An Efficient Deep Learning Approach to Detect Various Diseases Using Chest X-ray Images

Submitted by

SANZANA MAHRUKH HASSAN
21101237
MD. ANIK KHAN
24241273
MD. ABID HOSSINE
20301392
MAYESHA ZAMAN LAMIA
21301686
PRITOM KUMAR SARKAR
20301372

A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science and Engineering

Department of Computer Science and Engineering
Brac University
February 2025

Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

Student's Full Name & Signature:

Sanzana

SANZANA MAHRUKH HASSAN
21101237

Anik

MD. ANIK KHAN
24241273

MD. ABID HOSSINE
20301392

MAYESHA.

MAYESHA ZAMAN LAMIA
21301686

Pritom

PRITOM KUMAR SARKAR
20301372

Approval

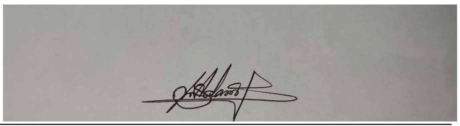
The thesis/project titled "An efficient deep learning approach to detect various diseases using chest x-ray images" submitted by

1. SANZANA MAHRUKH HASSAN (21101237)
2. MD. ANIK KHAN (24241273)
3. MD. ABID HOSSINE (20301392)
4. MAYESHA ZAMAN LAMIA (21301686)
5. PRITOM KUMAR SARKAR (20301372)

Of Fall, 2024 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science on February 03, 2025.

Examining Committee:

Supervisor:
(Member)

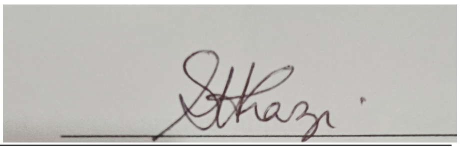


Dr. Md. Ashraful Alam
Associate Professor
Department of Computer Science and Engineering
Brac University

Program Coordinator:
(Member)

Md. Golam Rabiul Alam
Professor
Department of CSE
Brac University

Head of Department:
(Chair)



Dr. Sadia Hamid Kazi
Chairperson and Associate Professor
Department of Computer Science and Engineering
Brac University

Abstract

We propose and demonstrate an efficient deep-learning approach to classify various diseases using chest x-ray images. The proposed system comprises several steps: image acquisition, preprocessing, and classification of various diseases. The datasets include X-ray images of various diseases such as pneumonia, COVID-19, lung opacity, and normal chest images. Raw X-ray images and the dataset from Kaggle are preprocessed using image resizing and augmentation. Finally, a neural network-based deep learning model is applied to classify the disease. Different CNN architectures: ResNet50, ResNet101, EfficientNet, DenseNet121, and AlexNet are investigated for the classification, and the best-performing architecture is used in the model, to design a custom-made model named X_Net. By incorporating certain layers from both ResNet101 and DenseNet121 . The ResNet101 and DenseNet121 models gave 94% and 92% accuracy, respectively, where the rest of the models gave lower accuracy than them. Our proposed model achieves a higher accuracy of upto 96.5%.

Keywords: Keywords: CNN, EfficientNet, AlexNet, ResNet50, ResNet101, DenseNet121, Attention Mechanism, and deep learning algorithms.

Nomenclature

- Convolutional Neural Network (CNN)
- Congenital Heart Defect (CHD)
- BackPropagation Neural Network (BPNN)
- Support Vector Machine (SVM)
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC)
- Graphics Processing Unit (GPU)
- Chest X-ray (CXR)
- Generative Adversarial Network (GAN)
- Tuberculosis (TB)

Table of Contents

Introduction

0.1 Background

Thoracic conditions are frequently used to refer to ailments of the chest, which include esophageal diseases. These ailments cover a wide range of ailments that impact our heart, lungs, ribs, throat, esophagus, aorta (the major artery in our body), and other tissues in our chest.

Smoking, infection, and air pollution are the main causes of lung illnesses. Lung illnesses are largely influenced by genetics. Pneumonia or lung infection is an illness brought on by a virus, bacterium, or fungus. Inflammation of the lung's air sacs results in pneumonia, which can affect one or both of the lungs. Pneumonia symptoms include fever, sputum, coughing, and chest pain. While anybody can have pneumonia, certain age groups are more vulnerable to the illness than others. They comprise seniors 65 years of age or older and newborns up to two years old. Early diagnosis and treatment of the illness stop problems from developing. Infectious particles can spread COVID-19 when they are inhaled or come into contact with the mouth, nose, or eyes. Although the risk is greatest when people are near to one another, the virus can spread across greater distances, especially indoors, when tiny airborne particles are dispersed in the atmosphere. Additionally, touching one's lips, nose, or eyes after coming into contact with infected surfaces or items might spread the virus. Even in the absence of symptoms, people can still spread the virus and remain infectious for up to 20 days. On a chest X-ray, opacity can show the following conditions: fluid in air spaces, thickening of air space walls, thickening of lung tissue, pulmonary edema, inflammation, blood vessel damage and bleeding, malignant development, and fibrosis. These procedures employ image processing algorithms to identify pertinent data from digital chest X-ray images and detect the samples based on the presence or absence of diseases. If enough annotated chest pictures are utilized in the training phase, deep-learning models may be trained to identify trends and produce accurate forecasts.

0.2 Convolutional Neural Networks

Convolutional brain organizations, or CNNs or ConvNets, are a subclass of brain networks that are especially great at handling input with geography looking like a framework, similar to pictures. A twofold portrayal of visual information makes up a computerized picture. It is made up of pixels arranged in a grid-like pattern with values for each pixel that indicate its brightness and color. To enhance the accuracy and minimal square error attained in the diagnosis of chest ailments, a deep convolutional neural network (CNN) is utilized. Traditional and deep-learning-based networks are used for this purpose to categorize the majority of common thoracic disorders and to display comparison outcomes. Neural networks that are backpropagation (BPNN) and competitive (CpNN). [2]

We have used Conv2D in our models. A tensor of outputs is obtained by convolving the layer input with the convolution kernel created by this layer across a single spatial (or temporal) dimension. A bias vector is generated and appended to the outputs if use_bias is set to True. Lastly, activation is applied to the outputs as well if it is not None. In a conv2D layer, a filter or kernel "slides" across the 2D input data to multiply the elements one by one. Consequently, the results will be summed together into a single output pixel. [24]

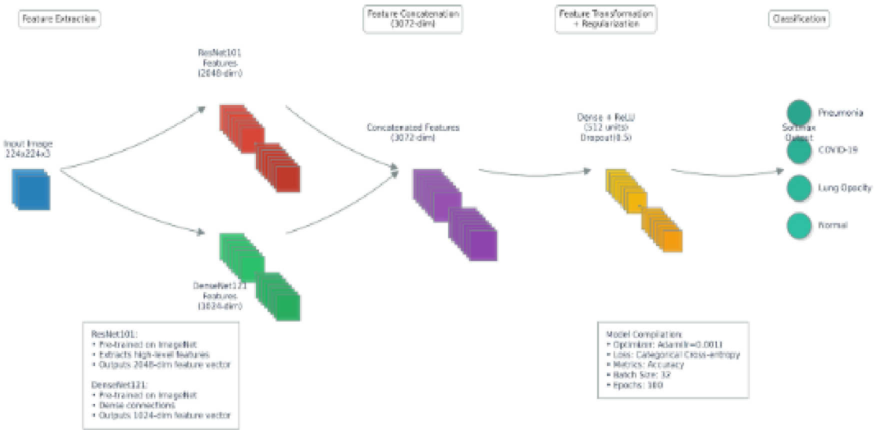


Figure 1: Schematic diagram of a basic convolutional neural network (CNN)

0.3 Knowledge distillation

CNNs have demonstrated outstanding results in a variety of real-world applications and are commonly utilized in image-processing tasks including object identification, picture segmentation, and classification. Convolutional layers are applied to input pictures by CNNs, which then employ starting functions to create indeterminate, merge layers to reduce the extent, and fully connected layers to generate the ultimate output. Weights are changed throughout training to reduce output variations. CNNs are frequently utilized in image processing jobs because, once trained, they can categorize fresh pictures. [25]

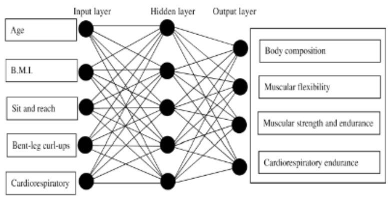


Figure 2: BPNN Structure

Of the three, the CNN may attain the very lowest mean square type error. The study concluded that shallow networks, such as BPNN and CPNN, were unable to match CNN's recognition rate.

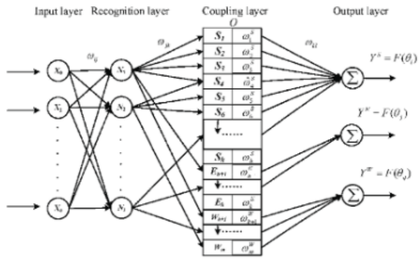


Figure 3: CPNN Structure

0.4 Aims and Objectives

The motive of this research is to contribute to the directory of significant chest disease identification by presenting the concept of an advanced automated system. The system that will be provided will employ cutting-edge computer vision techniques, such as neural networks and computational imaging, to accurately identify and classify chest ailments. Through the use of a sizable dataset that includes images of classified chest lesions, machine-learning models will be trained and assessed for pursuing a high degree of accuracy in illness detection.

Research Problem

0.5 Motivation

In this world, at present time, by using the Deep Learning process for detecting diseases by chest X-ray (CXR) images, the most critical challenges demand thorough analysis and state-of-the-art solutions. So, the first and foremost thing is to persist in addressing the class imbalance, which becomes specifically uttered when merchandising with very rare diseases. For every researcher, the methodologies in employment to handle this variance warrant closer study and refinement. The shortage of data for rare and severe conditions gives rise to a significant hurdle, leaving no choice but to novel approaches to ensure that deep learning models are not only trained effectively but can also accurately and efficiently detect and classify those diseases that are too rare to be encountered. With the purpose of making a near-perfect diagnosis when encountering patients suffering from those diseases. So, it involves poking about into the complication of data augmentation methods, transfer learning, and many more techniques that can shore up the model's caliber or capacity to discern patterns in limited datasets.

Furthermore, the other dreadful challenge lies in the trials and tribulations of training deep learning models constructively for chest X-ray analysis. Unlike X-rays of localized injuries such as a broken hand, chest X-rays lack the detailed nuances that make identifying abnormalities a more intricate task. The complexity of the chest area demands a closer examination of model architectures, feature extraction methodologies, and the incorporation of domain-specific knowledge to ensure that the model can effectively discern subtle yet crucial indicators of respiratory and cardiovascular conditions. Enhancements in model training approaches are imperative to extract meaningful insights from less detailed chest X-ray images and thrive the overall accuracy of disease detection.

0.6 Limitations

The multi-class classification approach introduces different levels of complexity and why deep learning is applied to chest X-ray analysis. The model has to distinguish between normal and abnormal conditions and also accurately classify different diseases within the chest area. This is a significant obstacle, particularly when suitable treatment prescriptions need exactitude. Deep learning models for multi-class classification in the medical domain are more intricate to create and refine because of the requirement for extremely precise and targeted predictions. Researchers must investigate ways to enhance model architectures, training protocols, and class-specific characteristics to guarantee dependable predictions and contribute to more accurate patient diagnosis and treatment recommendations. Data augmentation strategies, a cornerstone for enhancing the robustness of deep learning models, require further optimization in chest X-ray analysis. Some images lack the detailed granularity seen in some other medical imaging modalities, effective augmentation becomes crucial for expanding the diversity of the training dataset. Researchers need to explore innovative approaches, possibly incorporating generative adversarial networks (GANs) or other synthetic data generation techniques, to make sure of the well generalization model to a broad spectrum of chest X-ray images. This optimization of data augmentation strategies holds the key to improving model performance and adaptability to varying imaging conditions. Dealing with the issue of model uncertainty, self-assurance estimation is principal for the broader harmonization of deep learning models into clinical decision-making processes. Beyond simply achieving high accuracy, understanding the indeterminacy associated with anticipation and relaying confidence periods become significant aspects of model comprehensibility and consistency. Researchers must investigate advanced techniques for uncertainty estimation, exploring Bayesian approaches, probabilistic modeling, or other methodologies to provide clinicians with an understanding of the reliability of the model's presumptions. This not only improves the trustworthiness of the deep learning models but also supports more enlightened and optimistic decision-making by healthcare professionals. One of the challenges that appears large in the area of medical imaging research, specifically for chest X-ray analysis, is the difficulty in acquiring inclusive datasets. Medical datasets frequently require fieldwork and collaboration between researchers and healthcare providers, which adds logistical complexity.Establishing strong data sharing structures, collaborating with medical institutions, and abiding by stringent ethical standards to protect patient privacy are some strategies for overcoming these obstacles.

In addition, multi-class classification was used here. For huge datasets and a large amount of training sessions, we were not able to perform further more approaches , more models, which might have affected our accuracy a bit for some models. Such as ResNet34 and ResNet50 gave a very low accuracy than the rest of the models.

In addition, binary classification was used here. For huge datasets and a large amount of training sessions, we were not able to perform multiclass classification, which might have affected our accuracy a bit for some models. Such as EfficientNet gave a very low accuracy than the rest of the models.

Moreover, when commencing the research one ofthe major limitations we faced was the availability and credibility of the dataset. Even after being affiliated with a diagnostic center, we did not have X-ray images of the chest specifically, in abundant quantities. There was also the ethical issue of whether some data was permitted to be used by the patients. As a researcher, we wanted to ensure the models were trained using a compatible and complete dataset. To make the algorithms as perfect as possible, a different database would be needed, So, we needed to resort to other options to get a dataset with perfect usability. To resolve this an award-winning COVID-19 dataset from the Kaggle community is used. This dataset was again crosschecked by healthcare professionals and research associates to verify its credibility.

In addition, binary classification was used here.For huge datasets and a large amount of training sessions, we were not able to perform multiclass classification, which might have affected our accuracy a bit for some models.Such as EfficientNet gave a very low accuracy than rest of the models.

Moreover, when commencing the research one of major limitations we faced was the availability and credibility of the dataset. Even after being affiliated with a diagnostic center, we did not have x-ray images of the chest specifically, in abundant quantities. There was also the ethical issue of whether some data was permitted to be used by the patients. As a researcher we wanted to ensure the models were trained using a compatible and complete dataset.With the intention of making the algorithms as perfect as possible, a different database would be needed, So, we needed to resort to other options to get a dataset with perfect usability. To resolve this an award- winning COVID-19 dataset from the Kaggle community is used. This dataset was again crosschecked by healthcare professionals and research associates to verify its credibility.

Additionally, to train and test our selected model, we faced significant runtime errors in the compiler. It is suspected that due to the large batch of data, this runtime error occurred. Thus, there is the complication of identifying the appropriate amount of resources needed to fluidly run the machine learning models. Resources like computing power, storage, and GPU power of the computing device need to be taken into consideration so that the models do not run into errors as frequently. To achieve such computational efficiency and devices, resources like time, finances, logistics, and human resources also need to be invested. This is an ongoing discourse among us and many such researchers as to what would be the exact amount of time and logistics needed to perfect machine learning models and algorithms.

Fundamental for maintaining the highest standards of privacy and patient protection guidelines and furthering research in chest X-ray analysis. In brief, there are several complex issues associated with applying deep learning to chest X-ray interpretation for disease identification, which need thorough research and creative solutions. Researchers need to address the class disparity, train models efficiently in the lack of fine-grained picture details, handle the difficulties of multi-class classification, maximize data augmentation techniques, deal with model uncertainty, and face the moral and practical difficulties of acquiring datasets.

