Predicting lung diseases through analysis of Chest x-rays using Deep Learning and interpreting predictions using GRAD-CAM

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***Abstract*—Pneumonia is the world's leading cause of death among children under 5 years of age, accounting for 16% of all deaths. is an inflammatory condition affecting the air sacs in the lungs, often caused by infection with bacteria, viruses. The diagnosis of pneumonia is compassed by scrutinizing X-ray images of the chest the most reliable method to detect pneumonia. In the absence of an enough number of expert radiologists, computer vision can aid in the diagnosis of X-ray images , where Artificial intelligence is becoming increasingly significant in our daily lives. this study aim to develop more powerful image classifier for diagnosing pneumonia using an deep learning approach. we have implemented a very popular convolutional neural network models known as VGG16 , RestNet50 for the diagnosis of pneumonia. and the technique called Gradient-weighted Class Activation Mapping (Grad-CAM) is implemented for each class to aid doctors in interpreting results more easily. we obtained the dataset from Guangzhou Women and Children's Medical Centre for Children's age from 1 to 5 year old. we reached an accuracy with level 95.99 for RestNet50 and 96.53 for VGG16 .**

***Index Terms*—Keywords: Pneumonia ,CNN ,Deep learning , ResNet , VGG**

I. Introduction

In recent years, the field of machine learning has seen a significant focus on Computer-Aided Designs (CAD). This research domain has proven to be pivotal, especially in the context of medical applications such as the detection of conditions like breast cancer, analysis of mammograms, and identification of lung nodules. Existing CAD systems have demonstrated their effectiveness in supporting medical diagnoses. When it comes to applying Machine Learning (ML) techniques to medical images, the identification of significant features becomes paramount. Traditional approaches often relied on manually crafted features to develop CAD systems for image analysis [1][2][3]. However, these handcrafted features had limitations that varied depending on the specific tasks and were unable to provide a comprehensive set of meaningful features.

The introduction of Deep Learning (DL) models, particularly Convolutional Neural Networks (CNNs), has showcased their inherent capability to automatically extract valuable features in image classification tasks [4] [5]. This feature-extraction process necessitates the use of transfer learning methods, wherein pre-trained CNN models learn generic features from extensive datasets like ImageNet. Subsequently, these learned features are transferred to the specific task at hand. The availability of pre-trained CNN models such as AlexNet [6], VGGNet [7], Xception [8], ResNet [9], and DenseNet [10] significantly streamlines the process of extracting meaningful features. Furthermore, utilizing these high-rich extracted features in image classification improves overall performance [11]. This approach, coupled with advanced classification techniques, enhances the accuracy of image categorization.

The subroutines employed in chest screening primarily for detecting lung nodules have versatile applications extending to the diagnosis of various other illnesses, such as pneumonia, effusion, and cardiomegaly. Pneumonia, in particular, stands out as a life-threatening infectious disease affecting millions, especially those aged 65 and above, with underlying chronic conditions like asthma or diabetes [12],when it comes to diagnosing pneumonia, chest X-rays emerge as a highly effective method for assessing the extent and location of the infection within the lungs. Despite its efficacy, interpreting chest radiographs is a challenging task for radiologists. The appearance of pneumonia in chest X-ray images can be indistinct, leading to potential misinterpretations and confusion with other diagnoses. Evaluating chest X-rays, especially in pneumonia cases, becomes intricate as conditions like congestive heart failure or lung scarring can mimic pneumonia, contributing to misclassifications within the dataset.

This challenge underscores the significance of developing an algorithm capable of detecting thoracic diseases like pneumonia. Such an algorithm not only aids in accurate diagnoses but also enhances accessibility to clinical settings, especially in remote areas. In this study, we developed pre-trained deep learning models to improve their performance for pneumonia detection, the key contributions of this study encompass (a) a comparative analytical examination of different pre-trained CNN models as feature extractors for chest X-ray analysis and (b) Comparing the best-analyzed classifier with other studies to further enhance overall performance.

