

Automated Diagnosis of Pneumonia from Chest X-Ray Images Using Convolutional Neural Networks

Preeti P Mulge¹, Dr. Savitha Patil²

¹*M.Tech. Scholar, Dept. of Computer Science & Engineering (Co-Ed.), Sharnbasva University, Kalaburagi, Karantaka-India*

²*Associate Professor, Dept. of Computer Science & Engineering (Co-Ed.), Sharnbasva University Kalaburagi, Karantaka-India*

Abstract—Pneumonia is a severe infectious disease that usually results from a bacterial infection within the alveoli of the lung. The infection can cause the lung to become inflamed with pus, which makes breathing difficult and can have other serious health consequences. Medical practitioners commonly utilize imaging such as chest X-ray, ultrasound, or biopsy of lung tissue to properly diagnose pneumonia; however, improper diagnosis can lead to the incorrect course of treatment, potential worsening of a patient's condition, and in extreme cases, death.

With the rising advances in deep learning and more specifically deep learning approaches using Convolutional Neural Networks (CNNs), we can now potentially help clinical practitioners accurately diagnose pneumonia more efficiently through the use of a deep learning method that automatically detects and classifies patients as being healthy or affected using chest X-ray images. In this study, we discussed the proposed deep learning method, implemented using CNNs, to automatically detect the patients as healthy or affected based on the chest X-ray images. The dataset consisted of 20,000 chest X-ray images resized to 256x256 pixels and loaded in batches of 32 until all images were loaded. The trained model achieved a performance evaluation of 95% accuracy.

The results of the study show that the proposed CNN model can quickly and accurately determine the presence and distinction between COVID-19, bacterial pneumonia, and viral pneumonia using chest X-ray images. This study demonstrates the clinical feasibility of the model and its potential to quickly identify pneumonia type for appropriate treatment.

Index Terms—pneumonia detection; Chest X-ray; deep learning; CNN (Convolutional Neural Network); medical imaging; COVID-19 classification

I. INTRODUCTION

While pneumonia is not the only cause of morbidity and mortality worldwide, it is one of the leading causes, especially in vulnerable populations such as children, the elderly, and the immunocompromised. As a major cause of morbidity and mortality, a timely and accurate diagnosis is crucial for collation treatment and management of the disease. Chest X-ray imaging is common, cost-effective, and easily available to clinicians for assessing pneumonia. However, they require considerable expertise to a level of proficiency to interpret, and there remains the consistency and accuracy of the radiologist in making a diagnosis. Furthermore, occasional settings may have limited access to skilled radiologists. Recent progress in deep learning, particularly Convolutional Neural Networks (CNNs), has created opportunities to automate medical image analysis with impressive accuracy. CNNs have demonstrated tremendous capability for real-time image classification and pattern recognition, so they are intended to analyze complex visual data such as chest radiographs. With an understanding of hierarchical feature representations from numerous datasets, CNNs will distinguish normal lungs from pneumonia- infected lungs.

This project hopes to develop an automated approach for pneumonia detection and classification, based on chest X-ray images and also driven by CNN-based deep learning models. The proposed automated system will use pre-trained neural networks (such as VGG16, ResNet50 or EfficientNet) in addition to transfer learning and fine-tuning approaches for medical imaging tasks. This automated system will be trained

and evaluated on the established datasets such as the Chest X-Ray Images (Pneumonia) dataset or NIH ChestX-ray14 (Kaggle), both of which contain labelled radiographic images of pneumonia and healthy cases.

The framework includes key components such as preprocessing the image data, data augmentation for enhanced model generalization, and evaluating model performance through metrics like accuracy, precision, recall, and AUC-ROC. The objective was to create a reliable, scaleable, and interpretable diagnostic decision support tool that could help medical practitioners recognize pneumonia earlier, therefore potentially alleviating diagnostic time, and improving clinical outcomes.

By incorporating deep learning into the diagnostic processes, this project progressed the broader vision to use technology to create intelligent and accessible healthcare.

