and shifting the images, and adjusting the intensity of their colors. In addition, transfer learning with VGG16 and ResNet50V2 was used to classify thoracic radiographs, preserving patterns of large data sets and facilitating the detection of lung pathology.

This technique increases the accuracy and efficiency of computer-aided diagnosis, with models optimized by 'Adam' and evaluated with binary cross-entropy and accuracy. Table 1 details the architecture of the CNN model for thoracic radiographs, highlighting the layers and parameters for feature extraction. Table 1 presents a CNN model with Conv2D and MaxPooling2D layers, from 32 to 256 filters, dropout, and dense layers, with 6,821,441 parameters, to classify images, especially in radiographs. VGG16, adapted for thoracic radiographs, was integrated, improving lung pattern detection by modifying the top layer and applying ImageNet weights.

Table 2 sets out the adapted VGG16 architecture, detailing the relevant layers and their parameters, thus highlighting the essential modifications for medical image classification. Table 2 shows the architecture of the VGG16 model, highlighting convolutional and MaxPooling2D layers that process 224x224x3 images. With 14,714,688 trainable parameters, this model effectively classified pathologies in thoracic radiographs, highlighting its ability for efficient feature extraction. It follows a similar procedure to describe the ResNet50V2.cas model.

Table 2. Details of the CNN model architecture design

Layer Type	Output Dimension	# Parameters
Conv2d (Convolutional Layer)	(Not defined, 224, 224, 32)	896
Max_Pooling2D (Maximum Grouping)	(Not defined, 112, 112, 32)	0
Conv2d (Convolutional Layer)	(Not defined, 112, 112, 64)	18496
Max_Pooling2D (Maximum Grouping)	(Not defined, 56, 56, 64)	0
Dropout (Regularization)	(Not defined, 56, 56, 64)	0
Conv2d (Convolutional Layer)	(Not defined, 56, 56, 128)	73856
Max_Pooling2D (Maximum Grouping)	(Not defined, 28, 28, 128)	0
Conv2d (Convolutional Layer)	(Not defined, 28, 28, 256)	295168
Max_Pooling2D (Maximum Grouping)	(Not defined, 14, 14, 256)	0
Dropout(Regularization)	(Not defined, 14, 14, 256)	0
(Flattening)	(Not defined, 50176)	0
(Dense Cover)	(Not defined, 128)	6422656
Dense 1 (Dense Cover)	(Not defined, 64)	8256
(Dense Cover) 2	(Not defined, 32)	2080
(Dense Cover) 3	(Not defined, 1)	33

Table 3. Architecture adapted from the VGG16 model

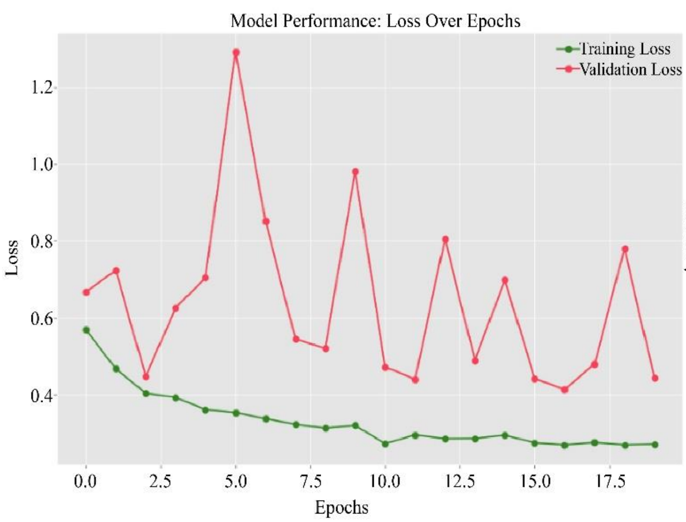
Model: "vgg16"		
Layer (type)	**Output Dimension**	**Number of Parameters**
InputLayer(InputLayer)	[(Not defined, 224, 224, 3)]	0
Conv2D (Block 1 - layer 1)	(Not defined, 224, 224, 64)	1792
Conv2D (Block 1 - layer 2)	(Not defined, 224, 224, 64)	36928
MaxPooling2D(Maximum Grouping)	(Not defined, 112, 112, 64)	0
Conv2D (Block 2 - layer 1)	(Not defined, 112, 112, 128)	73856
Conv2D (Block 2 - layer 2)	(Not defined, 112, 112, 128)	147584
MaxPooling2D (Maximum Grouping)	(Not defined, 56, 56, 128)	0
Conv2D (Block 3 - layer 1)	(Not defined, 56, 56, 256)	295168
Conv2D (Block 3 - layer 2)	(Not defined, 56, 56, 256)	590080
Conv2D (Block 3 - layer 3)	(Not defined, 56, 56, 256)	590080
MaxPooling2D (Maximum Grouping)	(Not defined, 28, 28, 256)	0
Conv2D (Block 4 - layer 1)	(Not defined, 28, 28, 512)	1180160
Conv2D (Block 4 - layer 2)	(Not defined, 28, 28, 512)	2359808
Conv2D (Block 4 - layer 3)	(Not defined, 28, 28, 512)	2359808
MaxPooling2D (Maximum Grouping)	(Not defined, 14, 14, 512)	0
Conv2D (Block 5 - layer 1)	(Not defined, 14, 14, 512)	2359808
Conv2D (Block 5 - layer 2)	(Not defined, 14, 14, 512)	2359808
Conv2D (Block 5 - layer 3)	(Not defined, 14, 14, 512)	2359808
MaxPooling2D (Maximum Grouping)	(Not defined, 7, 7, 512)	0
GlobalMaxPooling2D (Global Grouping)	(Not defined, 512)	0