The structure of this paper is organized as follows: Section 2 delves into related research in the same field. Section 3 provides details about the dataset used, while Section 4 outlines the applied methodology, divided into multiple stages. Section 5 details the experimental setup for different variants of pre-trained CNN models and the results obtained with various classifiers. Section 6 comprises results and discussions regarding the final accuracy achieved.

II. Related Work

In recent times, there has been a growing focus on the application of Machine Learning (ML) algorithms for the detection of thoracic diseases, particularly within the field of medical image classification. Lakhani and Sundaram (2017) [13] introduced a method for detecting pulmonary tuberculosis, employing the architectures of two distinct deep convolutional neural networks (DCNNs), namely AlexNet and GoogleNet. Additionally, deep learning techniques were utilized by Huang et al. [14] for lung nodule classification, specifically aimed at diagnosing lung cancer.

Addressing the challenge of abnormality detection in chest X-rays, Islam et al.[15] explored the performance of various Convolutional Neural Networks (CNNs) using the publicly available OpenI dataset [16]. To further advance the exploration of machine learning in chest screening, Wang et al. (2017) [17] contributed to the field by releasing a more extensive dataset consisting of frontal chest X-rays.

The study [18] introduced an innovative hybrid algorithm designed for image segmentation in chest X-rays. This algorithm seamlessly integrates two metaheuristic approaches: the Slime Mould Algorithm (SMA) and the Whale Optimization Algorithm (WOA). Referred to as HSMA-WOA, this hybrid algorithm aims to address the limitations of each individual algorithm, striving for improved segmentation outcomes. The evaluation of the algorithm utilized a dataset comprising 100 chest X-rays and included a comparative analysis against other state-of-the-art segmentation algorithms. The findings demonstrated that HSMA-WOA surpassed the performance of other algorithms in terms of segmentation accuracy, sensitivity, specificity, and F1 score. The article concludes by suggesting that HSMA-WOA holds promising potential as an effective and accurate approach for image segmentation in medical imaging applications.

A Deep Learning (DL) system was devised for the specific purpose of pneumonia identification [19]. The researchers conducted binary classification, employing the SoftMax classifier to gauge the DL system's efficacy in disease recognition. The application of AlexNet resulted in the successful identification of over 98% of the images within the considered database, moreover, Tilve et al.[20] delved into a comprehensive study where they evaluated and compared the effectiveness of various computer-assisted techniques for identifying lung diseases. They proposed an enhanced model capable of pneumonia detection, incorporating multiple machine learning (ML) techniques such as KNN, CheXNet, DENSENET, CNN, RESNET, and ANN. Notably, their findings highlighted that the CNN model exhibited superior detection accuracy and proved effective in identifying a variety of lung diseases.

III. Methodology

Pneumonia detection is approached in this study using a deep learning methodology, specifically a convolutional neural network (CNN) on a Kaggle dataset of 5,863 chest X-ray images. The dataset, which was compiled from pediatric patients at Guangzhou Women and Children's Medical Center, is clinically relevant and diverse. This dataset was chosen because of its large size, clinical origin, and balanced distribution of Pneumonia and Normal cases. For accurate Pneumonia detection, the proposed CNN model aims to effectively distinguish between these classes.

A. Dataset

In this study, we utilized a dataset sourced from Kaggle , which is organized into subfolders for each image category (Pneumonia/Normal) and further structured into three folders (train, test, and val). The dataset encompasses a total of 5,863 X-ray images (JPEG format), with two distinct categories: Pneumonia and Normal. The images were acquired through standard clinical procedures for pediatric patients aged one to five, from retrospective cohorts at the Guangzhou Women and Children's Medical Center in Guangzhou. Notably, the dataset is characterized by an imbalanced distribution, with a ratio of 1,583 images labeled as Normal to 4,272 images labeled as Pneumonia.

In Figure.1 , The normal chest X-ray (left panel) depicts clear lungs without any areas of abnormal pacification in the image. Bacterial pneumonia (middle) typically exhibits a focal lobar consolidation, in this case in the right upper lobe (white arrows), whereas viral pneumonia (right) manifests with a more diffuse "interstitial" pattern in both lungs.