II. LITERATURE SURVEY

There are many studies that have evaluated the use of deep learning architectures, particularly Convolutional Neural Networks (CNNs) for the detection and classification of pneumonia from chest X-ray images. The models have been shown to have good accuracy and reliability and can be productively integrated into real-world healthcare environments. One study used VGG16 and ResNet152V2 architectures to demonstrate that they achieved accuracies of 96.56% and 95.34% respectively, which affirmed that CNN models can reasonably support pneumonia diagnosis using 5,836 labelled images [1]. Another study presented a solid CNN-based model with training and validation accuracies of 88.16% and 88.45% respectively, supporting its reliability in diagnostic testing [2]. A further study presented a CNN model with a test accuracy of 83.75%, supporting its real-world healthcare potential [3]. Transfer learning using Xception and VGG16 models are used to increase performance yet reported only up to 89.23% accuracy also accounting for points of concern, such as the effect of imbalanced data [4]. In a different study with pre-trained CNNs such as VGG-16 and ResNet-50 as architecture, they reported an overall accuracy of 86.78%, noting a validation accuracy of 90.78%, precision of 89.88% and sensitivity of 95.97% [5]. In other approaches, ensemble models

using combinations of architectures had been made an effort, through which an accuracy of 88.99% was noted. In addition to reporting precision of 0.9861 and recall of 0.9813 [6]. With several other study results mentioning their Computer-Aided Diagnosis (CAD) system based on CNNs and their reported accuracy were very consistent, with as high of an accuracy of 98.59% indicating successful classification of chest X-rays as normal or pneumonia affected [7][8]. One study reported a VGG16 with a weighted average ensemble model that achieved 89% accuracy overall and discussed how it could be applied where resources are limited [9]. There was also research performed with a ResNet50 model which had a test F1-score of 86% which would be helpful for radiologists to assist them in making accurate and timely diagnosis [10]. Another study described combining ensemble learning with transfer learning in a study that demonstrated potential for very accurate predictions and clinical implementation [11]. There are now many studies published reporting high CNN model performance with pneumonia detections, as well as very strong test accuracy, sensitivity, specificity results. This type of analysis provides evidence for their contribution in automated detection systems and the overall improvement of patient outcomes [12][13]. Multiple studies report ensemble models using VGG16 and MobileNetV2 and InceptionV3 achieved significant test accuracy of a near 88.63%. These provide researchers with considerable improved speed and accuracy rates in diagnosis [14][15]. Additionally, there has been a discussion with lightweight CNN models to effectively reduce memory and computation requirements and maintain important targeted diagnostic or advanced trained model performance with methods of large dataset preprocessing approaches like progressive resizing and contrast enhancement where appropriate to guarantee suitability for key resource limited environments. For example, VGG16 achieved 85% test accuracy with "no pneumonia" precision of 0.94 and "pneumonia" precision of 0.95 [17]. In some studies, researchers proposed a modified architecture to already established CNN models that achieved up to 89% accuracy overall, including options that reduce dependency on the commonly required expert radiologist [18]. VGG16 has been successfully utilized for preprocessing steps in pneumonia detection pipelines [19]. Then, recent work implemented

transfer learning along with models such as AlexNet and adversarial training to enhance generalization performance when combining real and synthetic chest X-ray images [20].

III. PROBLEM STATEMENT

The manual detection and diagnosis of pneumonia from chest X-ray images can be affected by human error and variability, particularly in lower resource environments with limited access to radiological expertise. Conventional means of manual diagnosis of pneumonia from chest radiographs can take time and often lack consistency. The aim of this project is to develop an automated diagnostic system that is based on deep learning, specifically Convolutional Neural Networks (CNN), to detect and classify pneumonia having high accuracy when using chest radiographs. The goal is to enhance the diagnostic ability speed, precision and access in clinical settings, as well as more remote environments.

IV. OBJECTIVES

- To understand different biomedical terms associated with pneumonia.
- To understand different scenarios of pneumonia (viral or bacterial).
- To understand various data acquisition methods.
- To know about different image processing pre-trained models.
- To develop a web application to analyze Pneumonia disease using chest X-ray.

V. ALGORITHM AND METHODS

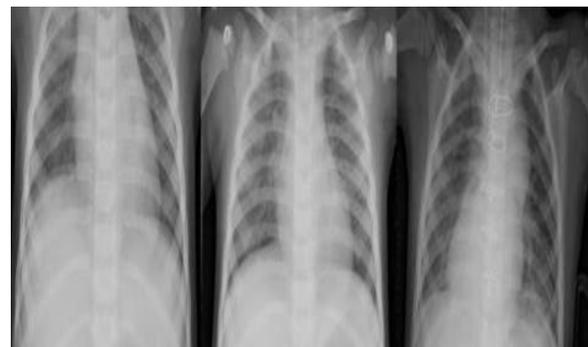
5.1 Data Acquisition

The database used to examine the model's performance includes a total of 5863 X-ray pictures from the Kaggle. This database is split into 3 folders (Train, Test, Val) with subfolders for each type of image (Pneumonia / General). All the images were standardized to a fixed A, a few samples of Common and Pneumonia images are shown in Figure 1. Chest X-ray images always have indications of limited brightness because of the low dose of exposure in patients; chest X-ray images always have black, white and grey pants. The lung areas on both sides of the thoracic cavity can be