3.4. Training Models

A kaggle dataset was used for the training process. This image set included 5216 for training, 624 for testing and 16 for validation. These images were divided into two classes: 4273 showed lungs with pneumonia, and 1583 were healthy lungs. In this training phase, the parameters of the two models were adjusted until their performance was optimized. This is crucial to ensure that the models work in the best way, not only with the training data but also that they generalize correctly with the test and validation data. The findings have shown that these approaches have great potential for application in diagnosing pneumonia, offering a reliable and accurate tool.

4. Results and Discussion

After training, we analyzed the results of the two CNN models (VGG16 and ResNet50-v2) with transfer learning. The ResNet50-v2 model obtained the best performance and adaptability, being the best classifier for this work, demonstrating great capacity to learn and generalize, which indicates its great potential for this type of task. On the other hand, the VGG16 model, in the test set, also showed significant results after epoch 50 in training, achieving an accuracy of 84.13% and a loss rate of 6.20%. These metrics reflect that the model has a great ability to make accurate predictions. Figure 6(a) shows how the model loss evolved during training. Although the loss is steadily decreasing, the validation loss shows some volatility. These results indicate that the model may have problems generalizing with new data. On the other hand, Figure 6(b) shows a similar behavior. In it, the training accuracy increases steadily, and the validation accuracy shows some fluctuations, so it could be pointed out that it presents an overfitting. These findings indicate that adjustments must be made in the architecture of the models to improve the training process, for which the dropout had to be included, to prevent the model from learning the training data by heart.