Fig. 1: Chest X-ray comparisons—Normal (left), bacterial pneumonia (middle), and viral pneumonia (right)

B. Data Pre-Processing

Different Pre-processing techniques can be used to prepare the dataset for effective analysis this involves resizing all the images and normalizing the pixel values, ensuring standardized input for the neural network. Normalization improves an image, enlarging its brightness to fill the entire dynamic range to reduce the distribution of noise.

As part of the pre-processing phase, the dataset is divided into training, validation, and test sets. Subsequently, 65% for training, 35% for testing, and 10% of the training for validation. The model is trained to recognize patterns and features in chest X-ray images that indicate the presence or absence of pneumonia. It represents the first step in utilizing convolutional neural networks (CNNs) for pneumonia detection, emphasizing the significance of the pre-processing steps in preparing the data for effective model training and validation.

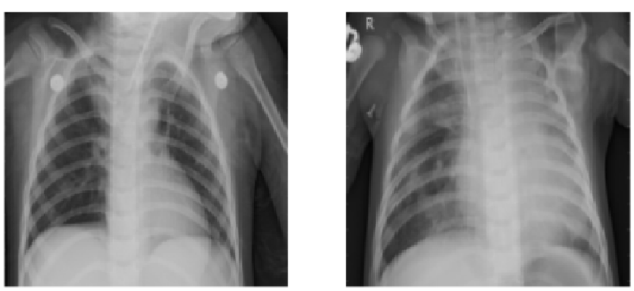

Fig. 2: Example of Resized and Normalized Chest X-ray Normal (Left) Pneumonia (Right)

C. Model Architechture

The input data is fed into the model for feature extraction following the pre-processing stage. Features from the images can be extracted in this step and fed into the classification for use in the following prediction processes.Two deep learning models, RestNet50 [9] and VGG16 [7], have been used in this work.

1) VGG16: we employed VGG16 neural network architecture. Initialized with pre-trained weights from ImageNet, the VGG16 model was customized for an input shape of (224, 224, 3), and its fully connected layers were excluded (include_top=False). The resultant feature extraction layers were easily incorporated into a Sequential model by carefully choosing to make each layer's weights non-trainable, which allowed for the preservation of all the valuable information extracted from the ImageNet dataset. A Flatten layer was carefully added after the VGG16 layers to convert the 3D output to a 1D vector. To produce the final binary classification output, a Dense layer with a single unit and a sigmoid activation function was added immediately after. The accuracy metric for reliable assessment, a binary cross-entropy loss function, and the Adam optimizer were carefully used in the model's compilation. and configured the model for 5 epochs with a batch size of 16. This architectural framework strategically leverages the hierarchical features learned by VGG16 on ImageNet, adapting them to the nuanced demands of our binary classification task. The choice to retain the pre-trained layers non-trainable guarantees the retention of important historical information, while the ensuing trainable layers are optimized to tackle the particular nuances of our targeted problem. Our comprehensive analysis of the model's architecture in Figure . 3.