identified readily by X-ray which is almost black the lungs will have blacked. The heart is located between the lungs as well, and it appears nearly white on an X-ray because the X-ray beams can easily penetrate the heart. Bones are made of protein and are very dense, hence, the X-ray beams cannot penetrate them and thus the bones are seen as almost white on the X-ray film. Ku also note that the bones have distinct edges.



(a)



(b)

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

5.2 Data Pre-processing

Our original images contain RGB coefficients in the 0-255 range, but such values would be too high for our models to process, assuming a typical learning rate, hence we want to apply our model with values between "0" and "1," not just where we are scaling with a factor of 1/255. shear range is for randomly applying shearing transformations, and zoom range is for randomly zooming inside pictures, horizontal flip is specifically for randomly flipping half of the images horizontally - this is relevant when we have no horizontal asymmetry (e.g. real-world pictures).

5.3 Proposed Network

The study created a CNN model that was able to extract features of chest X-ray images and use them to determine if a patient had pneumonia. In our CNN Architecture, we started with 32 filters and increased them, layer by layer. Built a model with a Conv2D layer, then a Carpooling layer. A kernel size is preferable to be an odd number, like 3x3.

Activation functions such as Tanh, ReLU, etc could be used, but ReLU is the preferred option. Input shape is where the image width & height takes place like in the last dimension being the color channel. After the CNN layers, we Flatten the input and then went into the ANN layers.

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

$f(x) = \max(0, x)$ $S(x) = \text{Sigmoid}$ $f(x) = \text{ReLU}$

We used the activation function SoftMax for the last (ANN Layers) layers and defined the units as the total number of classes, used sigmoid for the binary classification and set unit to 1.

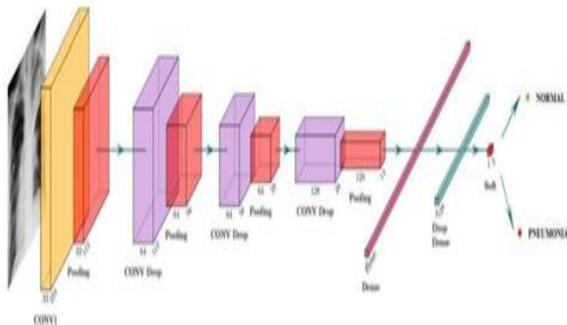


Fig 2. Details of proposed DL mode

5.4 Working Theory

Convolutional neural networks refer to a sub- class of neural networks: they have all the properties of the neural networks but specifically designed for input images, therefore their architecture is then more particular: they are composed of two main blocks.

Conv Layers

The first block delineates the particularity of this type of neural network, since this acts as the feature extractor. It does this by employing some template votes by applying convolution filtering operations. The first layer generally filters the image by different convolution kernels will return "feature maps", which then are normalized (with an activation function) and/or resized.

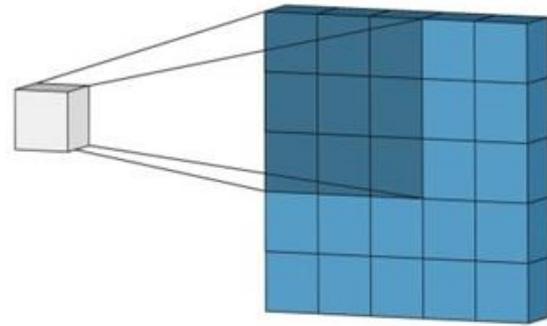


Fig: 3 Convolved features

Pool Layers

The second block is not reminiscent of a CNN: this is in fact at the end of all neural networks used for classification. The values in the input vector are manipulated (combined linearly, combined using activation functions) and return a new vector to the output. This last vector has as many elements as there are classes: element I now is the probability that the image belonged to class I. So, each element therefore is between 0 and 1, and the sum of all is worth 1. The last layer of this block (and thus, the network), applies a Sigmoid function (for for binary classification) or a RELU function (for further classes) as an activation function.