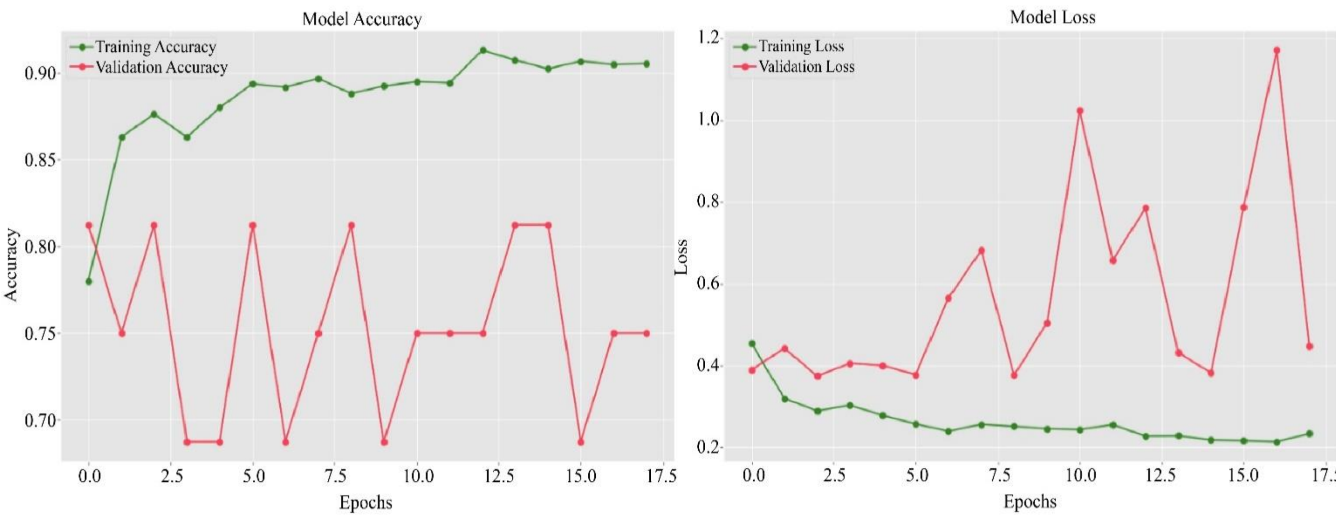


(a)

(b)

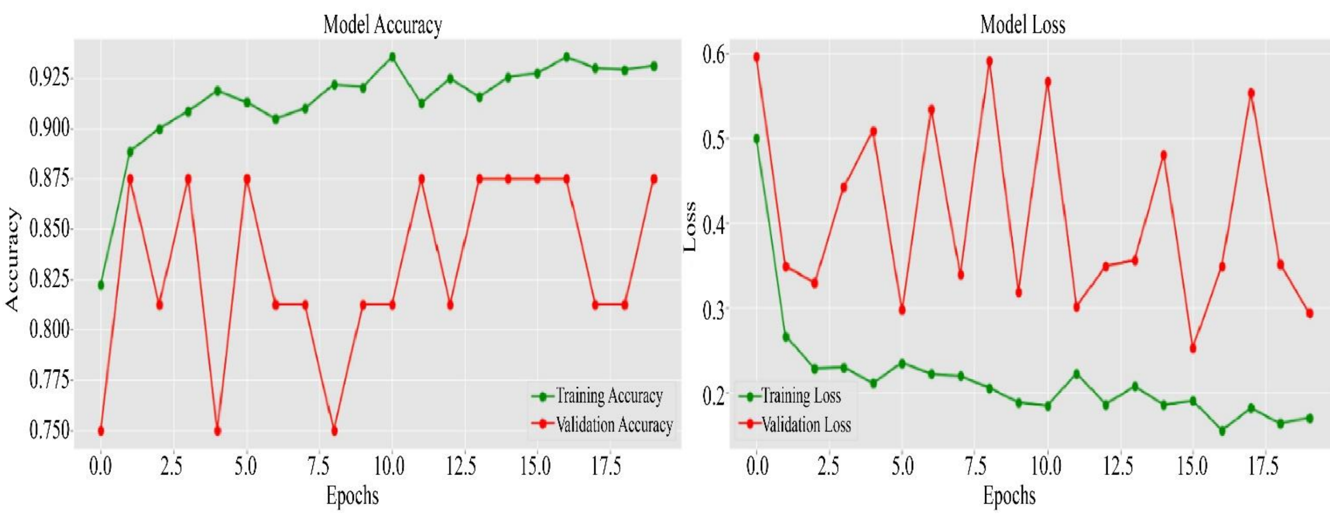
Fig. 6 Here, we compare how well Deep Learning models perform in classifying chest X-rays, 6(a)-6(b) shows losses, training accuracy and model validation

Figure 7(a), and 7(b) show how the VGG16 model behaved after applying transfer learning. Although it achieved a high training accuracy rate, the validation variability was worrying, indicating that the model presented overfitting with the training data. For this study, no additional technique was applied to refine the model, but it could be done so that the model does not learn the data by heart. Overall, the VGG16 model achieved an accuracy rate of 66.51% and a loss of 56.80% in the test set. Although these results are significant, there is room to optimize its generalization ability, specifically after epoch 20. At this point, it is worth highlighting the importance of rigorous evaluation to find a middle ground where the model retains what has been learned without losing the flexibility to adapt to new data. Although these results are significant, validation performance could be improved by addressing the overfitting problem with new techniques. For example, regulatory techniques such as dropout, this technique helps the model not to depend too much on certain neurons. One could also resort to data augmentation so that the model learns to generalize better with data it has not seen before. Figure 8(a) and 8(b) show the result of the ResNet50-v2 model. In it, very significant metrics are appreciated, with an accuracy of 90.8% in the test set and a loss of 25.57%, which proves to be an attractive tool for image classification. However, the accuracy during validation presented some variability, and the loss in validation also presented some oscillations. This indicates that, despite presenting good performance, the model can still be adjusted and calibrated for better results. These findings reaffirm that the ResNet50-v2 model integrated with transfer learning is an excellent choice for image classification tasks. While the results are significant, there is still room to improve the model by applying regularization techniques or adjusting some hyper-parameters to reduce variability and generalize better with new data.