Research Objectives

The principal research objective is to investigate existing deep learning models that can yield better results on current methodologies and techniques that are used for chest disease detection. Reviewing previous research and articles is also imperative to contribute to innovation in medical image analysis and facilitate the development of reliable and scalable diagnostic tools for improved patient care. To make the disease identification more straightforward and level, the focus is primarily on the detection of four types of chest diseases or conditions. These medical conditions, or the central focal point of our research, are pneumonia, COVID-19, Lung opacity, and normal chest images. The leading objective hence is to analyze to find the most effective chest disease detection methodologies for the aforementioned conditions that our focus is upon.

Furthermore, the focus is given to controlling image acquisition and processing to ensure the least inconvenience when using them in the CNN models. Suitable image acquisition protocols will be developed so that chest x-ray images are of high quality and fair in all aspects. In this case, factors like lighting, resolution, and patient positioning are controlled so that the image positions are alike. Consequently, investigating appropriate image processing operations such as levels of resizing or augmentation needs to be determined. Thus, this will also contribute to the aspects of image processing in chest imaging and disease detection. Then, another major objective is to evaluate and study existing deep learning algorithms such as AlexNet, EfficientNet, DenseNet, Sequential Model, etc. in the context of chest disease detection. Their efficiency is compared by varying different conditions and training the models on datasets with different characteristics. Emphasis is given to controlling other factors in all systems, such as age or gender, when changing other variables. More importantly, benchmarking each model's performance against established medical standards. In this way, the most suitable deep learning approach can be determined and commented on more decisively.

After comparing models mentioned above, a custom model was made called X_net which is more suitable for faster detection and higher accuracy.Additionally, Grad-CAM was also used to portray the visible changes in X-rays when it comes to different Chest diseases, which can make the detection more easier and faster.

There are also cases of addressing real-world clinical and environmental challenges, such as variations in patient demographics, X-ray image quality, and potential noise in the raw X-ray images. Then study how their effects are taken into account and solved. Also, in this case, datasets from diverse age ranges and robustness needs to be ensured. To enhance the overall precision and dependability of chest disease detection systems, an exploration of the possible incorporation of extra elements—like clinical data, patient details, and patient history—is feasible. The interpretability and explainability of the devised chest disease detection model are evaluated to ensure that patients and healthcare providers understand it. By doing so they can understand the disease identification decision of the model to a greater degree. Acting and training the model upon feedback mechanism will enhance acceptance and reliability among healthcare professionals. Therefore importance is placed upon acceptability and further improvement of the model.

Detailed Literature Review

Deep learning is such a technique that mainly revolutionized medical imaging, especially in analyzing chest X-rays (CXR) for detecting diseases. A deep learning type algorithm, Convolution Neural Networks (CNNs), has demonstrated some of its exceptional features in extracting complex features and classifying various diseases in CXR images, enabling automated disease detection.

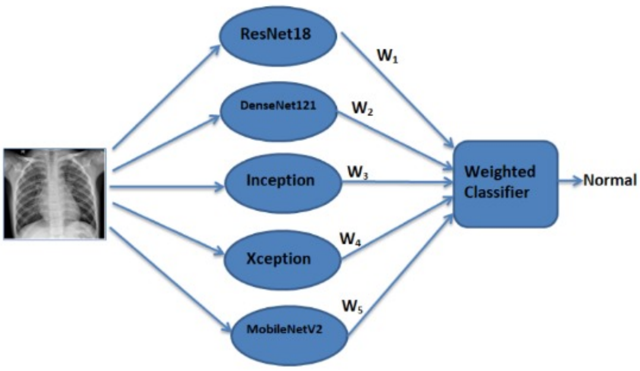


Figure 4: The X-ray image is used by various architectures of CNN

The above introduction provides a complete overview of recent research on Deep Learning applications in CXR imaging, which is for detecting respiratory and heart-related conditions. Deep Learning always has the potential to process automation of disease detection tasks that improves diagnostic results too precisely, and it increases the efficiency in healthcare-side imaging. Lastly, this reviews all new strategies to amplify the performance of deep-learning models like data augmentation, transfer learning, and combined methods and compares their performance with conventional processes using metrics such as vulnerability, relevancy, and precision of it.

According to Rumelhart, H. (1998, November), DenseNet states that this precise model has been expanded to detect 14 separate thoracic diseases, which include Pneumonia, Tuberculosis, Abnormal heart shape, and so on. [15]

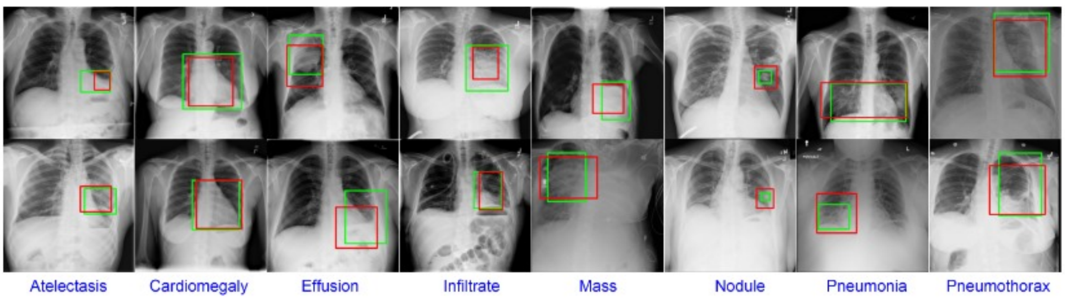


Figure 5: X-Ray images are annotated by Deep Learning

Moreover, Inception V3,(Hilmizen et al.'s study) achieved a high accuracy of 98.8% of binary classification between COVID-19 and general classes using the above CNN architecture Inception V3. In other medical reports, it has achieved nearly 96.4% and 98.43% accuracy in pneumonia classification using Inception V3,(Chouhan et al.) presented a precise model that combines Inception V3 with AlexNet, DenseNet121, efficientnet18, and GoogLeNet using the Adam optimizer. The study also showed almost similar results.According to efficientNet, the efficient net-50 architecture of CNN is being utilized for pneumonia classification, achieving an accuracy of 97.65% which is huge. They also developed a precise model called COVID-efficient net using pre-trained weights on ImageNet and the Adam optimizer, accomplishing an accuracy of 96.23% which was too close before it was developed. [5]

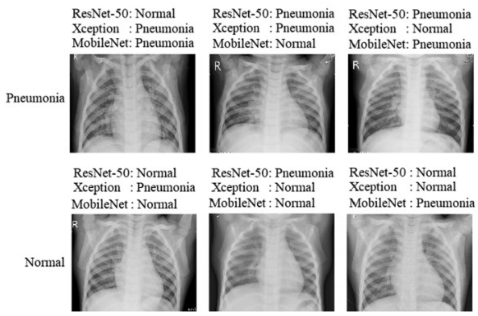


Figure 6: Comparison between Normal and Pneumonia using ResNet50, Xception, MobileNet

According to efficientNet, the efficient net-50 architecture of CNN is being utilized for pneumonia classification, achieving an accuracy of 97.65% which is huge. They also developed a precise model called COVID-efficient net using pre-trained weights on ImageNet and the Adam optimizer, accomplishing an accuracy of 96.23% which was too close before it was developed.

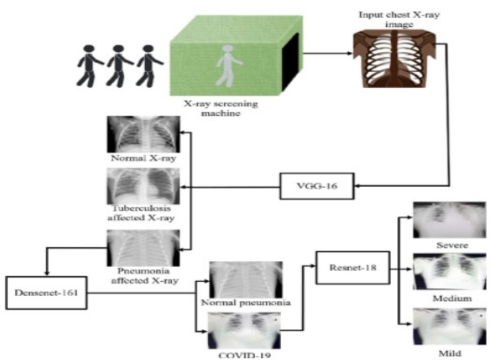


Figure 7: Comparison between Normal, Tuberculosis Pneumonia and COVID-19 X-Ray images using DenseNet-161, VGG-16, ResNet-18

According to (Martins, 2023) image segmentation in chest radiographs includes separating images into relevant zones to define anatomical structures for disease localization. To accurately segment lung fields, ribs, and other structures algorithms like U-net, Mask R-CNN, and FCN are used. Texture analysis, wavelet transforms, and histogram-based features are such feature extraction techniques that are used to capture relevant patterns and irregularities in chest radiographs. [20]

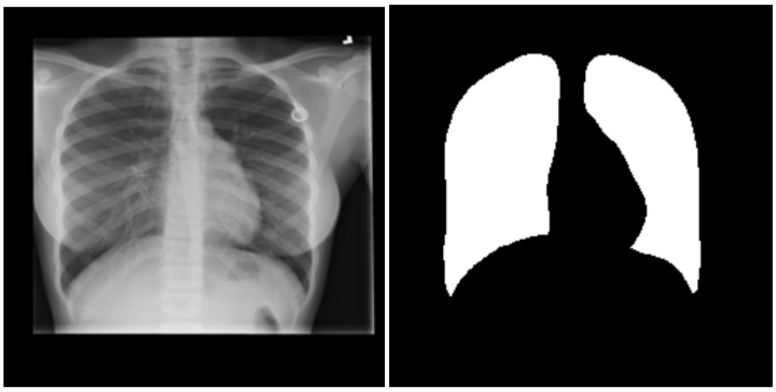


Figure 8: An image of Chest X-Ray vs Mask Image

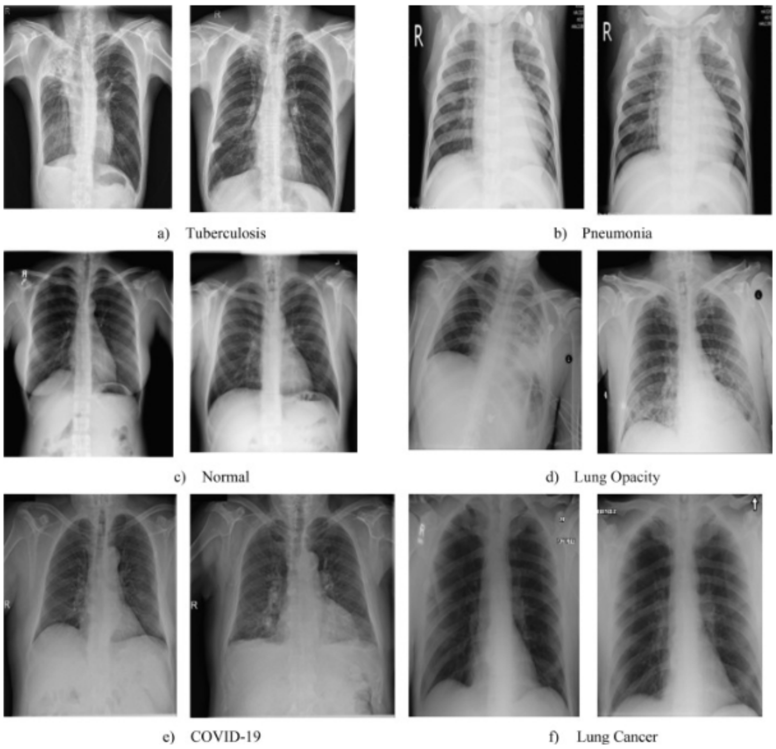


Figure 9: Detecting objects using the Deep Learning method

Last but not the least CNNs have redefined chest disease detection in radiology by obtaining hierarchical features from raw pixel data. Diseases like pneumonia tuberculosis and lung cancer are being detected with high precision and responsiveness.

By transfer training performance is further improved in which train CNN models are developed on plentiful image datasets beforehand. Combining image segmentation, feature extraction, and classification models represents an effective deep-learning method for detecting diseases in chest X-rays. This combination results in a comprehensive model for automated disease detection in chest X-ray images that has the key probability of significantly influencing clinical diagnosis and patient care.

CNNs have redefined chest disease detection in radiology by obtaining hierarchical features from raw pixel data. Diseases like pneumonia tuberculosis and lung cancer are being detected with high precision and responsiveness. By transfer training performance is further improved in which train CNN models are developed on plentiful image datasets beforehand.

0.7 Efficient Techniques

An efficient deep-learning approach for chest X-ray disease detection is the combination of image segmentation, feature extraction and classification models. With this combination a complete model for automated disease detection in chest X-ray images has the ke probability to make a considerable impact in clinical diagnosis and patient care.

0.7.1 Image Segmentation Techniques

In chest radiographs image segmentation involves separating images into relevant regions to specify anatomical abnormalities for disease localisation. For accurate segmentation of lung fields, ribs and other structures, algorithms like Googlenet, ResNet DenseNet, architecture of CNN and FCN are used. To capture appropriate patterns and abnormalities in chest radiographs feature extraction algorithms like texture analysis, wavelength transforms, and histogram based features are used.

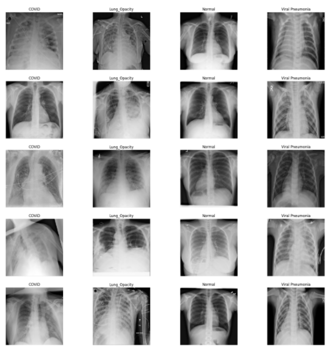


Figure 10: Various images created by using different Algorithms of CNN

In the field of chest disease detection in radiology CNNs have modernized the area by learning hierarchical features from raw pixel data. Diseases like pneumonia, abnormal shape of heart, etc with high precision and responsiveness can be detected by CNN algorithms. [16]

0.7.2 Transfer Learning

In the field of deep learning transfer learning is an impactful technique. In chest X-ray disease detection transfer learning has made a substantial impact. From a large dataset a model is trained by transferring knowledge or features into a smaller executable dataset to narrow down. Models like CNN, ImageNet are mainly used for transfer learning as a starting point for learning all the necessary features related to chest X-ray images [17]

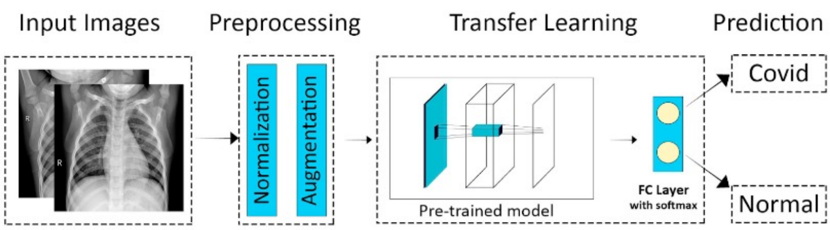


Figure 11: Transfer Learning (includes Pre-trained model)

In chest X-ray disease detections there are multiple methods to utilize transfer learning. To extract high level attributes from chest X-ray images, CNN model is used as a fixed feature extractor as the model can extract high level features. But there is a catch because if the target dataset is not small and this can be insufficient to train a CNN model from scratch. While the network is developed on a large dataset, changing the pretrained model using backpropagation with a smaller learning rate is a hassle. To adjust the feature which is splitted between the origin and the targeted domains the domain adaptation techniques are used. [28]

(C) Respiratory Diseases Detection

Methods like normal chest X-ray are helpful in detecting diseases like respiratory diseases. Some diseases may not show visible science on cxr, specially in early stages or mild forms. For an extensive evaluation imaging centers like CT Scan, functional test, and clinical assessment are mostly needed because without them the detection would not be accurate. A holistic approach, considering clinical context and using multiple diagnostic centers, is crucial for accurate diagnosis and management of respiratory diseases.Pneumonia may initially appear normal, but the absence of characteristic signs does not rule out pneumonia, especially in the early stages.