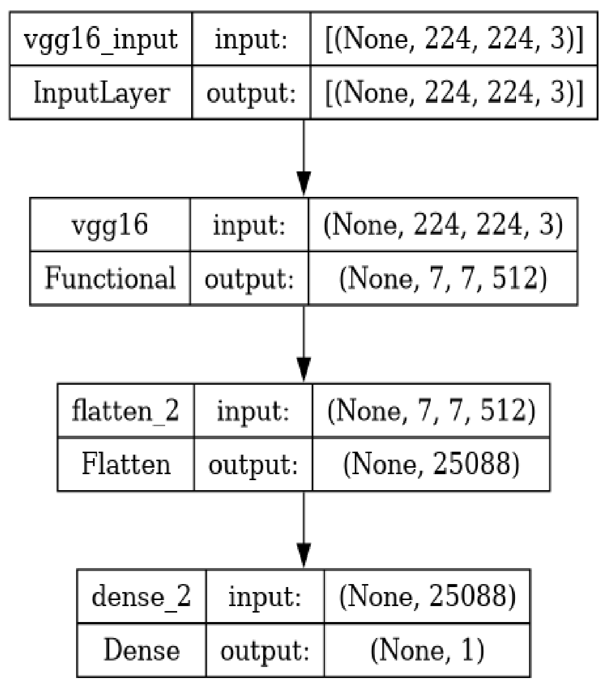

Fig. 3: VGG16 Model Architecture

2) ResNet50: we used The ResNet50V2 model, pre-trained on the ImageNet dataset, was utilized as a feature extractor with an input shape of (224, 224, 3). We modified it to fit our binary classification task by adding a Sequential model to the remaining layers and removing the fully connected layers by setting include_top to False. The pre-trained layers' weights were frozen in order to preserve the integrity of the learned features. A flatten layer was added after the feature extraction layers to convert the 3D output into a 1D vector. After that, a 128-unit Dense layer with ReLU activation was added, and batch normalization was applied for added stability. A Dropout layer with a rate of 0.5 was carefully positioned to reduce overfitting. The model's final layer, which was designed for binary classification, was a Dense layer with a single unit and sigmoid activation. Using the Adam optimizer with a learning rate of 0.0001, optimization was performed using the binary cross-entropy loss function. and configured the model for 5 epochs with a batch size of 16. The model's performance is evaluated based on the binary cross-entropy loss and accuracy metrics during training. Our comprehensive analysis of the model's architecture in Figure. 4

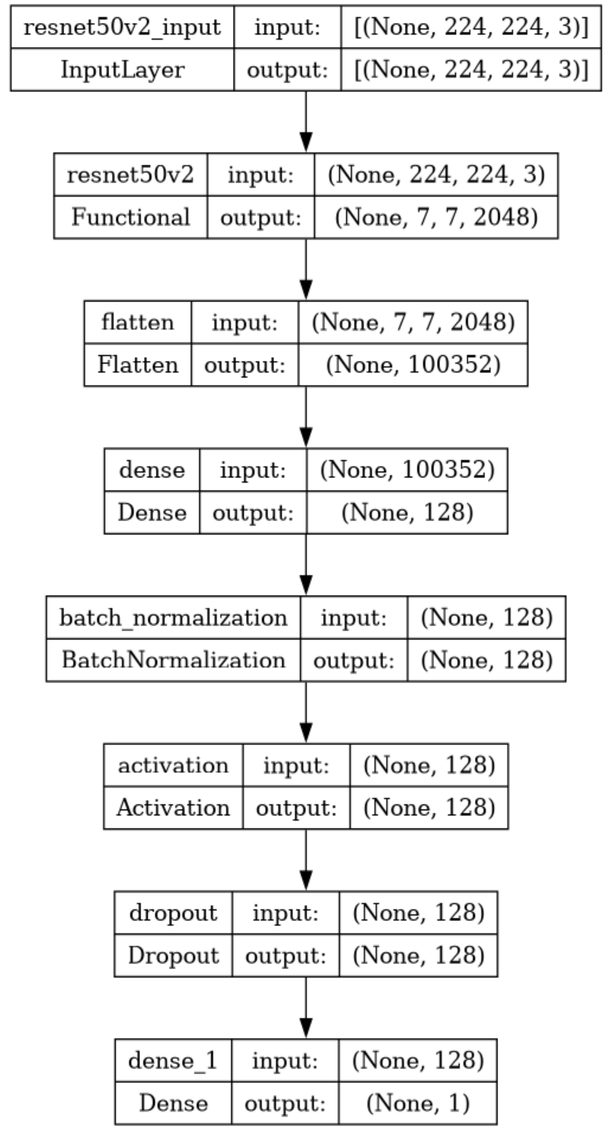

Fig. 4: RestNet50 Model Architecture

D. Evaluation Metrics

the estimated results of the suggested model are based on a number of measures, including accuracy, precision, F1-score, and recall. Four concepts, "false positive," "true positive," "false negative," and "true negative," need to be clearly defined in order to use these measurements. The term "false positive (FP)" describes samples that are expected to belong to positive classes but actually belong to negative classes. Samples that are both positive and members of the positive class are referred to as "true positives (TP)". Samples classified as "false negative (FN)" are those that are expected to belong to the negative classes but really belong to the positive classes. Samples that are successfully predicted and correspond to the negative classes are referred to as "true negatives (TN)".