(a) **(b)**

Fig. 7 Here, we compare how well Deep Learning models perform in classifying chest X-rays, (a) ans (b) It presents the metrics of the VGG16 model, showing the learning curve and the variations during the validation tests



(a) **(b)**

Fig. 8 Here, we compare how well Deep Learning models perform in classifying chest X-rays, (a)-(b) presents the training metrics of the ResNet50-v2 model and the stability discrepancy in validation

After evaluating each model, the results showed that the ResNte50-v2 model, powered by transfer learning, achieved the best accuracy rate of 90.87% for classifying chest X-ray images in the test dataset and with a fairly low loss rate of 25.57%. These metrics reinforce not only its effectiveness but also its robustness in classifying medical images. While true, the results are promising. However, some variability was observed during validation, indicating that the model can still be improved for better results. Even so, this model becomes optimal for specialized clinical applications where accuracy and reliability are key elements. Figure 9 shows how the ResNet50-v2 model classifies chest X-ray images. The image on the left was labeled “Normal”, with an accuracy of 99.84%. In this case, the lungs show a clean, uniform pattern, with no trace of abnormalities to indicate problems. On the other hand, the image on the right was classified as “Pneumonia” with an accuracy of 99.47%. In this image, one can see opaque areas with typical signs of a lung infection. These results demonstrate the efficiency of the model for this type of classification task, which could become an excellent tool for public health, capable of analyzing radiographs in a matter of seconds, providing accurate and updated information to make better and more timely decisions, and this in the world of medicine is a great step forward. With the advent of AI, specifically CNN models, medicine, particularly the early diagnosis and treatment of pathologies such as pneumonia, is experiencing great advances. In this case study, the ResNet50-v2 model has proven to be a useful tool for such tasks, achieving an accuracy of 90.87% in classifying pneumonia from chest X-rays. This reaffirms its effectiveness and demonstrates that it can be applied in real clinical settings, where early accuracy and speed are key factors.