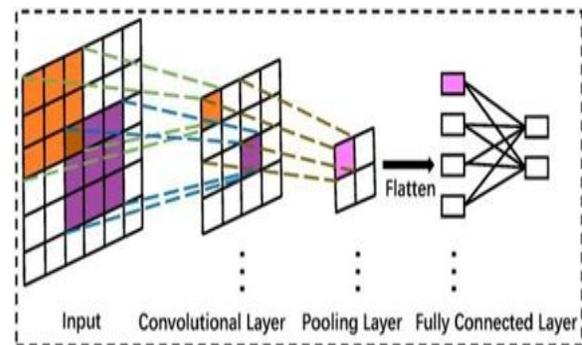


Fig. 4. Mathematics of Conv and Pooling Layer Activation Function

An activation function is the mathematical function that is applied to the output of a neuron in a neural network. It induces non-linearity into the network that allows the network to learn complex relationships between the inputs and outputs. Some of the frequently used activation functions include: sigmoid, ReLU, and tanh functions.

ReLU

Rectified linear unit is most widely used and preferred

activation function right now which ranges from 0 to infinity, All the negative values are converted into zero.

$$f(x) = \max(0, x)$$

Sigmoid

The sigmoid function also called as logistic function. having a characteristic can take any real value and map it to between 0 to 1. It decides which value to pass as output and what to not pass.

VGG16 Model

VGG16 is a popular deep learning architecture that is commonly used for image classification. VGG16 contains a total of 16 layers. VGG16 consists of 13 convolutional layers and 3 fully connected layers. The convolutional activations contain small filters with size of 3x3 with stride of 1, which are followed with max pooling. The final fully connected layers which generates the final classification task.

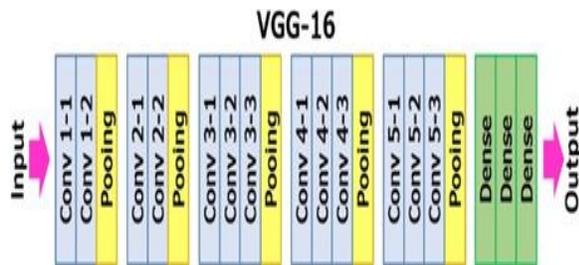


Fig. 5. VGG16 Model Sequence

VI. IMPLEMENTATION AND TESTING

We have analyzed the performance of these bellow CNN architectures namely; Alex Net, ResNet-50, and VGGNet-16.

Table 3. Analysis of model Performance for CNN Models with 32 Batch Size

CNN Model	Batch Size	Criterion	Normal	Infected with Pneumonia
VGG 16	32	Precision	0.92	0.89
		Recall	0.81	0.96
		F1-score	0.86	0.92
ResNet-50	32	Precision	0.85	0.85
		Recall	0.87	0.84
		F1-score	0.83	0.80
AlexNet	32	Precision	0.78	1.00
		Recall	1.00	0.88
		F1-score	0.85	0.94