In cases of heart abnormalities, normal CXR may not always reveal structural abnormalities, and conditions like congenital heart defects or cardiomegaly may require additional imaging modalities like echocardiography or cardiac MRI. In summary, a comprehensive approach that includes clinical assessment and, if necessary, additional imaging modalities is essential for accurate diagnosis and management of respiratory diseases. [6]

0.7.3 Viral Pneumonia

CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning is the title and According to (Rajpurkar, P., 2017) radiologists have faced difficulties in accurately identifying pneumonia in chest radiography due to the indistinct visual characteristics of pneumonia in X-ray images, its tendency to resemble other medical conditions, and its ability to imitate harmless abnormalities. 121-layer convolutional neural network trained on the ChestX-ray14 dataset and the variation observed among radiologists in diagnosing pneumonia has led to the investigation of automated detection systems that utilize deep learning models. One notable study by the authors involved collecting a dataset. The study assessed the efficacy of both individual radiologists and deep-learning models in detecting pneumonia. The findings demonstrated that the deep learning model outperformed the average performance of radiologists in detecting pneumonia and achieving an F1 score of 0.435 compared to the average radiologist score of 0.387.[22]

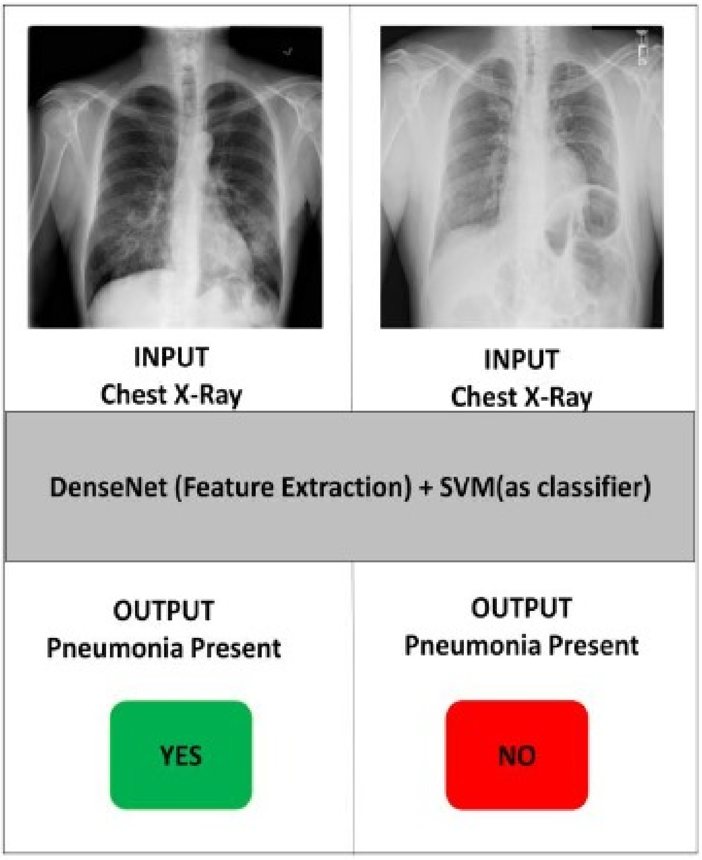


Figure 12: Input- Chest X-Ray image and Output- Pneumonia Present or Not

The authors compared their deep learning model, CheXNet, with previous studies on the ChestX-ray14 dataset. Their findings revealed that CheXNet surpassed prior results across all 14 diseases, suggesting that deep-learning models can exceed the performance of expert radiologists in chest X-ray detection. This research has significant implications, such as improvement mentioned in the clinical settings along with the help of automated detection by providing accurate diagnoses and benefiting populations with limited diagnostic imaging specialists.

According to (Ibrahim, A. U., 2021), the use of deep learning techniques for detecting various types of pneumonia using CTXR images includes non-COVID-19 and COVID-19 viral pneumonia. [10]

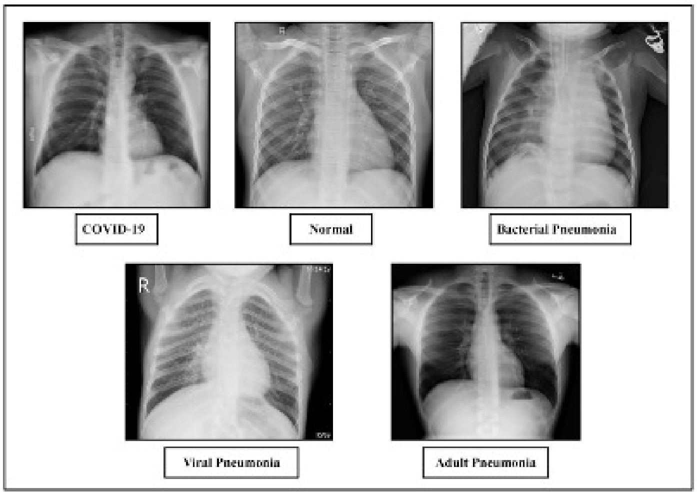


Figure 13: X-Ray images of COVID-19, Normal, Bacterial Pneumonia, Viral Pneumonia and Adult Pneumonia

It highlights the challenges of using standard methods like RT-PCR for COVID-19 detection and proposes CXR scans as a rapid and accessible alternative. The authors present a deep learning approach using a pre-trained AlexNet model for four-way classification, comparing each type of pneumonia with another. This approach provides a widespread analysis of the model's performance across different pneumonia types.

According to (C¸ allı, E., 2021), Deep Learning for Chest X-ray Analysis: explores the use of deep learning techniques for determining various types of pneumonia using CXR images, including COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia, and normal/healthy cases. The results demonstrate promising outcomes in terms of testing accuracy, sensitivity, and specificity, indicating the potential effectiveness of the deep learning model in accurately classifying CXR images for pneumonia detection. C¸ allı, E. (2021) conducted research centered on employing deep learning methods to identify cases of non-COVID-19 viral pneumonia, bacterial pneumonia, COVID-19 pneumonia, and normal/healthy instances of pneumonia through CXR images. In terms of accuracy, sensitivity, and specificity, the results are encouraging. Researchers developed the ability to distinguish between different types of pneumonia using CXR pictures by utilizing deep learning and transfer learning approaches. This suggests a viable solution for quick and precise pneumonia diagnosis .These sources provide a broader foundation for studies looking to use data analytics and technology to solve problems in healthcare. [4]

As described by (Hashmi, M. F. 2020), Efficient Pneumonia Detection in Chest X-ray Images Using Deep Transfer Learning, here, transfer learning is used to propose a unique technique for identifying pneumonia in chest X-ray pictures. This approach defeats the drawbacks of conventional techniques, namely overfitting and big datasets. To increase accuracy, it makes use of five distinct neural network architectures that have already been trained using an ensemble technique. Preprocessing chest X- ray pictures, data enhancement, transfer learning, extracted features, and ensemble categorization are all part of the methodology. The study demonstrates encouraging accuracy in detecting pneumonia in healthy chest X-ray subjects. Deep learning can assist specialists in completing laborious jobs, but it cannot replace doctors in medical diagnosis.[8]

In their 2021 study, GM and H. investigate the utilization of transfer learning to the detection of pneumonia in chest X-ray images. They confront issues such as overfitting, large datasets, and subtle patterns, and they also look at newer deep learning techniques to boost efficiency and accuracy. [1]

Five pre-trained neural network architectures, including VGG, ResNet, Inception, and DenseNet, are mentioned in the article as being used for feature extraction. These designs are presumably exploited for feature extraction in conjunction with an ensemble classifier, like random forests or logistic regression. The ensemble technique seeks to reduce individual model biases and increase overall accuracy by utilizing the advantages of various architectures to enhance the pneumonia detection system's overall performance. The ensemble approach aims to leverage the strengths of different architectures to improve the overall performance of the pneumonia detection system, mitigating individual model biases and enhancing overall accuracy.

According to (Kundu, R.,2021) "Pneumonia detection in chest X-ray images using an ensemble of deep learning models" presents a computer-aided diagnosis system for automatic pneumonia detection using chest X-ray images. [12] The system uses deep transfer learning to address the scarcity of available data for pneumonia detection. The ensemble framework combines the strengths of three convolutional neural network (CNN) models to enhance the accuracy of pneumonia diagnosis. The system captures diverse patterns and features from input chest X-ray images, improving performance compared to using a single model. The proposed ensemble framework achieved high accuracy rates on two publicly available datasets, outperforming state-of-the-art methods. The system's domain independence allows for application to a wide range of computer vision tasks. Overall, the developed system contributes to early diagnosis and curative treatment of pneumonia, offering potential benefits for healthcare and medical imaging applications.[14]

0.7.4 Covid

A classification method was developed through transfer learning and tuning of a CNN in research conducted by Grega Vrbančič and others. The classification method they propose utilizes the Grey Wolf optimizer algorithm for optimizing hyper-parameter values in transfer learning tuning. During the initial phases of COVID-19, it turned out to be more successful than anticipated. A dataset with 842 X-ray images was used to implement the proposed model, which achieved an overall accuracy of 94.76%.[27]

According to another research study by Heidari et al, pre-processing algorithms were used to transform chest radiology images to develop a new deep learning model. This model is used to inspect chest X-ray images to detect COVID-19 induced pneumonia. The preprocessing techniques include a histogram equalization algorithm and a bilateral filter application to generate two sets of images (that doesn't include the diaphragm region) produced from the original x-ray image. The study then uses a transfer learning method to train the VGG 16 based CNN model using the three sets of processed images. [9]

The original dataset contained 3 data groups: COVID-19-induced pneumonia, no COVID-19-infected pneumonia, and normal chest x-ray images. This large dataset of 8474 cases was used to train the model. Among these, in the subset of 2544 cases, the CNN model successfully achieved 94.5% accuracy in classifying the three groups of cases. There was also 98.1% accuracy in detecting COVID-19-infected pneumonia cases. [9]

Another research investigation by Albahli (et al) points out that training a neural network becomes more laborious as its depth increases. The convergence time rises sharply and efficiency falls. In due course, such a model that takes high time and computational power is undesirable in clinical settings. The study mentions that the use of ResNet-34 achieved a top-five validation error of 5.71% and ResNet-152 achieved a top-five validation error of roughly 4. 49%, the convergence rate of ResNet is noticeably faster compared to other CNNs. This encourages using a ResNet architecture to improve training and model engineering. [3]

In recent research by S.R Nayak et al, ResNet-34, ResNet-50, and AlexNet provided accuracy of 98.33%, 97.50%, and 97.50% accuracy which was the highest among eight different CNN models tested. The study encouraged the use of datasets from multiple sources such as the dataset prepared by Cohen JP and the ChestX-ray8 dataset. The results of this study also infer that the obtained sensitivity is highest (i.e.) forthe Covid-19 class when ResNet models are used. Hence eventually the study found the ResNet-34 model to have the highest performance with an accuracy of 98.33 and an F1 score of 0.9836. The second best model to perform was the AlexNet network with a precision of 96.72% , a sensitivity of 98.33%, and an F1 score of 0.9752. This leads to the rational use of a ResNet architecture or AlexNet for building a pre-trained CNN model in the detection of a class of diseases [21]

0.7.5 Lung Opacity

According to Khan Fashee Monowar, Convolutional Neural Networks for Lung Opacity Classification Using Chest X-rays where the models are Xception, DenseNet201, Inception V3, MobileNet and ResNet152 are some of the deep CNN architectures that were used in this study.The models ability to discriminate between lung opacity and other anomalies was less sensitive.Class imbalance problems, which are handled by a loss function with a weight.Starting a training program from scratch without utilizing regularization strategies or transfer learning.With 91.0% AUC and 83.95% accuracy, the Xception model performed best.Xception obtained 99.1% AUC, 97.19% sensitivity, and 95.71% accuracy when its lung opacity vs. normal chest X-rays were classified. [13]

According to Adam Jacobi,The baseline chest X-ray (CXR) sensitivity for COVID-19 lung disease detection is 69%, according to the publication. Nevertheless, it doesn't give precise accuracy numbers for the relevant deep learning models.In order to support the medical community in its fight against the pandemic, the paper's topic is the patterns and presentations of lung abnormalities on CXR in COVID-19.The usage of models for lung opacity detection, such as ResNet152, Xception, DenseNet201, Inception V3, AlexNet, and EfficientNet, is not specified. The clinical and radiological results are given greater attention than the specifics of how these deep learning models were applied.The paper describes the difficulties in identifying specific lung problems with CXR as opposed to CT, but it makes no drawbacks. [11]

In summary, the literature review that we analyzed, discuss the challenges and existing methods in detection of pneumonia, Covid-19, lung opacity from chest X-rays, while the CNN architecture will be used to enhance accuracy and after pre-model testing ResNet-34 was found to be most suitable in terms model engineering, training and more efficient epoch times

Work Plan

Here, we'll use CNN for investigational reasons. In image processing, neural networks with many convolutional layers are the main component. segmentation, classification, and other autocorrelation-containing data. Systems for both software and hardware Neural networks are designed to imitate the functioning of neurons in the brain of human beings. The "neurons" of CNN perform functions similar to those of the human frontal lobe and other creatures that interpret visual cues. This avoids the fragmented image processing challenge of conventional neural networks by arranging the layers of neurons to provide a full center view. We are planning to employ a 12-layered CNN model in our suggested approach, where the pictures are filtered at different degrees. The model will include three max-pooling layers and five convolutional layers. The model's ultimate output will be made up of layers that are either fully or densely coupled. Using collected and processed data using this model, the suggested model for illness identification in image processing aims to identify diseases in the chest. To do this, the model has to create a procedure that uses explainable AI to provide disease predictions, analyzes input data methodically, and accepts picture data as input through image capture and categorization. The process of illness identification is responsible for data acquisition, classification, and prediction. There are three steps to it .

0.8 Before Pre-Procesing:

0.8.1 Covid

COVID-19 is a highly contagious respiratory illness caused by the SARS-CoV-2 virus, leading to symptoms ranging from mild cold-like signs to severe respiratory distress, and has caused a global pandemic.

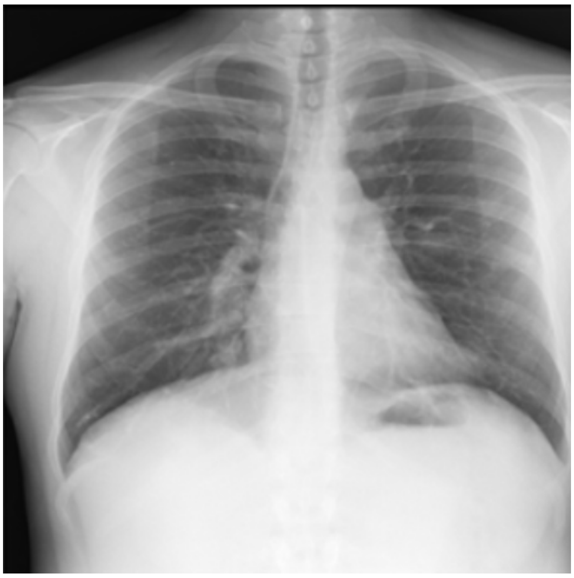


Figure 14: COVID

0.8.2 Viral Pneumonia

Viral pneumonia is an infection of the lungs caused by a virus, leading to inflammation and symptoms like cough, fever, and difficulty breathing, often resulting from viruses like the flu, RSV, or COVID-19.