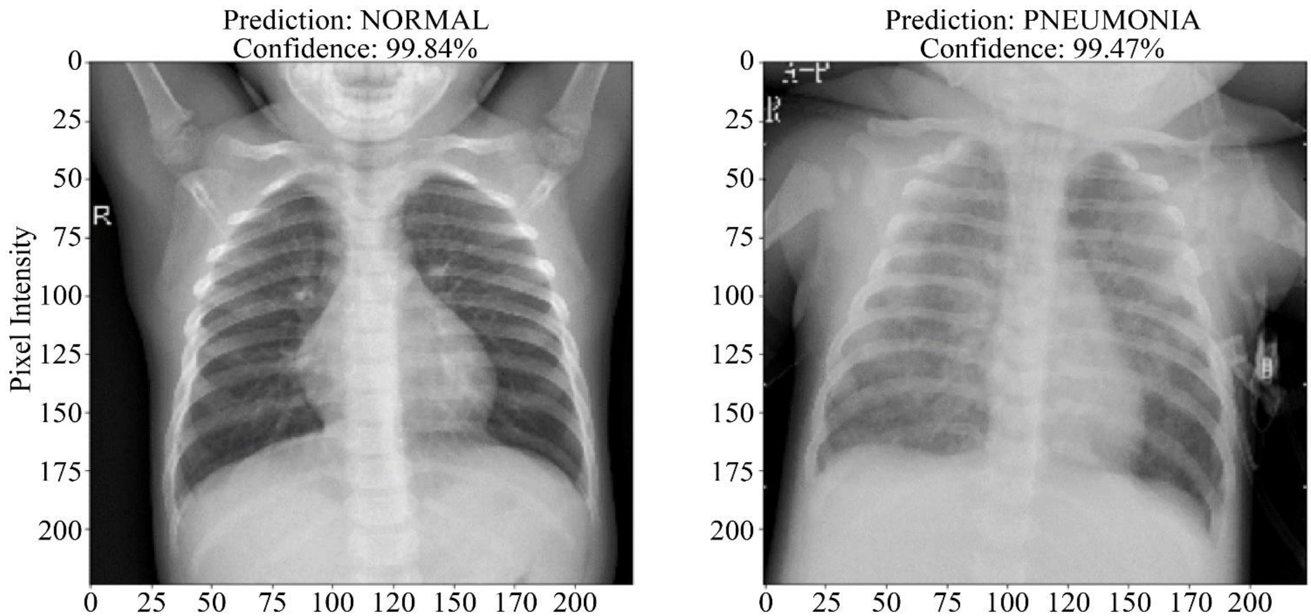


Fig. 9 Precision imaging with ResNet50-v2 versus chest radiographs

Also, previous studies, such as [31], have shown that the VGG16 and ResNet50-v2 models can achieve accuracies between 93% and 98.1% in detecting pneumonia and COVID-19. Some investigations, such as [44], achieved an accuracy of 99.33% using lightweight CNNs. However, the advantage of our research with the ResNet50-v2 model is in the balance and adaptability they achieved, which makes it special. This difference in metrics from our research is probably due to different factors, such as the techniques used and the volume of the data set, among others. Other studies have gone even further. For example, by combining Xception with ResNet50-v2 and VGG16, they have achieved close to 100% accuracy in COVID-19 detection.

This indicates that the choice of model and the size of the data set are key factors in maximizing diagnostic efficiency. However, the capability of these models is not limited to pneumonia or COVID-19 diagnosis alone. The VGG16 model, for example, has demonstrated a strong ability to identify features down to analyzing food components or classifying plants where image quality was not of high quality, demonstrating its ability to adapt to different datasets.

In the study [15], they trained a CNN model to diagnose COVID-19, which achieved an accuracy of 89.99%, even though it had difficulties in identifying the different types of pneumonia. This result correlates with our research findings, which have very similar metrics. On the other hand, in [25], they used transfer learning with optimized CNNs to improve pneumonia diagnosis, helping to improve the efficiency and accuracy of prediction. In this context, and for this type of task, the ResNet50-v2 model is presented as a key tool for diagnosing pneumonia. It achieved an accuracy of 90.87% in the classification of chest radiographs, being able to adapt to new data, which makes it a strategic ally for physicians. These features enable earlier and more accurate diagnoses and mark a before and after in the integration of AI in medical practice.

5. Conclusion

This work aimed to analyze two CNN models pre-trained to identify pneumonia from a dataset composed of chest X-ray images. To achieve this, transfer learning techniques were used. The results indicate that the ResNet50-v2 model is an effective tool for classifying pneumonia, achieving an accuracy of 90.87% and a loss rate of 25.57%. These results demonstrate the model's ability to handle clinical diagnoses in real-world settings. What makes the ResNet50-v2 model stand out in this type of task is its adaptability and its ability to avoid overfitting, which is very important when trying to generalize with new data. Compared to other traditional CNN architectures, such as the VGG16, this model behaves in a more balanced way, making it a much more reliable choice for this type of diagnostic task.

However, it is not just a matter of choosing the right model. This work also highlights the importance of carefully configuring the model parameters to ensure that they are more accurate and reliable in real situations in the clinical field. This approach not only improves timing, timely decision-making, and accuracy in predicting certain tasks but also represents a major step forward in how to apply DL in medical image analysis. In future work, a possible line of research would be to combine chest X-rays with other types of medical data, such as CT scans, to enrich the diagnosis. This integration would allow a more accurate results approach. On the other hand, the implementation of explainable AI techniques can help clinicians understand how the model arrives at such conclusions. Also, it would be important to develop lighter and more efficient versions of the model to run locally on less powerful hardware, such as mobile devices or low-performance computers. Regarding the limitations we found when training the models, 1) the performance of the CNN models is directly related to the quality and diversity of the dataset. Another limitation has to do with differentiating the types of pneumonia. For example, like other models, ResNet50-v2 had difficulty differentiating between different types of pneumonia and other lung conditions with similar symptoms. Also, it was evident that the model required careful adjustment of hyper-parameters and processing techniques to achieve its best version. This process is laborious and requires technical and specialized knowledge, which may limit its implementation in resource-limited environments.

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