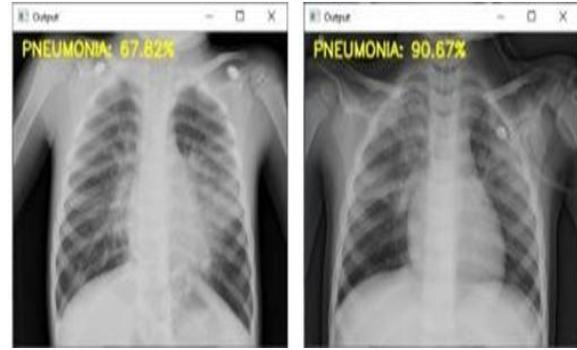


Fig 6 ResNet-50

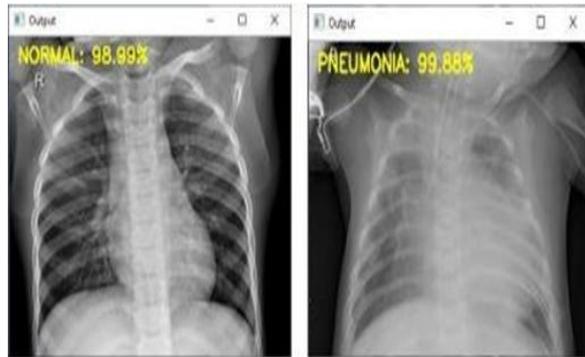


Fig 7 AlexNet

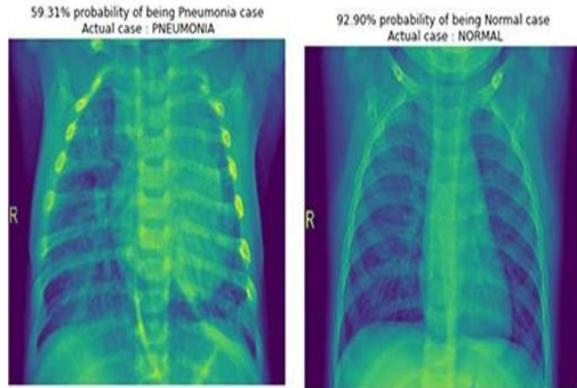


Fig 8 VGG16

VII. RESULTS

7.1 Pre-processing Image

For this step, we will utilize an Image Augmentation process to artificially increase the size of the image training dataset.

Image Augmentation increases the size of the dataset by altering the original training set images, ultimately increasing the varietal difference of the dataset, therefore increasing the model's ability to predict new images.

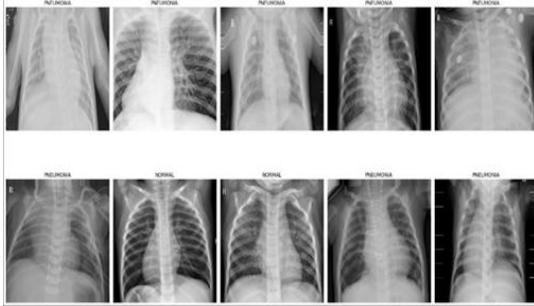


Fig. 9 Images from the Augmented Dataset

7.2 Confusion Matrix

Now let's interpret the outcome of the confusion matrix. The top left (TP) indicates how many images were predicted accurately as normal cases, and the bottom right (TN) indicates how many images were predicted correctly as pneumonia cases. The pneumonia case is represented by top right as incorrectly predicted as pneumonia but actually was a normal case. Bottom left as incorrectly predicted Normal case images, but actually pneumonia cases.

