# Deep Learning and Grad-CAM for the Diagnosis of Pneumonia Based on X-Rays

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2023 International Conference on Innovations in Engineering and Technology (ICIET) | 979-8-3503-0999-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICIET57285.2023.10220839

***Abstract*—Millions of people throughout the world suffer from pneumonia, an extremely serious respiratory disease. An early and accurate diagnosis is crucial for the quick and effective treatment of pneumonia. Deep learning approaches have recently demonstrated promise in the recognition of medical imaging, particularly X-ray pictures. We propose deep learning-based method for recognising pneumonia from X-ray pictures in this paper. To categorise photos, we employ a convolutional neural network (CNN), and the Grad-CAM method visualises the model's predictions. The results of our investigation indicate that our proposed approach may successfully and reliably detect pneumonia in X-ray images and provide visual reasons for the predictions. By increasing the effectiveness and precision of pneumonia diagnosis, the application of this methodology has the potential to have a substantial impact on the medical industry.**

***Keywords*—Convolutional Neural Network (CNN), GradCAM, Deep Learning, X-ray images, Pneumonia**

## I. INTRODUCTION

A serious respiratory condition that affects a lot of individuals worldwide is pneumonia. For rapid and successful treatment of pneumonia, an early and precise diagnosis is essential. New strategies for diagnosing pneumonia have emerged in recent years as a result of improvements in medical imaging technology. Particularly for processing medical images, especially X-ray pictures and deep learning algorithms have shown huge potential.

Convolutional neural networks (CNNs), which are a kind of deep learning algorithm, have demonstrated that they perform exceptionally well in image classification tasks including the recognition of medical illnesses from X-ray pictures. For medical professionals, these models' judgements can be complex and challenging to understand. We propose the GradCAM technique to address this issue by emphasising particular regions in X-ray pictures that have greatest impact on the final decision and by visualising the predictions made by the deep learning models.

In this paper, we explain deep learning based method for visual estimation and description for pneumonia identification from X-ray pictures that utilises the GradCAM algorithm. The regions in the X-ray pictures that contribute to the predictions are visually represented in our suggested technique, which detects pneumonia with high accuracy. The use of this technology could considerably increase the effectiveness and precision of pneumonia diagnosis in the medical industry.

Our project seeks to provide a reliable and effective deep learning method for identifying pneumonia in X-ray pictures and visual explanation techniques. In the past, radiologists' subjective assessments have been used to make the bulk of pneumonia diagnoses, which can lead to disparities and inaccurate diagnoses. Deep learning techniques and X-ray imaging are becoming more widely available, and this presents an opportunity to use these tools to increase the precision and regularity of pneumonia diagnosis.

In the world of medicine, determining the cause of pneumonia continues to be quite difficult. The subjectivity of the diagnostic process has led to discrepancies and misdiagnosis despite improvements in medical imaging and treatment choices. Convolutional Neural Networks (CNNs), in particular, have emerged as powerful deep learning tools that have opened up new possibilities for the automatic processing of medical pictures, including X-ray images.

The accuracy and consistency of pneumonia diagnosis could be considerably enhanced by using our suggested methods. Medical professionals will have access to a trustworthy and effective tool for the diagnosis of this severe respiratory illness by utilising the power of deep learning and visual explanation approaches. The findings of this study will support continuing initiatives to increase the precision and effectiveness of medical treatment and diagnosis.

## II. Related Works

To assess performance of Vgg16 and Xception CNN networks in identifying pneumonia from X-ray pictures of the chest. Also models were trained using tuning and transfer learning. Then the results showed that Xception outperformed Vgg16 in sensitivity, normal precision, and pneumonia recall while Vgg16 exceeded Xception in accuracy, specificity, pneumonia precision, and pneumonia f1 score. The findings demonstrated that each network has distinct advantages in identifying pneumonia and non-pneumonia cases. Using an ensemble method, future work will combine the strengths of both networks to more accurately diagnose pneumonia from chest X-ray pictures. [1]

This research presents a novel approach for quantifying bias in chest X-ray (CXR) image collections. The classification objective is focused on the lungs, and methods including histogram analysis, selective picture occlusion, and activation heatmap visualisation are employed to find the discriminative features. The findings demonstrated that some datasets, such the COVID-19 and BIMCV collections, have higher bias issues than others. The widely-used COVIDcxr dataset shows that large biases can arise when combining datasets from several sources. Although a good classification rate based on features discovered by Deep Convolutional Networks can be achieved with this type of heterogeneous dataset, due to the blending of observations from multiple equipment, acquisition techniques, and processing software, actual performance for the clinical job may be lower [2].