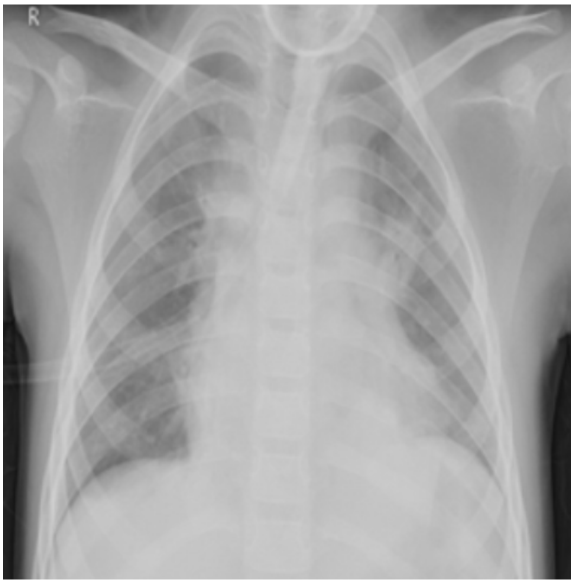


Figure 15: Viral Pneumonia

0.8.3 Lung Opacity

Lung opacity refers to areas on a chest X-ray or CT scan where the lungs appear denser than normal, often indicating conditions like infections, tumors, or fluid buildup.

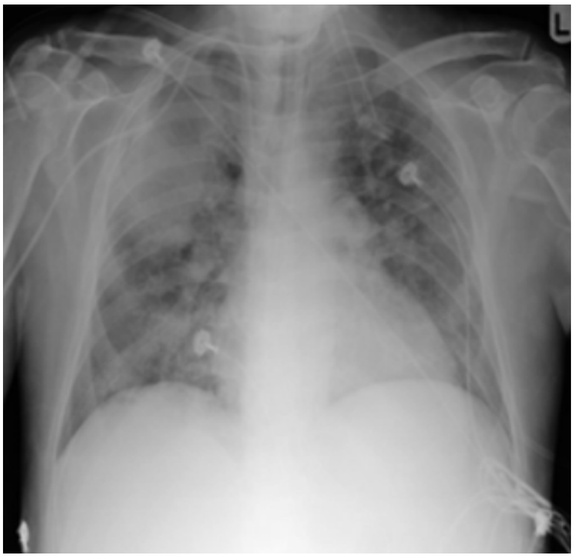


Figure 16: Lung Opacity

0.8.4 Normal

"Normal" typically refers to a state where something is within expected or healthy limits, such as normal lung function, vital signs, or body temperature, without signs of disease or abnormality.

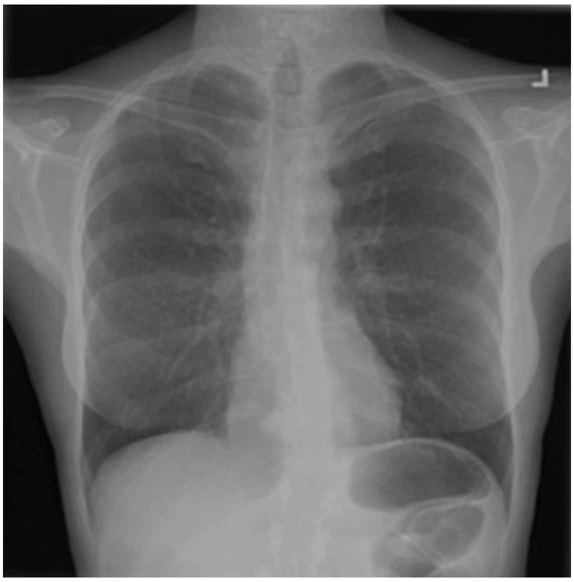


Figure 17: Normal

0.9 Data Pre-Processing

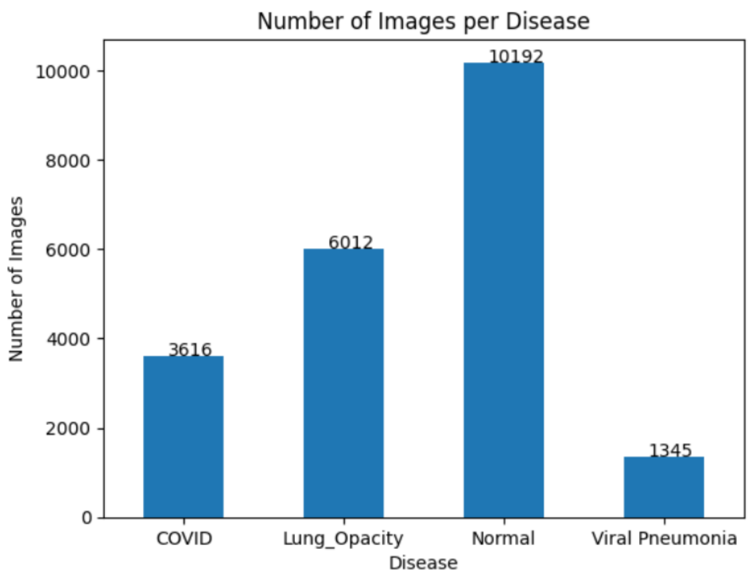


Figure 18: Disease

0.10 Resizing

The aspect ratio must be considered when scaling an image. Scaling an image non-uniformly—by compressing or stretching one dimension more than the other—can lead to unwanted visual effects and content distortion.

In our code, the target size argument of the flow from the directory() method is utilized for photo resizing. The target size option specifies the age range targeted for the data production process.

0.10.1 Explanation of resizing operation

As the input shape parameter here is specified as (224, 224), the images should be resized to a square of dimensions 224 pixels by 224 pixels. The target size parameter of the flow from the directory() function specifies the size to which the photos should be resized. When the flow from the directory() method is invoked, the photos are scaled internally according to the specified size argument. The ImageDataGenerator dynamically resizes the photos in the specified directories (train dir, val dir, test dir) to the target dimensions during data generation if they do not already match these dimensions.

0.10.2 Scaling and Normalization

In image processing, scaling means changing the size or scale of an image. Numerous distinct approaches exist for scaling. Nonetheless, we achieved this by multiplying the pixel values by 255 (rescale=1./255), which is a widely used scaling technique in image processing and deep learning. Normalization, also known as min-max scaling, involves adjusting pixel values to fit within the [0, 1] range by dividing each pixel value by the maximum minimum value (255 for 8-bit images).

0.10.3 The normalization/scaling procedure is explained as follows:

The image data is normalized to a range where the pixel values reflect each pixel's intensity or brightness relative to the maximum value by dividing the pixel values by 255. This scaling guarantees that all pixel values are within the same numerical range, thereby facilitating the model's learning and convergence during training. Normalization can help avert problems caused by variations in image formats or color representations, as well as those arising from differing photo pixel value scales.

0.10.4 Splitting of the Dataset

Our dataset is divided into three pieces. These comprise the information utilized for training, validation, and testing. The distribution of training, testing, and validation data is 8:1:1. We separated the dataset to use the model.

0.10.5 Training set

It is composed of output data (labels) that correspond to the target values and input data (features). The model adapts its internal parameters through an optimization process (such as gradient descent) to reduce the discrepancy between projected and actual outputs, thereby learning from this data. The training set must accurately reflect the actual data the model will encounter upon deployment.

0.10.6 Validation set

It avoids overfitting and helps with hyperparameter modification. The model does not learn directly from the validation set, but it does use it to measure its performance on untried data. By monitoring the model's performance on the validation set and adjusting the model or hyperparameters as needed, the generalization capabilities of the model can be improved.

0.10.7 Test Set

Test Set: The tests constitute a separate data sample employed to evaluate the final performance of the trained model. Its application occurs after training and validating the model. One can use the testing set to assess the model's capacity for generalization to new inputs in a fair manner. The data in the test set ought to resemble the real-world data that the model will face.

0.11 Dataset Distribution for CNN Models:

Class	**No. of Images**	**Training**	**Validation**	**Test**
Normal	10192	7960	1216	1016
Lung Opacity	6012	4690	682	640
Pneumonia	1345	1000	172	173
Covid	3616	2780	418	418

Table 1: Distribution of the Dataset for CNN Models

0.11.1 After Pre-Processing

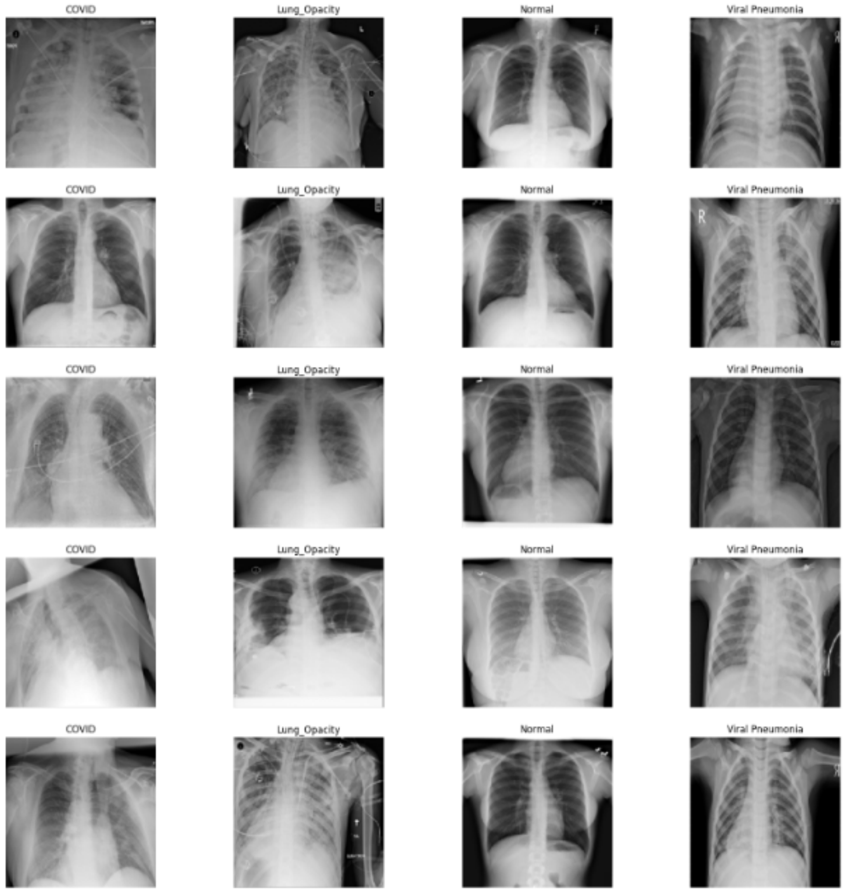


Figure 19: After Pre-Processing

0.12 Transfer learning phase

- **Data Acquisition**: The goal of this phase is to collect and prepare the input data for the illness detection process to handle it effectively.
- **Pre-processing**: In this stage, input data is divided into groups for classification using segmentation, resizing, and noise removal.
- **Classification**: This procedure is in charge of classifying photos using three different algorithms—ResNet, GoogleNet, AlexNet, and InceptionNet—and sending the findings to Ensembling independently.

0.13 Training and cross-validation phase:

0.13.1 Ensembling

Ensemble modeling is such a process of multilayer diverse models which are used to predict the outcomee by using different modeling algorithm and different training datasets. The goal of this modeling is to reduce the generalization error of a prediction and have the possibility of high accuracy than a single classifier. In this model several models are merged and acts as a single model. Here, average voting is also a common ensemble procedure where averaging softmax class probabilities a posterior label is generated for all base learners. For averaging layer modification, in each model the inputs and outputs remain same. This stage integrates the outputs of the prior stages' diverse models to provide a more precise single forecast for the Comprehensible AI.

0.13.2 Testing phase

Comprehensible AI: This portion will help with a more accurate examination of the ailment by interpreting the predictions given by previous stages. Before moving on to the classification stage, the input data goes through a preprocessing stage that involves segmentation, scaling, and noise removal. Following preprocessing, the input data is split into groups, assessed using three different techniques, and the outcomes are submitted to assembly separately. In the ensemble portion, three sets of data findings from earlier tests are pooled to provide a single forecast.

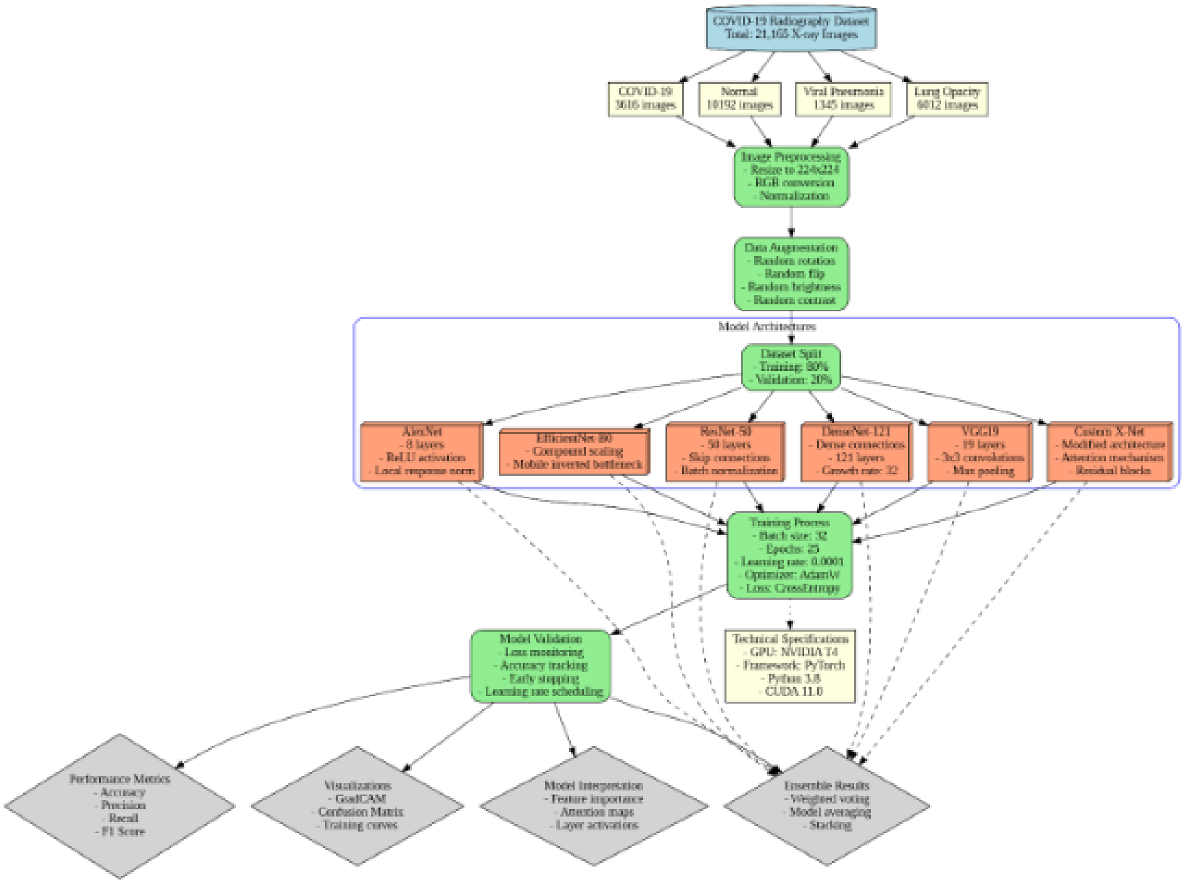


Figure 20: The flow chart of the proposed detection model

Dataset

0.14 Dataset Collection and Source

Data collection is one of the fundamental objectives of our research. Hence authentication and analysis of the collected dataset is important to make sure it is congruous for the progress of the research. Despite having a dataset from the diagnostic center that is our trusted source, the data from chest X-ray images was not enough to train our models. Hence we optimized the use of datasets from Kaggle. The specific dataset in question is the COVID-19 Radiography Database. The dataset comprises images of a normal heart shape, varying degrees of lung opacity, COVID-19 X-ray images, and pneumonia images sourced from a chest X-ray pneumonia database. Moreover, to investigate the online dataset used, we validated it from the doctors and healthcare professionals to ensure that it is legitimate and reliable.