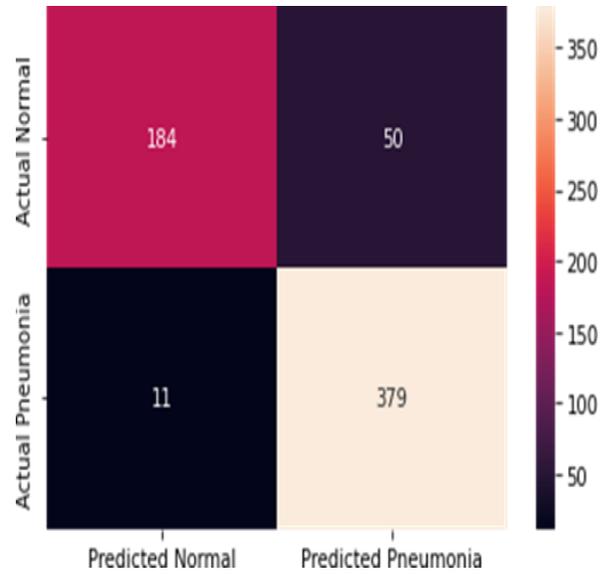


Fig. 10 Confusion Matrix

7.3 Visualizing some predicted images with percentage %

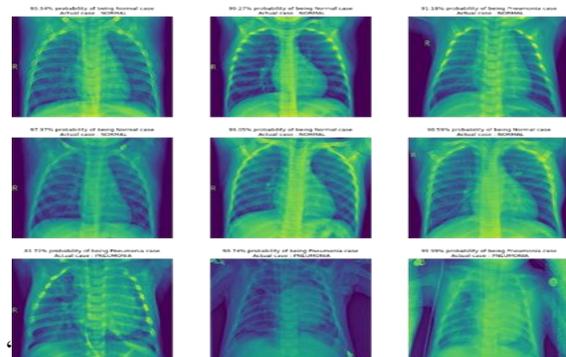


Fig. 11 Predicted Images

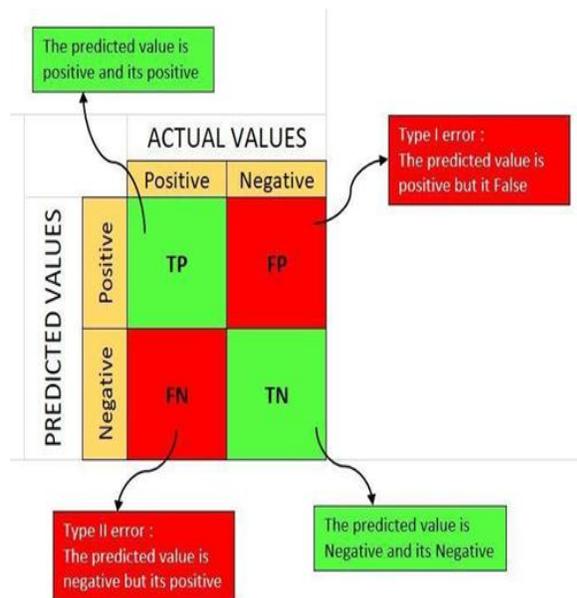


Fig:9 Mathematical Model

- This gives you a percentage estimate of the single image, which you may directly load from your hard drive by specifying its path
- Following importing the image like we did before we need to do the exact same data pretreatment steps, in order to input the test set into the model and get a prediction. You will also need to import tensorflow. keras. preprocessing. image. image class for your pre-processing.
- Import an image with maximum image size of (500,500), using grayscale channel
- To predict your case convert the image into an array and rescale it, dividing by 255, then extend dimension by axis = 0 just like you did prior.

7.4 User Interface Using Flask

Flask is a micro web framework written in Python that allows developers to build web applications quickly. It has straightforward and easy-to-use tools and libraries to help you route requests, manage HTTP requests and responses, and render templates. Flask is flexible and extensible and is a popular micro framework coder for people building web applications.

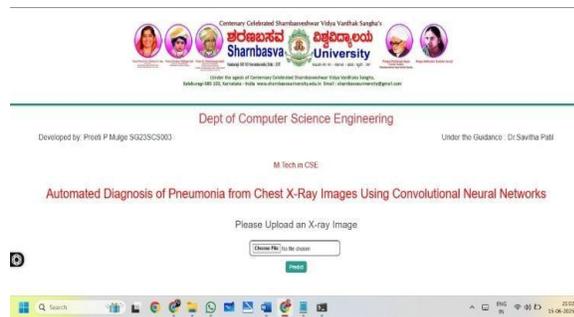


Fig:12 Home page



Fig:13 Person with pneumonia positive



Fig:14 Person with pneumonia negative

VIII. CONCLUSION AND FUTURE DIRECTION

This paper presented a CNN-based model aimed to detect pneumonia on a set of chest X-ray images. The specific contributions of this paper are as follows. We designed a CNN model to learn to extract the features from original images or from earlier feature maps. The model had only six layers consisting of ReLU activation function, drop operation and max-pooling, which were combined. The results of the obtained accuracy rate of 96.07%, and precision rate of 94.41% show that our proposed CNN model architecture is yielding promising results, when compared to leading CNN model architectures. We provided comparisons of several different input shapes and loss functions to show performance based on our proposed model. In the future, we aim to continue our research in search of more accurate classification architectures to detect two different types of pneumonia, virus and bacteria. In accordance with the discussion above, CNN model architectures present an exciting method to detect the disease on X-ray generated images.

REFERENCES

- [1] S. Shetty, M. N, M. Shetty, K. S, and P. D., "Detection of Pneumonia from Chest X- Ray Images," pp. 1–6, Mar. 2024, doi: 10.1109/icdcot61034.2024.10515758.
- [2] T. Babu, P. K. Naik, R. R. Nair, and K. Pallavi, "A Robust Convolutional Neural Network Architecture for Automated Pneumonia Detection from Chest X-ray Images," pp. 1–5, Sep. 2024, doi: 10.1109/iconat61936.2024.10775260.
- [3] G. Singh, K. Guleria, and S. Sharma, "An Efficient Convolutional Neural Network Model for Pneumonia Detection in Chest X-ray Images," pp. 1–5, Oct. 2024, doi: 10.1109/iemecon62401.2024.10845994.
- [4] M. Mujahid et al., "Pneumonia detection on chest X-rays from Xception-based transfer learning and logistic regression," *Technology and Health Care*, vol. 32, no. 6, pp. 3847–3870, Nov. 2024, doi: 10.3233/thc-230313.
- [5] C. S. Reddy, P. Kumar, S. B. Sunkara, R. PARIKH, N. Gainikadi, and R. Boda, "An Ensemble Approach for Pneumonia Detection