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP + TN + FP + FN}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

E. Model Interpretation

Deep learning models' interpretability in the field of medical imaging is essential for understanding how these models make decisions. Leveraging the powerful DenseNet architecture, we constructed a robust X-ray classification model for medical diagnoses. To take advantage of the model's feature extraction capabilities, it was pre-trained on ImageNet. We used Grad-CAM (Gradient-weighted Class Activation Mapping), a method that shows the areas of an image that influence the model's predictions, to improve interpretability. The pre-trained DenseNet layers are frozen in the built model, and then more layers are added for more abstraction. Providing a basis for feature extraction and classification, a dense layer with rectified linear unit (ReLU) activation, a flattening layer, and an average pooling layer were added. To improve the generalization of the model, a dropout layer was added. The last layer was a dense output layer for binary classification using softmax activation. This model was compiled using the Adam optimizer with a specific learning rate(0.0001) and a custom categorical smooth loss function. To improve the model's interpretability in a crucial medical setting, we seek to clarify the prominent areas in X-ray images that influence its diagnostic judgments. the model achieved an accuracy of 93.75, a recall of 93.75, a precision of 94.2, F1-score of 93.24 .

IV. Results

According to Table 1, the ResNet50 model had the lowest accuracy at 95.99 percent, whereas the VGG16 displayed the highest accuracy of 96.53 percent.

TABLE I: Experiment results for the Models

Model Epoch	Accuracy	Recall	Precision	F1-Score	Loss
ResNet5010	95.99	96.94	97.59	97.72	0.251
VGG16 10	96.53	97.21	97.95	97.58	0.188

In the evaluation of different models, specific performance metrics were observed after training for a certain number of epochs. The ResNet50 model, trained for 10 epochs, achieved an accuracy of 95.99, a recall of 96.94, a precision of 97.59, F1-score of 97.92 and a loss of 0.251. Likewise, the VGG16 model, also trained for 10 epochs, demonstrated impressive results with an accuracy of 96.53, a recall of 97.21, a precision of 97.95, F1- score of 97.58, and a loss of 0.188.

Figures 5-8 show, respectively, the accuracy and loss graphs from the testing and validation phases of the ResNet50 and VGG16 models. Because of its higher accuracy, the VGG16 best model. The results indicated. However, during training, epochs were 10, and batch sizes were 32. An early halting mechanism was put in place to prevent overfitting. An early halting mechanism is used when the model loses its ability to learn and tends to overfit

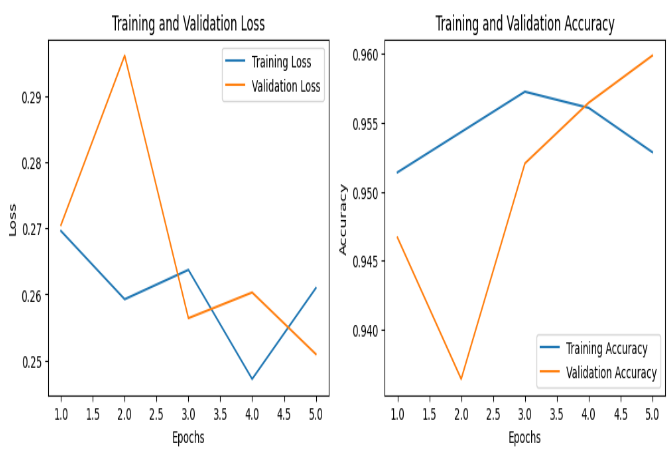

Fig. 5: Training and Validation Loss and Accuracy for ResNet50.