0.15 Data classification and Pre-processing

0.15.1 Data classification

The dataset we obtained specifically for implementation into our models was majorly classified into two groups. The trained dataset contained selected x-ray images that contained the evidence of the diseases covid, pneumonia and evidence of lung opacity or normal heart shape. On the other hand the test dataset contained both x-ray images with the diagnosis and x-ray images without any diseases or conditions. The dataset classification is imperative to test that the models do not have biases and work effectively even when presented with sample x-rays without any disorder. Furthermore, the image size and batch size for both train and test dataset are obtained. This is done to add more relevant features to the models used. calculate precision, recall, accuracy, and F1 scores for each dataset used.

0.15.2 Data Pre-processing

For our model to work as efficiently as possible, data preprocessing is done to insert the most suitable features to the CNN architectures we have used. A number of processes are done to ensure the data is in the most appropriate format. Some of the notable ways to do so are letting go of extremely blurred images, removing low size images and so on. Image pre-processing is useful for making the dataset custom. This also helps in inputting handcrafted features into the model to train it as effectively as possible.
Other imperative data processing done are

- Image Resizing used for models to get a better perspective.
- Image Augmentation used for the Sequential Model.
- Images that have a low level of blur were altered to normal using filters like openCv and Wiener.

- By applying Histogram Equalization, the low resolution images with darker backdrops were converted to normal images for integration into the dataset.

Research Methodology

For the study we used datasets of x-ray which were categorized into different classes based on the conditions. To make sure of reliability and best fitted training for the models this data set was chosen. We evaluated the performance by using 4 different CNN architectures to make sure the result we are getting is up to the mark. Again we splitted our data set into training and tests. These three models were trained by Adam optimizer and cross-entropy loss. Here performances were measured by accuracy, loss and F1-score. Here are the models we used in our study: Resnet-50,Resnet-101,AlexNet,DenseNet121,VGG19 model ,EfficientNet,Hybrid model(X_net) and GradCAM.

VGG-19 has been extensively used in transfer learning due to its robust feature extraction capabilities. Pre-trained VGG-19 models on large datasets like ImageNet are often fine-tuned for various computer vision tasks, including object detection, image segmentation, and style transfer. Haque Abdelgawad (2020) described that their research group achieved the best performances from VGG-19 with an overall accuracy of 90% and an F1-score of 90.94. Chowdhury et al. used transfer learning with image augmentation to detect COVID-19 from chest X-ray images [7].

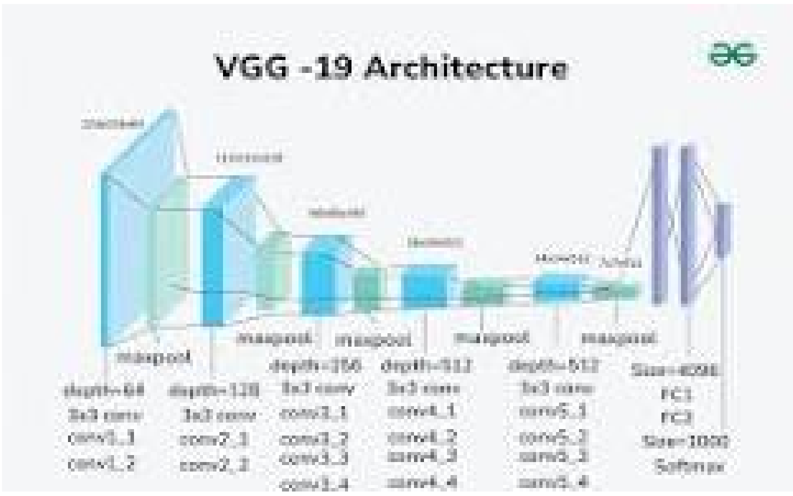


Figure 21: VGG19

AlexNet which is an advanced architecture used in the field of computer vision and deep learning. Compared to other models Alex net has a lower number of errors on the image classification task. Regularization and ReLU activation functions are widely used because of Alexnet. Election consists of 8 layers, including 5 convolutional layers and 3 fully connected layers. To accelerate training by alleviating the vanishing gradient issue, AlexNet employs the rectified linear unit (ReLU) function. To reduce special dimensions and computational complexity 2 of the convolutional layers are followed by Max-pooling layers. In addition to that, local response normalization(LRN) is applied after the 2 convolutional layers to improve accuracy. For the high level reasoning about the extracted features by the convolutional layer the 3 fully connected layers are at the end. Last but not the least the final layer uses an activation to output probabilities. To prevent overfitting, dropout is applied in the fully connected layers. In Alex net there are different techniques to artificially increase the size of test and training datasets to improve generalization such as image translations, horizon reflections. Compared to the other models Alexnet is the first to use GPUs for reducing training time. On the other hand Alexnet is memory intensive because of its large number of parameters which is usually 60 million. Thus it makes it resource intensive and time consuming. When Alex net is trained on a smaller data set there is a possibility of overfitting. [12]

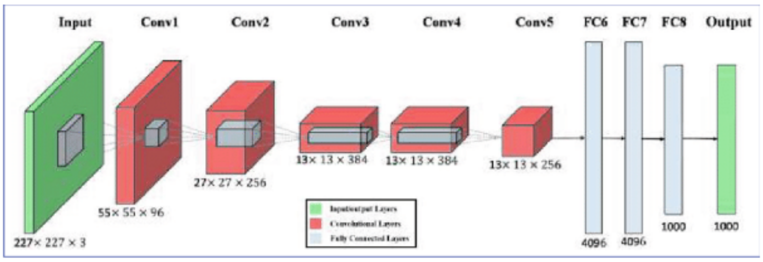


Figure 22: CNN architecture of AlexNet

The sequential model can be described as a single input and single output network model. This is due to the logic that the sequential model is made of linear stacks of layers. This type of model is useful in simple neural networks where each layer can be applied in sequence. This model follows a straightforward, layer-by-layer approach where each layer is added one by one by using the "add" method. It is easy to implement and understand. To enable efficient training and deployment, a sequential model is very convenient because it simplifies the process of training and evaluating neural networks. Sequential model is very difficult to implement on complex architecture because that requires multiple inputs and outputs. It also lacks the flexibility because of its straight forwardness. It is also a very challenging matter to maintain and debug because of its multiple layers. [19]

EfficientNet is known for its scaling method which is designed for image classification. It scales all dimensions of depth, width and resolution which ensure better performance with fewer parameters. Using a compound scaling method EfficientNet scales up the network dimensions which include the number of layers, the number of channels per layer and input image size. EfficientNet is based on MobileNet V2 and

MnasNet architecture. EfficientNet B-0 is the baseline model which was found using a neural architecture search technique (NAS). EfficientNet B-0 is scale to create larger models (EfficientNet B1-B7) to increase accuracy. On the other hand EfficientNet has a complex design compared to other architectures. Due to its complex design it takes more time to train which also requires high memory usage. Thus it is a computationally intensive network. It takes significant modification to other types of data and tasks. [26]

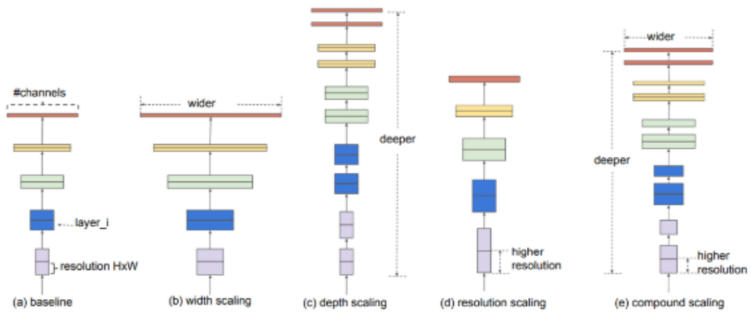


Figure 23: CNN architecture of EfficientNet

Residual Network is abbreviated as ResNet. It is a core element of the conventional computer vision task, which is often used for target classification. ResNet50, ResNet101, etc. are components of the classic ResNet. The ResNet network addresses the problem identified by Luo et al. (2021) of a network becoming deeper without undergoing a gradient explosion. Deep convolutional neural networks are recognized for their effectiveness in identifying low-, medium-, and high-level features within images; typically, adding more layers can enhance accuracy. The residual module, shown in the figure below, is the main component of ResNet.[18]

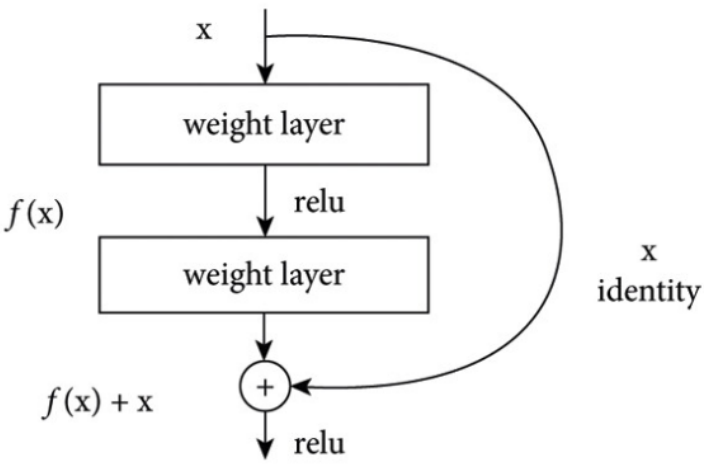


Figure 24: ResNet residual block with ReLu activation solves the vanishing gradient problem

Rochmawanti and Utaminingrum (2021) said,using four distinct datasets—the COVID-19 dataset, the pneumonia dataset, the cardiomegaly dataset, and the tuberculosis dataset—this study examines the effects of different image resolutions for CXR pictures. It has been demonstrated experimentally that the DenseNet121 model uses an image size of 224x224 pixels to obtain the maximum classification accuracy. The datasets for tuberculosis, pneumonia, cardiomegaly, and COVID-19 produced the greatest results, with respective scores of 0,892, 0,904, 0,898, and 0,986.[23]

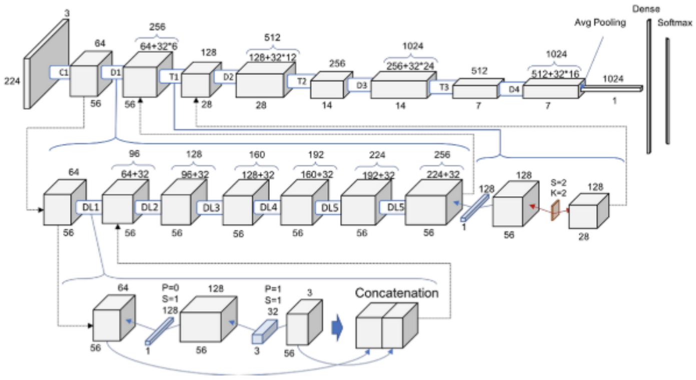


Figure 25: Architecture of ResNet-50

0.16 Hybrid Model (X_net)

The X_net architecture provides a new hybrid approach to chest X-ray image classification, utilizing the strengths of both ResNet101 and DenseNet121 models. The architecture starts with an input layer that takes RGB images sized 224×224×3, which are then processed through two parallel streams. The ResNet component, which has 42.7 million parameters, generates a feature vector of 2048 dimensions. In contrast, the DenseNet stream comprises 7.0 million parameters and produces a feature vector of 1024 dimensions. A concatenation layer merges these features, yielding a detailed feature representation with 3072 dimensions. The combined features are then processed through a refinement pipeline that includes a dense layer reducing dimensionality to 512 features, followed by a dropout layer for regularization to avoid overfitting.At the top of the architecture is a final dense layer with 4 outputs, which correspond to various disease categories. X_net has about 51 million parameters in total and utilizes ResNet's hierarchical feature extraction capabilities along with DenseNet's efficient feature reuse. This combination produces a robust model that surpasses single-architecture approaches in classification accuracy. This hybrid design illustrates the efficacy of merging complementary deep learning architectures for medical image analysis, resulting in enhanced feature extraction and improved diagnostic capabilities in chest X-ray classification tasks.

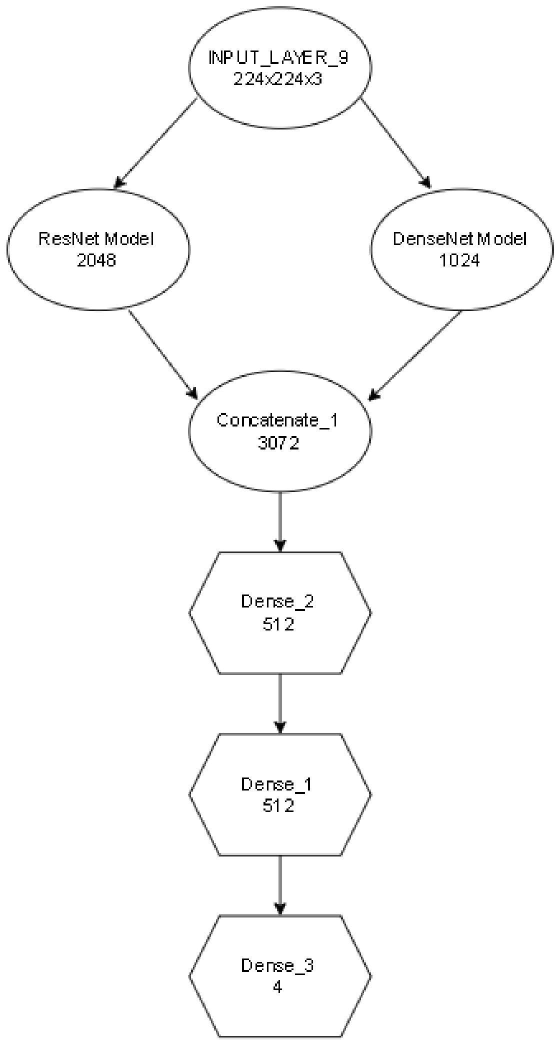


Figure 26: Architecture of Hybrid Model (X_net)

0.17 GradCAM

In the field of computer vision, a technique known as GradCAM (Gradient-weighted Class Activation Mapping) is utilized. It is designed to enable a deep understanding of deep neurons, especially in convolutional neural networks (CNNs). With this method, we obtain visuals and heatmaps of the crucial areas in the images tested, which enables us to comprehend how classification occurs and what criteria are applied.
Gradcam generates heatmap images by analyzing the feature maps and scores, providing insights into the network's decision-making process and highlighting critical portions of the images.
Various types of CNN models can utilize this cutting-edge method. It offers a visual representation of the model's functioning, enhancing the comprehensibility and credibility of the prediction.