On a dataset for the early identification of pneumonia, two CNN classifier models were trained. Model 3's three convolutional layers produced results of 92.31 percent validation accuracy, 98 percent recall, and 94 percent F1 score. Model 4 scored 91.67 percent accuracy, 98 percent recall, and 94 percent F1 score with four convolutional layers. Both models are highly recallable and work well for diagnostic purposes. The models were developed utilising a variety of strategies for optimization, and they can process X-ray pictures fast for accurate findings, assisting healthcare systems in providing effective care and lowering death rates. [3]

The study's objective was to investigate whether deep transfer learning might be used to identify pneumonia through chest X-ray input image. The deep learning models Inception V3, ResNet-50 and also DenseNet121 were trained via deep transfer learning as well as training from scratch. The models in the deep transfer learning approach were initially adjusted on a sizable dataset and then tested on a more focused dataset for the classification of pneumonia. The experiment's findings demonstrated that transfer learning performed better than training from scratch, which is a common tendency in deep learning but still has to be confirmed in medical domains. The researchers came to the conclusion that transfer learning can significantly improve performance with only a few training epochs, making it an economical choice for creating deep learning-based systems for medical diagnostics, such as the categorization of pneumonia. The results support transfer learning as a practical and successful clinical deployment technique [4].

Current pandemic highlights the importance of incorporating diagnostic decision assistance technologies into clinical decision making. To categorise chest X-ray (CXR) images, the authors introduce a training a Convolutional Neural Network on an unlabeled dataset of Chest X-ray images. This method demonstrates that CNN networks may be trained using semantically relevant images, in this case the ChestXpert dataset, instead of just natural photos, which reduces the requirement for labelled data, which is limited and expensive in the medical arena. The findings demonstrate the unsupervised model's competitiveness with supervised counterparts and its enormous development potential [5].

This proposed effort intends to accurately identify healthy and sick lungs from X-Ray pictures, including COVID-19 and pneumonia. With 95 percent accuracy for COVID-19, 80 percent accuracy for bacterial pneumonia, and 91.46 percent accuracy for viral pneumonia, a CNN model is employed for detection. The model is affordable and simple to use for researchers and medical professionals. An ensemble of models can boost accuracy, albeit at the expense of more time and computational resources [6].

The paper's main goal is to enhance medical diagnosis in regions with insufficient radiologists' availability. The objective is to make early pneumonia diagnosis easier in order to avoid negative outcomes in rural locations. To determine the most effective set of pretrained CNN models and classifiers for identifying pneumonia, the authors ran experiments on a variety of them. The findings indicated that the ideal pairing was SVM for classification and DenseNet-169 for feature extraction. Additionally, hyperparameter adjustment was carried out to enhance the model's functionality. The project's goal is to support the development of more effective strep throat detection algorithms by providing a potent pre-trained CNN model and classifier for future work in this field [7].

EEP networks, which have more complicated structures and need less processing power but are more accurate, are used in the method. Over fitting, which happens when there aren't enough training data, was dealt with via transfer learning and data augmentation. A weighted classifier was suggested as a useful way to properly mix various network architectures. The results of the experiment revealed that the proposed model had an accuracy of 98.85%, a high F1 score of 99.002, and an AUC score of 99.809, demonstrating its robustness and efficacy. The author advises that future studies might look into methods for more effectively estimating the weights for various models and for include patient history in forecasts [8].

The research presents PNet, an unique neural network design for detecting pneumonia in chest X-ray pictures. In comparison to other well-known models like AlexNet and VGG16, the authors of the research assert that the use of small size convolution filters for feature extraction yields higher accuracy and requires fewer parameters. They were able to detect pneumonia in medical photos with PNet with an accuracy of 92.79 percent and an F1 score of 0.9393, demonstrating the effectiveness of their method [9].

This research compares the efficacy of mask-RCNN and residual network in detecting pneumonia from chest X-ray pictures. The inability to locate pneumonia characteristics leads to the discovery that residual network outperforms mask-RCNN. The unbalanced dataset results in a significant gap in sensitivity and specificity. The ideal architecture for a pneumonia computer-aided diagnosis system can be found in future study by adjusting hyperparameters, using more complicated network structures, and enhancing the unbalanced dataset [10].