Figure 9-10 displays confusion matrices that summarize the accuracy and types of mistakes that the two different detection models (Resnet50 and VGG16) are making in determining whether the XRIs are pneumonia-related or not. The model's confusion matrix helps to assess the models' reliability in terms of their ability to minimize medical costs. The researchers used three metrics in Table 1 to assess the models' performance.

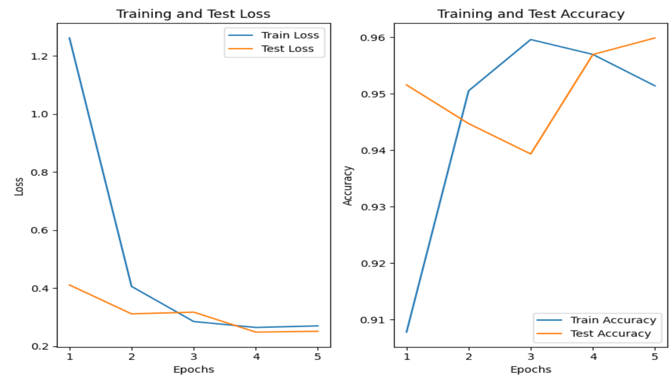

Fig. 6: Training and Test Loss and Accuracy for ResNet50.

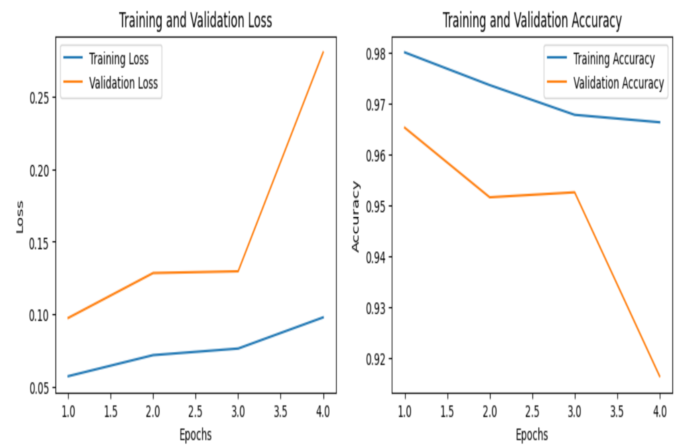

Fig. 7: Training and Validation Loss and Accuracy for VGG16.

Table. 2 presents a summary of various studies along with the corresponding accuracy percentages achieved through different methods for pneumonia detection. In the study conducted by Yue et al in 2020 [21], they employed a Convolutional Neural Network (CNN) achieving an accuracy of 91.4%. They also explored the performance of MobileNet 92%, ResNet18 85%, ResNet50 87%, and VGG19 90%.

Jain et al [22] in 2020 compared multiple models, including CNN model 1 85.26%, CNN model 2 92.31%, VGG16 87.28%, VGG19 88.46%, ResNet50 77.56%, and InceptionV3 70.99%. Jakhar K et al [23] in 2018 utilized a Deep CNN, achieving an accuracy of 84 Varshni et al [24] in 2019 explored several CNN models, such as CNN model 1 90.68%, CNN model 2 89.32%, CNN model 3 79.8%, and CNN model 4 74.98%.

In the context of our research conducted , we achieved promising results using ResNet50 95.43% and VGG16 96.85% for pneumonia detection. These findings contribute to the existing body of knowledge, showcasing the effectiveness of these models in enhancing accuracy for pneumonia diagnosis.

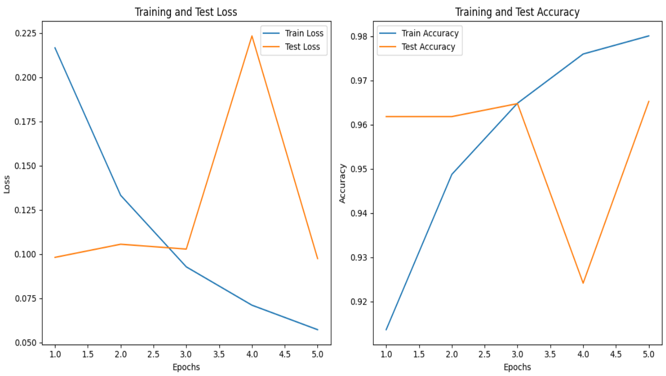

Fig. 8: Training and Test Loss and Accuracy for VGG16.