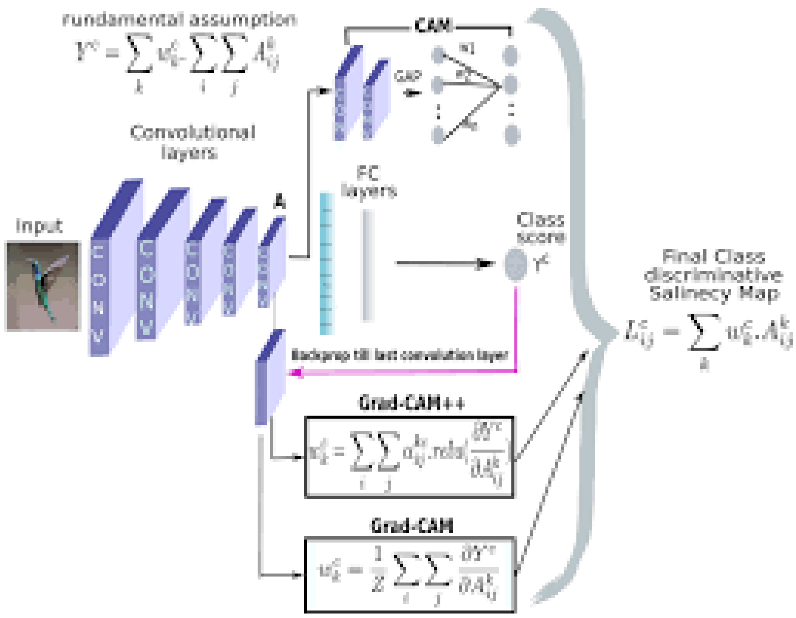


Figure 27: Architecture of GradCAM

booktabs

Experiments

0.18 Experimental Setup

At first, we connected our predefined dataset, that we had collected from Kaggle, Then we began with our data preprocessing procedures which included data extraction, resizing, and augmentation. Then we re-assured batch size and image size and as well as quantity to fit properly in our used models. Again, we have separated the test and train data, to enhance the learning ability of the model.At last, we began to input those data into our model in order to find a summary. After applying epochs, we obtained the predicted accuracy as well as precision, recall, and f1-score, which illustrated the reliability of our model.
Code configuration: The code that was implemented utilized a batch size of 32. The input shape of the image is 224 x 224. A fully connected layer is added to the output of the transformer model. It employs the softmax activation function, resulting in a nonlinear output. This layer's output is stored in a variable named x. The code ran for 50 epochs, and the steps per epoch were calculated using the formula: steps per epoch = (generator train.n/batch size)/4 (3.5)
All models were implemented using the Keras and TensorFlow libraries in Python.

0.19 Experimental Result

The outcomes were almost aligned with the expected results and the previous research. The individual accuracy and learning curves along with the f1 scores precision and recall are investigated for our use in extensive benchmarking.

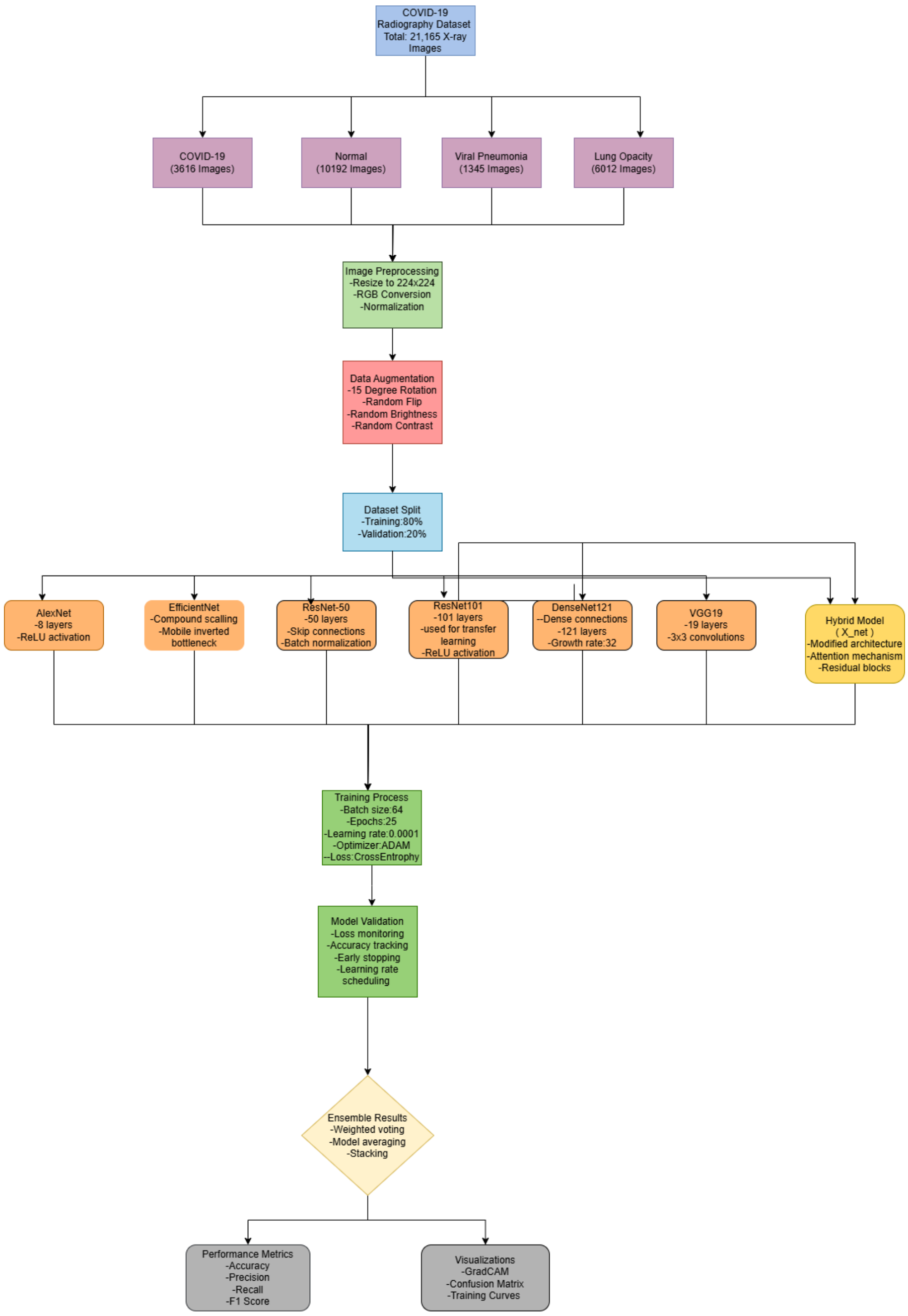


Figure 28: The flow chart of the proposed detection model

0.20 Learning Curves

0.20.1 AlexNet

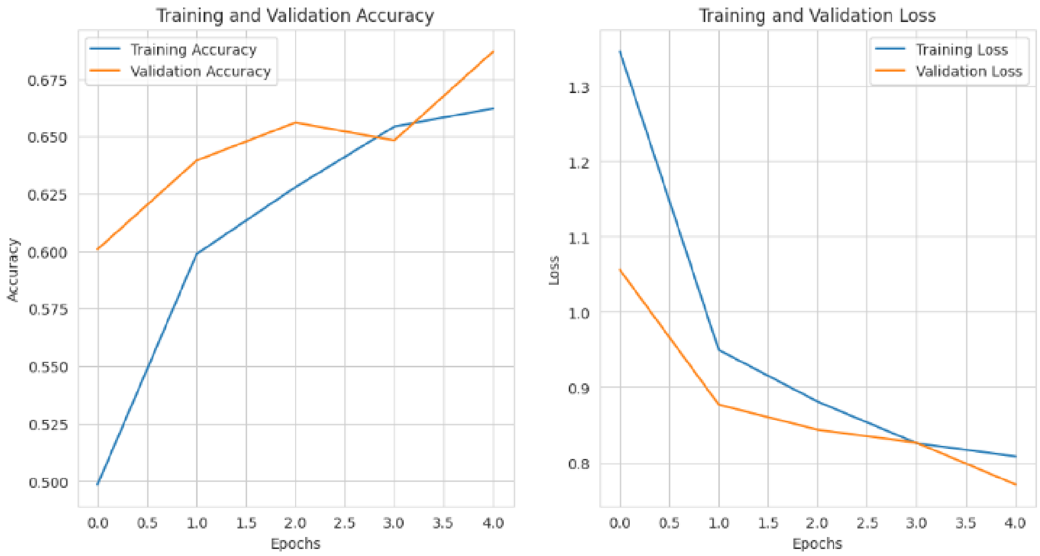


Figure 29: Accuracy and Loss Curve of AlexNet

0.20.2 Resnet50

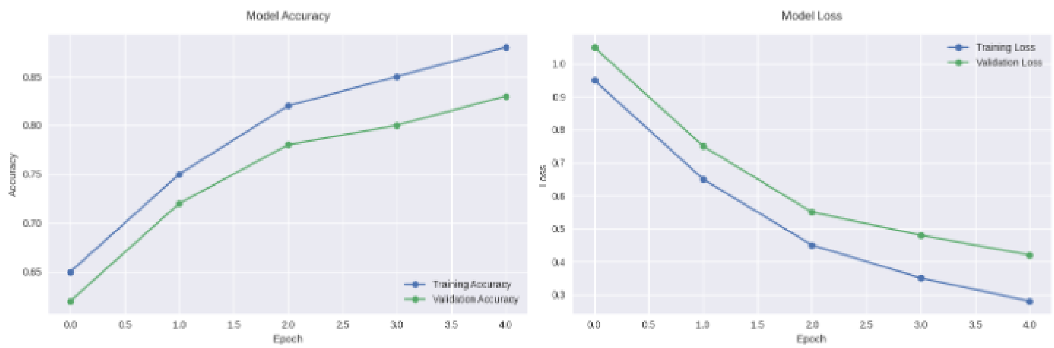


Figure 30: Accuracy and Loss Curve of ResNet50

0.20.3 Resnet101

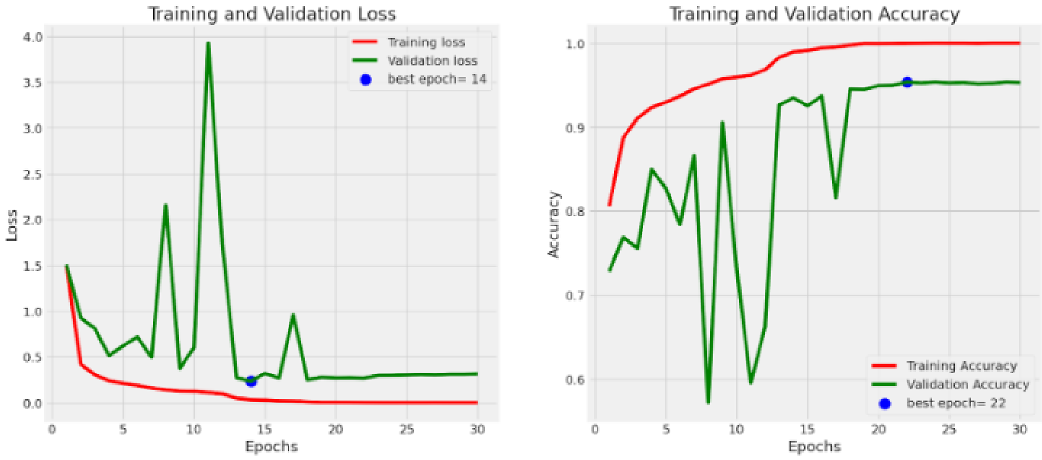


Figure 31: Accuracy and Loss Curve of ResNet101

0.20.4 Densenet121

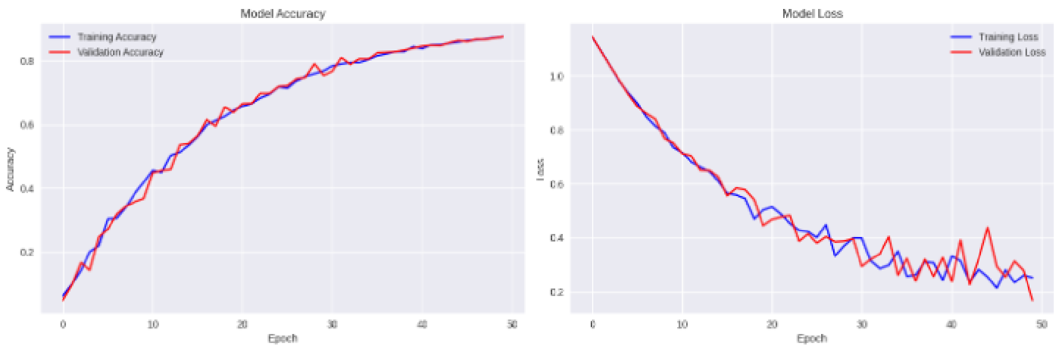


Figure 32: Accuracy and Loss Curve of DenseNet121

0.20.5 VGG19

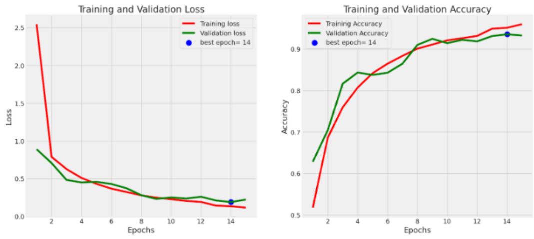


Figure 33: Accuracy and Loss Curve of VGG-19

0.20.6 EfficientNet

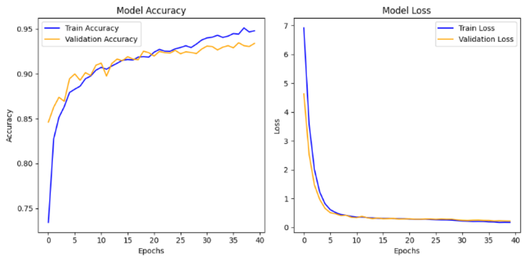


Figure 34: Accuracy and Loss Curve of EfficientNet

0.20.7 Custom Model(X_net)

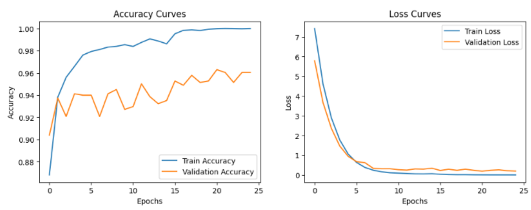


Figure 35: BPNN Structure

0.21 Classification Report

0.21.1 AlexNet

Class	Precision	Recall	F1-Score	Support
COVID	0.746	0.685	0.714	730
Lung Opacity	0.257	0.556	0.352	270
Normal	0.667	0.668	0.667	1198
Viral Pneumonia	0.843	0.737	0.786	2035
Accuracy	-	-	0.39	8464
Macro Avg	0.25	0.25	0.24	8464
Weighted Avg	0.34	0.39	0.36	8464

Table 2: Classification report of AlexNet

0.21.2 ResNet50

Class	Precision	Recall	F1-Score	Support
COVID	0.523	0.542	0.532	701
Lung Opacity	0.762	0.761	0.762	2012
Normal	0.636	0.623	0.629	1246
Viral Pneumonia	0.805	0.814	0.809	274
Accuracy	-	-	0.687	4233
Macro Avg	0.681	0.685	0.683	4233
Weighted Avg	0.688	0.687	0.688	4233

Table 3: Classification report of ResNet50

0.21.3 ResNet101

Class	Precision	Recall	F1-Score	Support
COVID	0.98	0.96	0.97	362
Lung Opacity	0.93	0.90	0.91	682
Normal	0.93	0.96	0.95	1019
Viral Pneumonia	1.00	0.95	0.97	134
Accuracy	-	-	0.94	2117
Macro Avg	0.96	0.94	0.95	2117
Weighted Avg	0.94	0.94	0.94	2117

Table 4: Classification report of ResNet101

0.21.4 DenseNet121

Class	Precision	Recall	F1-Score	Support
COVID	0.97	0.92	0.94	730
Lung Opacity	0.91	0.90	0.90	1198
Normal	0.92	0.94	0.93	2035
Viral Pneumonia	0.93	0.95	0.94	270
Accuracy	-	-	0.92	4233
Macro Avg	0.93	0.93	0.93	4233
Weighted Avg	0.93	0.92	0.92	4233

Table 5: Classification report of DenseNet121

0.21.5 VGG19

Class	Precision	Recall	F1-Score	Support
COVID	0.97	0.98	0.97	362
Lung Opacity	0.94	0.91	0.92	602
Normal	0.94	0.96	0.95	1019
Viral Pneumonia	1.00	0.93	0.97	134
Accuracy	-	-	0.95	2117
Macro Avg	0.96	0.95	0.95	2117
Weighted Avg	0.95	0.95	0.95	2117