## III. Methodology

### A. Data Collection

The first step in the process for the project "Deep Learning and Grad-CAM for the Diagnosis of Pneumonia Based on X-Rays" is "Data Collection." This step involves collecting X-ray pictures of people with and without pneumonia from a number of sources, including hospitals, clinics, and online datasets. The pictures must clearly and visibly show pneumonia symptoms, be of a high quality, and have the proper labelling. It's critical to have a balanced dataset with an equal amount of images for each class in order to prevent any bias in the model. Furthermore, the collected data must be cleaned, checked for inconsistencies, and split into training, validation, and test samples.First, the pre-processed data should be stored in a secure and accessible location for use in the next steps of the methodology.Count of cases in the data set shown in the below Figure 1.

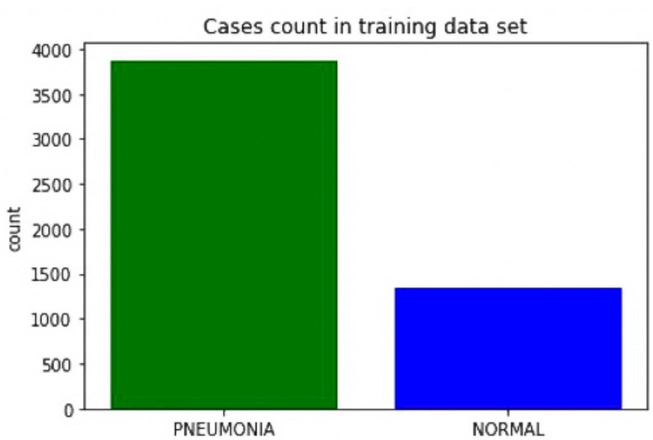


Figure 1: Cases count in training data-set

### B. Data Pre-processing

Image cleaning is performed by using 'cv2.resize' technique of OpenCV. Using the 'cv2.IMREAD_GRAYSCALE' flag, this method resizes the input image to a specific size (in this case, 256x256), then turns it into grayscale. As a result, the model only needs to analyse grayscale images of a set size during training, which helps to standardise the image size and minimise the model's complexity. For the model training, this entails getting ready the gathered X-ray pictures.

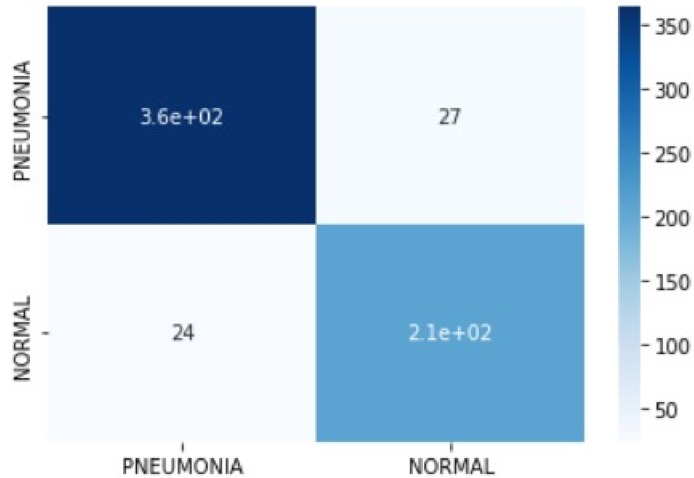


Figure 2: Vision transform confusion matrix

The pre-processed data should be verified and confirmed for consistency to make sure the photos are prepared for model training. The pre-processed data is then prepared for use in the methodology's model development phase, which comes next. Data pre-processing is a crucial step that ensures the model can properly process the X-ray pictures and boosts performance.Vision transform confusion matrix after pre-processing shown in Figure 2.

### C. Model Development

Model creation entails creating a deep learning model, such as a convolutional neural network, to recognise pneumonia in X-Ray pictures (CNN). To create a model that is accurate, efficient, and capable of generalising well to new data, a number of procedures must be taken.

The data are initially split into two groups training and validation. The model is next trained on the training set to minimise the loss function between the predicted and actual labels for the X-Ray images. The hyperparameters of the model, such as the learning rate and the number of hidden layers, are also adjusted during the training phase to improve its performance on the validation set.

Once the model has been trained, it is evaluated on the validation set to determine its accuracy and assess its performance. The results of the evaluation are used to refine the model as needed, by making changes to its architecture or hyper parameters.This procedure is repeatedly performed until the desired level of precision has been obtained.