- from Chest X-rays,” Informa, 2024, pp. 79–88. doi: 10.1201/9781003488682-12.
- [6] S. S. Chakravarthi, S. N. Meeravali, M. Irfan, and S. Sountharajan, “Enhanced Pneumonia Detection In Chest X-Rays Through Model Fusion,” pp. 102–109, Aug. 2024, doi: 10.1109/icetci62771.2024.10704158.
- [7] E. J. Palomo, M. A. Zafra-Santisteban, and R. M. Luque-Baena, “Pneumonia Detection in Chest X-ray Images using Convolutional Neural Networks,” pp. 16–21, Oct. 2022, doi: 10.1109/MetroXRAINE54828.2022.9967590.
- [8] “Pneumonia Detection in Chest X-ray Images using Convolutional Neural Networks,” 2022 IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE), Oct. 2022, doi: 10.1109/metroxraine54828.2022.9967590.
- [9] Pai, P. Kumar Pareek, M. S. Guruprasad, S. Chandrappa, and K.P. Bhargava, “Pneumonia Detection in Chest X-Rays Using Combined Approach of Deep Learning,” pp. 1–6, Aug. 2024, doi: 10.1109/nmitcon62075.2024.10699169.
- [10] F. Barneih, N. Nasir, A. Kansal, O. Alshaltone, T. Bonny, and A. Al-Shammaa, “Pneumonia Detection in Chest Images using ResNet50 Model,” pp. 01–X-ray04, Feb. 2023, doi: 10.1109/ASET56582.2023.10180737.
- [11] Bysani, S. Garg, A. Danda, T. Singh, J. C., and P. Duraisamy, “Detection of Pneumonia in Chest X-Ray Using Ensemble Learners and Transfer Learning with Deep Learning Models,” pp. 1–8, Jul. 2023, doi:10.1109/icccnt56998.2023.10307035.
- [12] N. Garg, A. Bhadra, S. Gupta, S. Dhangar, and S. P. Jadhav, “Pneumona Disease Detection using Deep Learning,” International Journal for Science Technology and Engineering, vol. 11, no. 3, pp. 13–16, Mar. 2023, doi:10.22214/ijras.2023.49341.
- [13] Kumar and R. Sethuraman, “Pneumonia Detection using Chest X-ray Images using CNN Algorithm,” International Conference Intelligent Computing and Control Systems, pp. 496–501, May 2023, doi: 10.1109/ICICCS56967.2023.10142861.
- [14] Cyriac, N. Raju, and Y. W. Kim, “Pneumonia Detection using Ensemble Transfer Learning,” Information and Communication Technology Convergence, pp. 479–484, Oct. 2022, doi: 10.1109/ICTC55196.2022.9952532.
- [15] “Pneumonia Detection using Ensemble Transfer Learning,” 2022 13th International Conference on Information and Communication Technology Convergence (ICTC), Oct. 2022, doi: 10.1109/ictc55196.2022.9952532.
- [16] M. Vallisha, V. Khot, and N. Nagarathna, “Pneumonia Detection Using Anterior Chest X-Ray Images,” pp. 1–4, Apr. 2024, doi: 10.1109/icetcs61022.2024.10543420. Kumar, and V. Bhaiyya, “Detection of Pneumonia Using Deep Learning,” International journal of next-generation computing, Feb. 2023, doi: 10.47164/ijngc.v14i1.1023.
- [17] M. Beri and N. Sharma, “VG-16 Model-Based Pneumonia Detection with Chest X-Ray Images,” pp. 1588–1593, Dec. 2024, doi: 10.1109/icicnis64247.2024.10823362.
- [18] Kar, N. Akhtar, and M. Rahman, “An Approach for Detecting Pneumonia from Chest X-Ray Image Using Convolution Neural Network,” Springer, Cham, 2020, pp. 735–743. doi: 10.1007/978-3-030-68154-8_63.
- [19] N. Borkar, A. Zararia, R. Gangbhoj, P.
- [20] Athar, R. N. Asif, M. Saleem, S. Munir, M.R. Al Nasar, and A. Momani, “Improving Pneumonia Detection in chest X-rays using Transfer Learning Approach (AlexNet) and Adversarial Training,” pp. 1–7, Mar. 2023, doi: 10.1109/ICBATS57792.2023.10111193.