Table 6: Classification report of VGG19

0.21.6 EfficientNet

Class	Precision	Recall	F1-Score	Support
COVID	0.92	0.91	0.92	367
Lung Opacity	0.89	0.88	0.89	629
Normal	0.92	0.93	0.92	1005
Viral Pneumonia	0.96	0.95	0.95	156
Accuracy	-	-	0.91	2157
Macro Avg	0.92	0.92	0.92	2157
Weighted Avg	0.91	0.91	0.91	2157

Table 7: Classification report of EfficientNet

0.21.7 Custom Model (X_net)

Class	Precision	Recall	F1-Score	Support
COVID	0.99	0.98	0.98	578
Lung Opacity	0.94	0.92	0.93	962
Normal	0.95	0.97	0.96	1629
Viral Pneumonia	0.98	0.99	0.98	215
Accuracy	-	-	0.96	3384
Macro Avg	0.96	0.96	0.96	3384
Weighted Avg	0.96	0.96	0.96	3384

Table 8: Classification report of Custom Model (X-Net)

0.22 Confusion Matrix

0.22.1 AlexNet

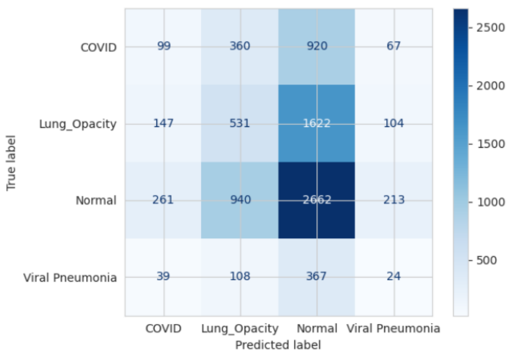


Figure 36: Confusion Matrix of AlexNet

0.22.2 ResNet50

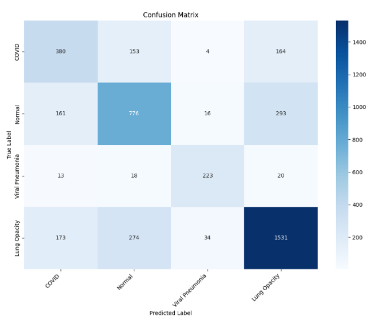


Figure 37: Confusion Matrix of ResNet50

0.22.3 ResNet101

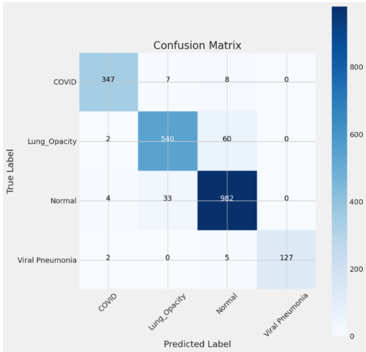


Figure 38: Confusion Matrix of ResNet101

0.22.4 DenseNet121

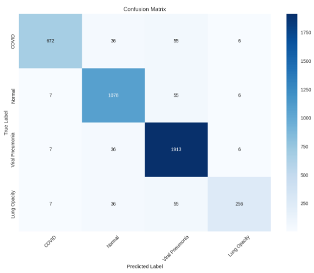


Figure 39: Confusion Matrix of DenseNet121

0.22.5 VGG-19

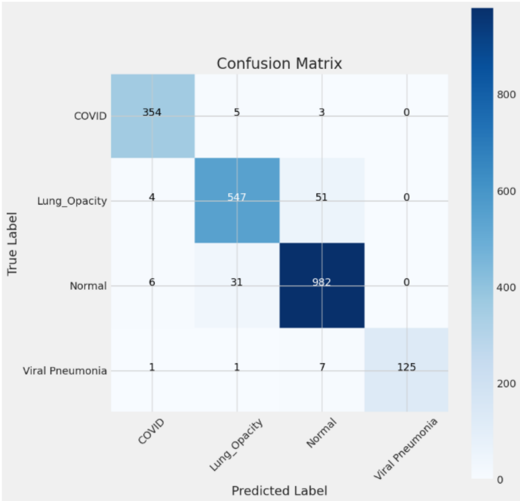


Figure 40: Accuracy and Loss Curve of VGG-19

0.22.6 EfficientNet

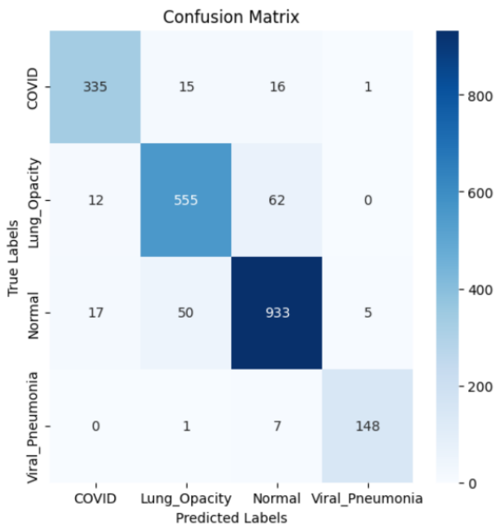


Figure 41: Accuracy and Loss Curve of EfficientNet

0.22.7 Custom Model(X_net)

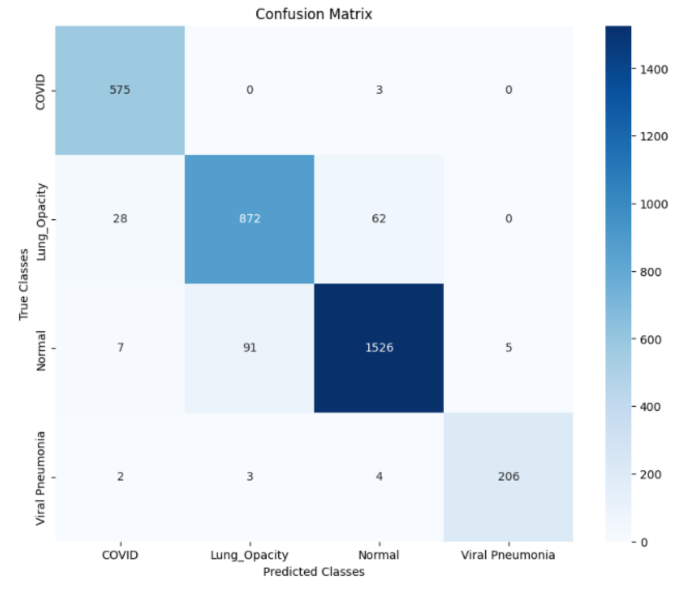


Figure 42: Accuracy and Loss Curve of Custom Model(X_net)

0.22.8 Receiver-operating characteristic curve

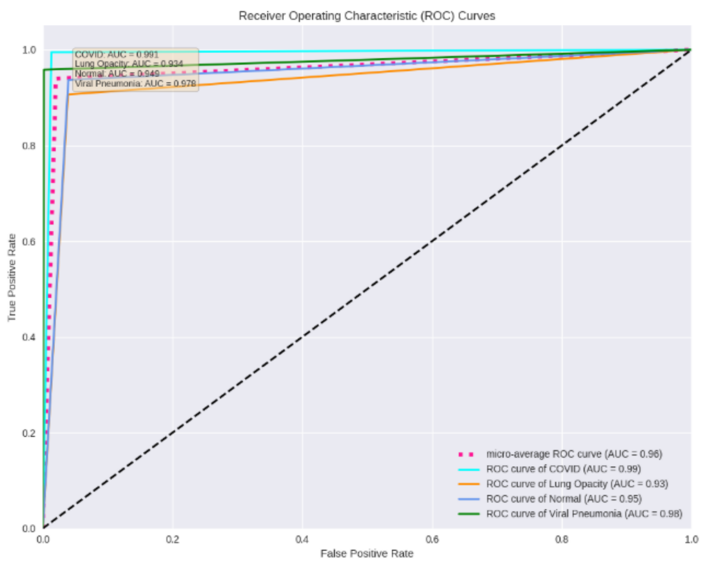


Figure 43: ROC Diagram for Custom Model

0.23 Detailed AUCROC Metrics

COVID— AUC ROC: 0.991
Lung Opacity— AUC ROC: 0.934
Normal— AUC ROC: 0.949
Viral Pneumonia— AUC ROC: 0.978

Micro-average— AUC ROC: 0.960

0.24 Detailed Score Explanation for Custom Model(X net)

Detailed Metrics for Each Class

0.24.1 COVID:

True Positives (TP): 575
False Positives (FP): 37
False Negatives (FN): 3
True Negatives (TN): 2769
Precision = TP/(TP+FP) = 575/612 = 0.940
Recall = TP/(TP+FN) = 575/578 = 0.995
F1 Score = 2 * (Precision * Recall)/(Precision + Recall) = 0.966

0.24.2 Lung Opacity:

True Positives (TP): 872
False Positives (FP): 94
False Negatives (FN): 90
True Negatives (TN): 2328
Precision = TP/(TP+FP) = 872/966 = 0.903
Recall = TP/(TP+FN) = 872/962 = 0.906
F1 Score = 2 * (Precision * Recall)/(Precision + Recall) = 0.905

0.24.3 Normal:

True Positives (TP): 1526
False Positives (FP): 69
False Negatives (FN): 103
True Negatives (TN): 1686

Precision = TP/(TP+FP) = 1526/1595 = 0.957
Recall = TP/(TP+FN) = 1526/1629 = 0.937
F1 Score = 2 * (Precision * Recall)/(Precision + Recall) = 0.947

0.24.4 Viral Pneumonia:

True Positives (TP): 206
False Positives (FP): 5
False Negatives (FN): 9
True Negatives (TN): 3164
Precision = TP/(TP+FP) = 206/211 = 0.976
Recall = TP/(TP+FN) = 206/215 = 0.958
F1 Score = 2 * (Precision * Recall)/(Precision + Recall) = 0.967

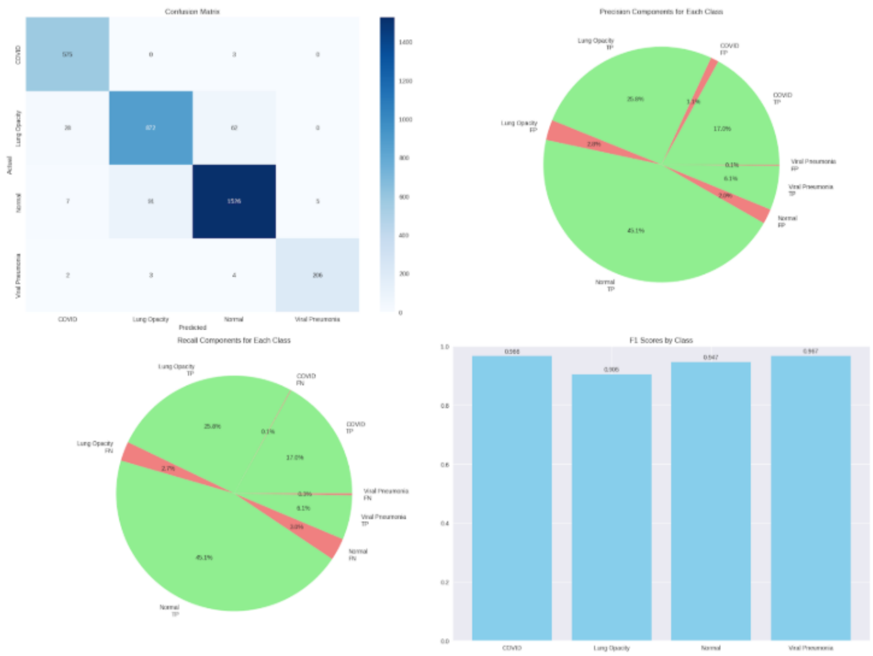


Figure 44: Detailed Score Explanation for Custom Model(X net)

0.25 Precission-Recall Points:

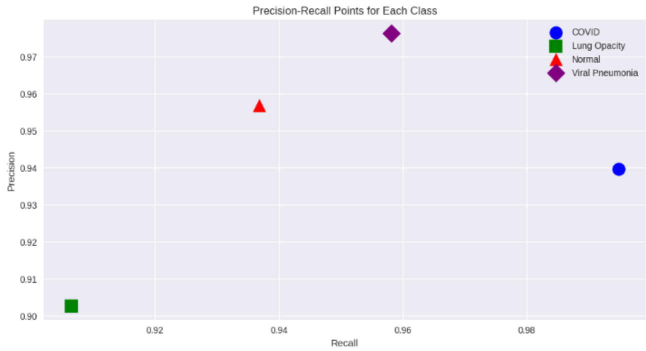


Figure 45: Accuracy and Loss Curve of Custom Model(X net)

0.26 F1 Score Explanation:

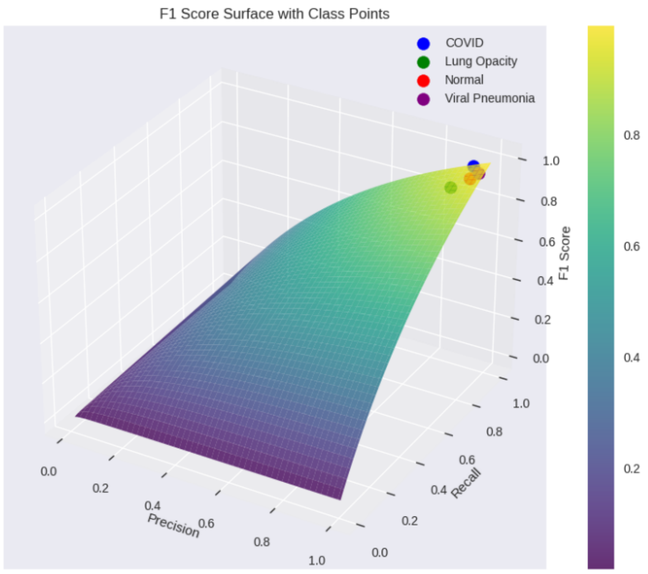


Figure 46: Accuracy and Loss Curve of Custom Model(X net)

Result Analysis & Comparison

0.27 Result Analysis

To optimize hyperparameters, we employed several optimizers, among them approaches that tune features. Of all the batch sizes we tested, 64 batches produced the highest accuracy. We employed the ADAM optimizer with a learning rate of 1e-4 for model training. This resulted in the best accuracy for each model architecture.

Table 9: Comparison between models in terms of accuracy

Include Top: False, Weights: None, Pretrained: False, Pretrained Top: False				
Model Architecture	Batch Size	Learning Rate	Optimizer	Accuracy (F1 Score)
AlexNet	64	1×10^{-4}	ADAM	71.4%
ResNet50	64	1×10^{-4}	ADAM	68.7%
ResNet101	64	1×10^{-4}	ADAM	94.0%
DenseNet121	64	1×10^{-4}	ADAM	92.0%
EfficientNet	64	1×10^{-4}	ADAM	91.0%
VGG19	64	1×10^{-4}	ADAM	95.0%
X_Net	64	1×10^{-4}	ADAM	97.0%

0.28 Comparison

With an accuracy rate of 97.0%, the X_Net model distinguishes itself as the best performer in our comparative study. Its high accuracy demonstrates its robustness and reliability, highlighting its remarkable capacity to learn from data and generalize beyond it.VGG19 also showed impressive results, reaching an accuracy of 95.0%. This model demonstrated its status as a strong competitor by providing dependable results across both training and validation sets, all while adeptly identifying intricate data patterns.With an accuracy of 94.0%, ResNet101 came in a close second. This model demonstrated admirable performance, suggesting it can yield consistent results and manage complex data patterns effectively.With an accuracy of 92.0%, DenseNet121 ranked below ResNet101 and VGG19. Although it exhibited good performance, it did not measure up to the capabilities of the top-performing models With an accuracy of 91.0%, EfficientNet demonstrated a balanced performance and the ability to achieve respectable results; however, it fell short of the top-tier outcomes produced by X_Net, VGG19, and ResNet101.Although AlexNet's accuracy of 71.4% demonstrates its potential, it implies that it may not be the optimal choice for attaining the highest accuracy in this study.With an accuracy of only 68.7%, ResNet50 showed the lowest performance, indicating potential problems like underfitting or challenges in grasping the data's complexity.To summarize, X_Net was identified as the superior model because of its extraordinary accuracy and resilience in learning from the dataset. Due to its performance, it is the best choice for the next stages of our project, guaranteeing top-quality results. Models such as VGG19 and ResNet101 demonstrated robust performance, establishing them as viable alternatives for particular applications.