Lastly, once the model has been optimized, it is saved for deployment in a real-world setting. This involves saving the model and its parameters so that it can be used for making predictions on new X-Ray images. It is possible to develop an accurate and effective deep learning model to detect pneumonia in X-Ray images by following this methodology. Figure 3 shows an X-ray image of an attention map.

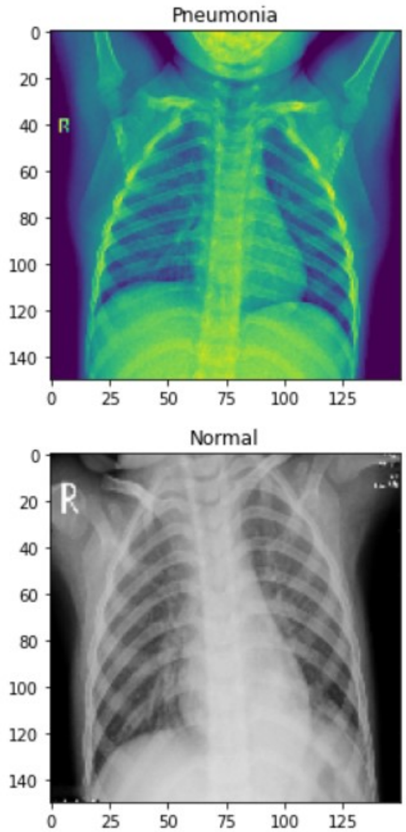


Figure 3: Chest X-ray image attention map

The model evaluation step's goal is to assess the deep learning model's performance in detecting pneumonia in X-Ray images. This step is critical for ensuring that the model is accurate, effective, and generalizes well to new data.
Analyze model performance: On the validation set, examine the model's accuracy, precision, recall, and F1-score. These indicators provide a detailed analysis of the model's effectiveness and aid in identifying potential areas for improvement.
Visualize model predictions: Visualize the model's predictions on the validation set to understand better its behaviour.This aids in finding trends in the behaviour of the model and figuring out why some forecasts were off.
Analyze false positive and false negative cases: To determine the causes of the model's inaccurate predictions, analyse false positive and false negative cases. The model can be improved upon using this data to make it more accurate and perform better.
Compare model performance with baseline: Compare the deep learning model's performance to that of a baseline model, such as a traditional machine learning algorithm, to determine the advantages and limitations of using deep learning for the task.
Determine the optimal threshold: Determine the best prediction threshold, as this can have a big impact on the model's effectiveness. The threshold value is the value that distinguishes between positive and negative predictions.

These evaluations allow us to assess the deep learning model's performance in detecting pneumonia in X-Ray input image and identify areas for improvement. The results of the model evaluation step can be used to refine the model and ensure that it is accurate and effective for deployment in a real-world setting.

Evaluation accuracy and loss shown as graph in below Figures 4 and 5.