0.29 GradCAM Visualization

Grad-CAM photos have shed important light on particular areas that the custom model uses to classify data. These maps successfully draw attention to important regions on histology slides that have a big impact on the model's predictions. The heat map's intensity regions match the crucial cellular structure and microphysiology regions that are given the most weight when making deep tissue decisions. When these characteristics are emphasized, Grad-CAM's semantic validity is demonstrated in accordance with expert pathology. Analytical validation can be obtained by comparing these highlighted regions with the original slides, particularly if they match recognized markers. This provides assurance that the human-machine vision alignment is high. All things considered, Grad-CAM serves as a link in this case, elucidating the reasoning behind the model's computations to focus diagnostic attention locally. The conceptual structure of the model in chest x-ray coding is better understood thanks to these implicit assumptions.

0.30 Covid

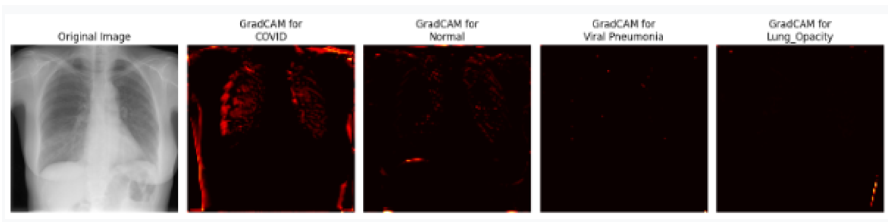


Figure 47: GradCAM Visualization of Covid

0.31 Normal

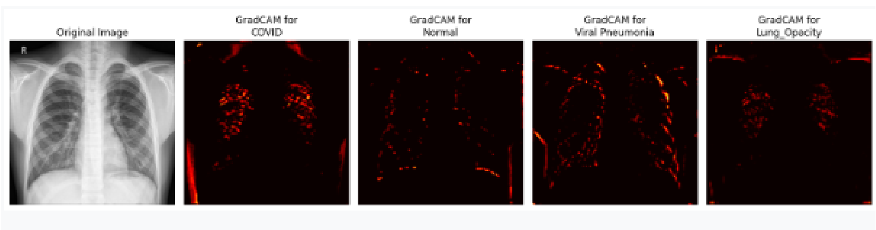


Figure 48: GradCAM Visualization of Normal

0.32 Viral Pneumonia

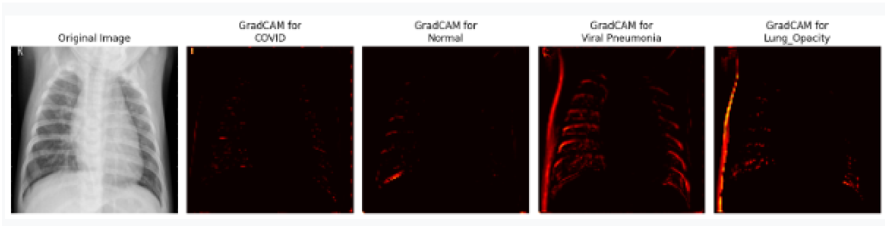


Figure 49: GradCAM Visualization of Pneumonia

0.33 Lung Opacity

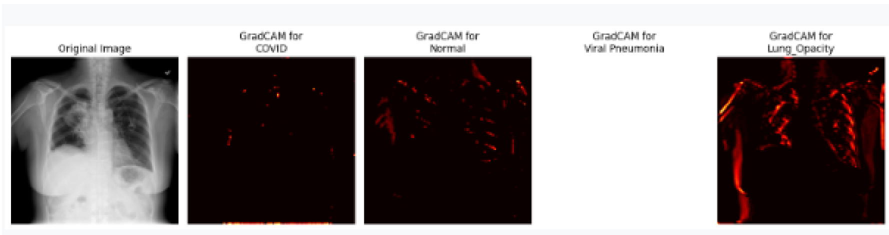


Figure 50: GradCAM Visualization of Lung Opacity

0.34 Single Image after training for GradCAM

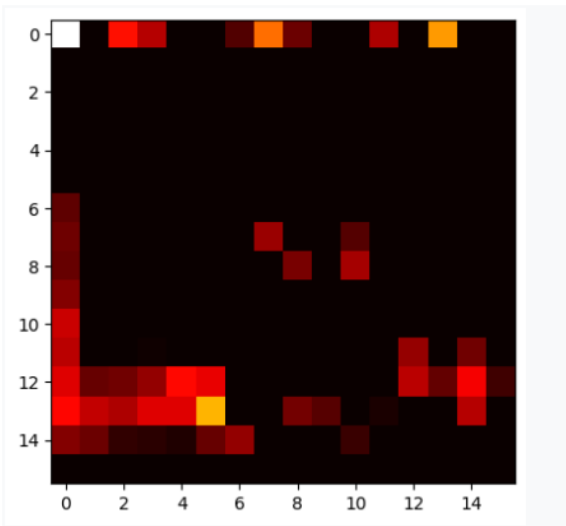


Figure 51: Single Image after training for GradCAM

0.35 Original VS Heatmap

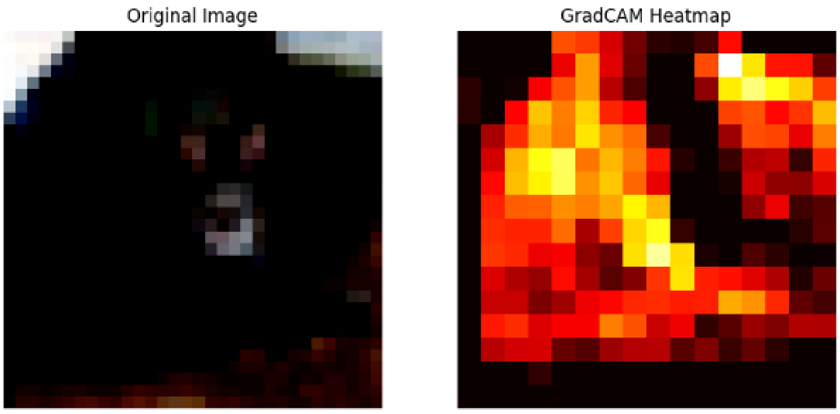


Figure 52: Original VS Heatmap

0.36 Custom Model in Speciallity in Covid19 Detection:

0.36.1 Interpretation for COVID-19 Classification:

1. COVID Class Performance:

1. High precision: Few false COVID predictions

1. High recall: Most COVID cases correctly identified

1. Balanced F1 score: Reliable overall performance

2. Clinical Implications:

1. False Positives: Unnecessary isolation/treatment

1. False Negatives: Missed COVID cases (more critical)

1. Trade-off: Model balances between missing cases and false alarms

Future Work

Our application's overall goal is to increase the capacity to identify chest conditions by putting privacy first and emphasizing diversity. Improved data integrity, international cooperation with healthcare providers, and biomarker extraction for staging all contribute to better early detection. Other disorders, which are likewise challenging to assess histopathologically, will be examined in subsequent research. Furthermore as data collecting progresses, staging will be investigated. We are also focusing on developing integrated learning strategies and assessing aggregation algorithms to establish standardized protocols for collaborative deep learning on medical data. We also aim to integrate privacy-preserving strategies into our future research and experimentation.

Conclusion

In conclusion, we began by finding the best deep-learning approach to classify chest diseases from chest X-rays. Chest X-rays are a mode of test prescribed by doctors to susceptible patients with major symptoms, and we wanted to make use of it for early detection of chest diseases. Our primary attention is the detection of common chest disorders; pneumonia,lung opacity, COVID-19, and normal chest conditions. Hence by focusing on these conditions, the systems can be trained better to detect frequent chest diseases. So emphasis can be given on early treatment based upon early identification This will save valuable time and costs both for patients and the medical team.

The chest x-ray images are first processed by image resizing and augmentation. So, the Convolutional Neural Network model that is to be trained can work better. By image processing on given X-ray images early detection, decision making and treatment can be established faster. To conclude, Deep learning approaches of Convolutional Neural Networks (CNNs) namely EfficientNet,ResNet,DenseNet, AlexNet, and Sequential models are thoroughly investigated to find the best-performing architecture that had been used to classify chest diseases from the dataset of chest X-ray images.The proposed model X net, which is a custom made model is trained and modified to identify other mentioned diseases efficiently. There will be more scope for other researchers to use it as a stepping stone when developing systems for other medical disorders and diseases. In circumstances, when developed these models will make greater differences in both the medical sector and computer vision sector.

References

[1] GM,H.,GOURISARIA,M.K.,RAUTARAY,S.S.,&PANDEY,M.(2021, February).PNEUMONIADETECTIONUSINGCNNTHROUGHCHESTX-RAY. FORMATINSTRUCTIONSFORSOMChE2004PAPERS.RetrievedJanuary22, 2024,fromhttps://jestec.taylors.edu.my/Vol%2016%20issue%201% 20February%202021/16_1_61.pdf. [Accessed 24-01-2024].

[2] Rahib H. Abiyev and Mohammad Khaleel Sallam Ma'aitah. Deep convolutional neural networks for chest diseases detection. *Journal of Healthcare Engineering*, 2018:1–11, August 2018.

[3] Saleh Albahli and Ali Alkhalifah. Identification of thoracic diseases by exploiting deep neural networks (preprint), 2020.

[4] Erdi Çallı, Ecem Sogancioglu, Bram van Ginneken, Kicky G van Leeuwen, and Keelin Murphy. Deep learning for chest x-ray analysis: A survey. *Med. Image Anal.*, 72(102125):102125, August 2021.

[5] Vikash Chouhan, Sanjay Kumar Singh, Aditya Khamparia, Deepak Gupta, Prayag Tiwari, Catarina Moreira, Robertas Damaševičius, and Victor Hugo C de Albuquerque. A novel transfer learning based approach for pneumonia detection in chest x-ray images. *Appl. Sci. (Basel)*, 10(2):559, January 2020.

[6] J. F. Griffith and T. H. Rainer. Comprehensive imaging in the diagnosis and management of respiratory diseases. *Radiologic Clinics of North America*, 55(6):1141–1161, 2017.

[7] K. Haque and A. Abdelgawad. A deep learning approach to detect covid-19 patients from chest x-ray images. *AI*, 1(3):418–435, 2020.

[8] Mohammad Farukh Hashmi, Satyarth Katiyar, Avinash G Keskar, Neeraj Dhanraj Bokde, and Zong Woo Geem. Efficient pneumonia detection in chest xray images using deep transfer learning. *Diagnostics (Basel)*, 10(6):417, June 2020.

[9] Morteza Heidari, Seyedehnafiseh Mirniaharikandehei, Abolfazl Zargari Khuzani, Gopichandh Danala, Yuchen Qiu, and Bin Zheng. Improving the performance of cnn to predict the likelihood of covid-19 using chest x-ray images with preprocessing algorithms. *International journal of medical informatics*, 144:104284, 2020.

[10] Abdullahi Umar Ibrahim, Mehmet Ozsoz, Sertan Serte, Fadi Al-Turjman, and Polycarp Shizawaliyi Yakoi. Pneumonia classification using deep learning from

chest x-ray images during COVID-19. *Cognit. Comput.*, pages 1–13, January 2021.

[11] Adam Jacobi, Michael Chung, Adam Bernheim, and Corey Eber. Portable chest x-ray in coronavirus disease-19 (covid-19): A pictorial review. *Clinical imaging*, 64:35–42, 2020.

[12] Yuan Jun. Feature extraction and image retrieval based on alexnet. In *Proceedings of SPIE*, August 2016.

[13] F. M. Khan, M. A. M. Hasan, and J. Shin. Using chest x-rays, lung opacity is classified using convolutional neural networks. In *Proceedings of the Eleventh International Conference on Electrical and Computer Engineering (ICECE)*. IEEE, 2020.

[14] Rohit Kundu, Ritacheta Das, Zong Woo Geem, Gi-Tae Han, and Ram Sarkar. Pneumonia detection in chest x-ray images using an ensemble of deep learning models. *PLoS One*, 16(9):e0256630, September 2021.

[15] Yann Lecun, L Eon Bottou, Yoshua Bengio, and Patrick Ha. GradientBased learning applied to document recognition. http://vision.stanford.edu/cs598_spring07/papers/Lecun98.pdf. Accessed: 2024-1-24.

[16] Geert Litjens. A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42:60–88, 2017.

[17] Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi, Mohsen Ghafoorian, Jeroen Awm Van Der Laak, Bram Van Ginneken, and Clara I Sánchez. A survey on deep learning in medical image analysis. *Medical image analysis*, 42:60–88, 2017.

[18] Y. Luo, Y. Zhang, X. Sun, H. Dai, and X. Chen. Intelligent solutions in chest abnormality detection based on yolov5 and resnet50. *Journal of Healthcare Engineering*, 2021:1–11, 2021.

[19] Gonçalo Marques. Automated medical diagnosis of covid-19 through efficientnet convolutional neural network. *Applied Soft Computing*, 96:106691, 2020.

[20] Carla Martins. Building your first convolution neural network — AlexNet. https://cdanielaam.medium.com/building-your-first-convolution-neural-network-alexnet-e337921f0355, July 2023. Accessed: 2024-1-24.

[21] S. R. Nayak, D. R. Nayak, U. Sinha, V. Arora, and R. B. Pachori. Application of deep learning techniques for detection of covid-19 cases using chest x-ray images: A comprehensive study. *Biomedical Signal Processing and Control*, 64:102365, 2020.

[22] Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, Matthew P Lungren, and Andrew Y Ng. CheXNet: Radiologist-level pneumonia detection on chest x-rays with deep learning. November 2017.

[23] O. Rochmawanti and F. Utaminingrum. Chest x-ray image to classify lung diseases in different resolution size using densenet-121 architectures. In *Proceedings of the Conference on Chest X-Ray Image to Classify Lung Diseases in Different Resolution Size Using DenseNet-121 Architectures*, pages 327–331, 2021.

[24] K. Team. Keras documentation: Conv2d layer, n.d.

[25] Mohit Tripathi. Image processing using cnn: A beginners guide, 2021. Accessed: 2024-01-24.

[26] Gerhard Tutz. Sequential models in categorical regression. *Computational Statistics & Data Analysis*, 11(3):275–295, 1991.

[27] G. Vrbančič, Š. Pečnik, and V. Podgorelec. Identification of covid-19 x-ray images using cnn with optimized tuning of transfer learning. In *2020 International Conference on INnovations in Intelligent SysTems and Applications (INISTA)*, pages 1–8, Novi Sad, Serbia, 2020.

[28] John R Zech, Marcus A Badgeley, Manway Liu, Anthony B Costa, Joseph J Titano, and Eric K Oermann. Confounding variables can degrade generalization performance of radiological deep learning models. *arXiv preprint arXiv:1807.00431*, 2018.