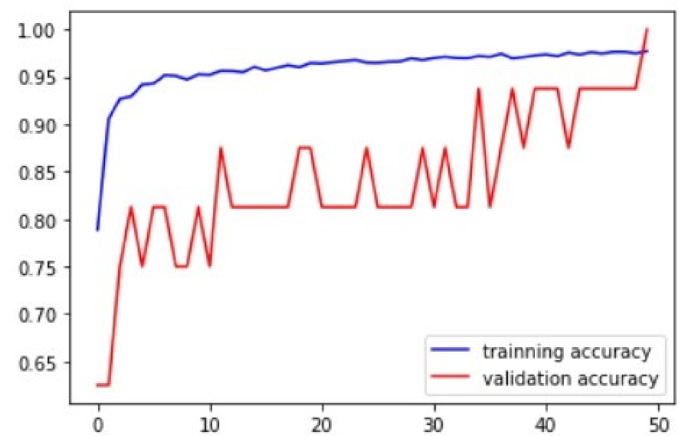


Figure 4: Evaluation accuracy

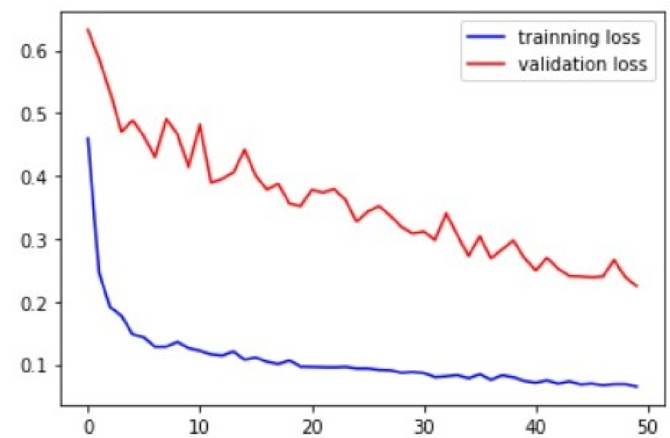


Figure 5: Evaluation loss

*D. Gradient-weighted Class Activation Mapping (Grad-CAM)*

Apply the Grad-CAM technique to the deep learning model that was developed in Step 3.This produces a heatmap that highlights the regions of the X-Ray image where the model is making predictions. Visualize the heatmap generated by Grad-CAM to get a better understanding of the model's behavior. The heatmap highlights the X-Ray image regions that the model is using to make predictions, and provides a visual representation of the model's decision-making process. Analyze the heatmap to determine why the model made the predictions that it did. This information can be used to identify areas for improvement and refine the model and alidate the results of the Grad-CAM visualization by comparing the heatmap with the actual X- Ray images and the model's predictions. This helps to ensure that the heatmap accurately represents the model's decision- making process.

By using Grad-CAM to visualize the decision-making process of the deep learning model, it is possible to learn more about the model's behaviour, and identify areas for improvement. The results of the visualization using Grad-CAM can be used to refine the model and ensure that it is accurate and effective for detecting pneumonia in X-Ray images.

### *E. Deployment*

The deployment step involves using the optimized deep learning model for making predictions on new X-Ray images. This is the final step in the deep learning and Grad-CAM methodology for detecting pneumonia in X-Ray images.
Load the optimized model: Load the optimized deep learning model that was developed and evaluated in Steps 3 and 4. This involves loading the model and its parameters so that it can be used for making predictions.
Make predictions on new data: Use the optimized model to make predictions on new X-Ray images. The model will provide a prediction for each image, indicating whether or not the image contains pneumonia.
Validate the predictions: Validate the predictions made by the model by comparing them to the actual labels for the new X-Ray images. This helps to ensure that the model is accurate and effective when applied to new data.
Monitor the performance: Monitor the performance of the model over time to ensure that it continues to perform well on new data. This can be done by periodically evaluating the model on a validation set and making adjustments as needed to ensure that its performance remains optimal.

By following this methodology and deploying the optimized deep learning model, in a real-world setting, pneumonia can be detected in X-ray images. The model can be used to make predictions on new X-Ray images and provide valuable information for medical professionals in the diagnosis and treatment of pneumonia.

## IV. CONCLUSION AND FUTURE WORK

In conclusion, the deep learning and Grad-CAM presented methodology for pneumonia diagnosis in X-ray pictures offers a reliable and effective method for completing the task.It becomes a helpful tool for clinicians in the diagnosis of pneumonia thanks to the integration of the deep learning model with Grad-CAM visualization, this helps to improve forecast accuracy and reliability. The methodology's element of constant development makes sure the model stays current and applicable, giving patients the greatest outcomes possible. Overall, this methodology offers a strategy that has the potential to significantly enhance patient outcomes for identifying pneumonia in X-ray pictures.

The combination of deep learning and Grad-CAM for the X-ray-based diagnosis of pneumonia is a rapidly growing subject with a number of potential directions for further study. Exploring the use of larger datasets to increase the precision and generalizability of deep learning models is one path for future research. To better capture the spatiotemporal characteristics of X-rays, more intricate designs like 3D CNNs can be investigated.

Future research should also focus on how to incorporate clinical data into deep learning algorithms. The accuracy of pneumonia diagnosis can be increased by including data such as patient demographics, medical history, and clinical symptoms.

Grad-CAM, which creates heatmaps of the areas of the X-ray image that are most suggestive of pneumonia, can also improve the interpretability of deep learning models. This can aid medical professionals in better comprehending the diagnosis' underlying principles and locating any potential areas of uncertainty. In order to enhance the diagnosis of pneumonia and other respiratory diseases, deep learning and Grad-CAM can also be applied to other medical imaging modalities, such as CT scans and MRI.

The exploration of ethical principles and considerations for the use of deep learning and Grad-CAM in medical imaging should address ethical issues like privacy, bias, and the possibility of misdiagnosis. In general, the application of deep learning and Grad-CAM for the diagnosis of pneumonia based on X-rays is a field that is rapidly developing and has significant potential to enhance the results for patients and healthcare systems.

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