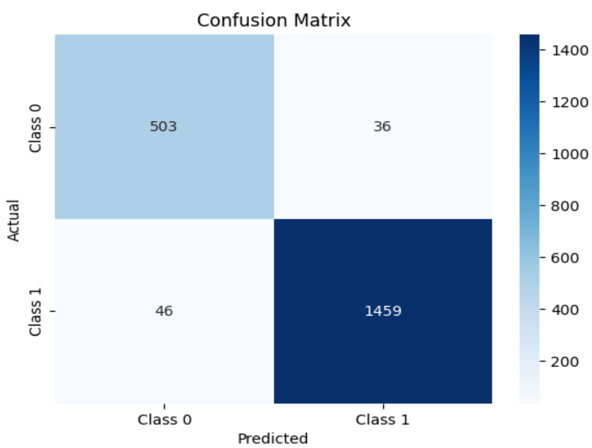

Fig. 9: Confusion Matrix for ResNet50.

In our pneumonia prediction study using the DenseNet model for chest X-ray images, we employed the GRAD-CAM interpretability technique. as shown in Figures 11 and 12 The results revealed insightful heatmaps, with warmer colors (red and yellow) indicating regions of high importance for the model's predictions related to pneumonia. Cooler colors (blue) signified areas with lesser influence. The visualizations provided by GRAD-CAM enhance the model's transparency, showcasing its accurate identification of pneumonia-related abnormalities in chest X-ray images. These heatmaps offer an intuitive and concise representation of the key features influencing the model's decisions.

V. Conclusion

With the use of models such as ResNet50, VGG16, numerous pneumonia detection models will be assessed in this study using a vast data set of XRIs. After preprocessing the images, these models were applied to the chest XRI data set.

According to the results, the VGG16 model had the highest accuracy at 96.85 It should be noted that the VGG16 would be

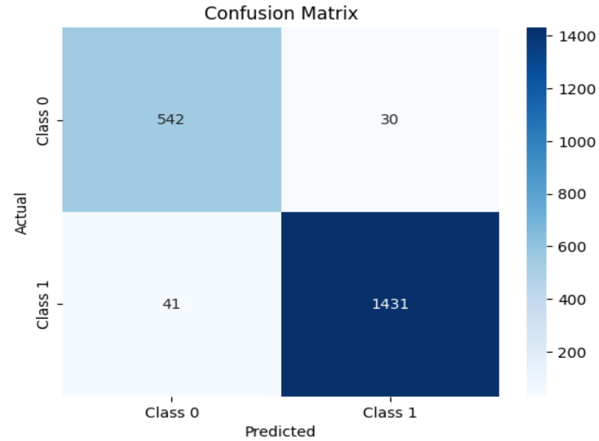

Fig. 10: Confusion Matrix for VGG16.

TABLE II: Comparison of the accuracy values published in the earlier studies using the same data set, with that noted using the proposed approach

Study	**Year**	**Methods**	**Accuracy (%)**
Yue Z,et al [21]	2020	CNN	91.4
		MobileNet	92
		ResNet18	85
		ResNet50	87
		VGG19	90
Jain, et al [22]	2020	CNN model 1	85.26
		CNN model 2	92.31
		VGG16	87.28
		VGG19	88.46
		ResNet50	77.56
		InceptionV3	70.99
Jakhar K, et al [23]	2018	Deep CNN	84
Varshni, et al [24]	2019	CNN model 1	90.68
		CNN model 2	89.32
		CNN model 3	79.8
		CNN model 4	74.98
Our Research	2024	ResNet50	95.99
		VGG16	96.53

more helpful in diagnosing pneumonia than the other methods, which in volves the health care provider reviewing the patient's medical history, performing a physical examination, and ordering diagnostic procedures such as a chest X-ray. This information helps in identifying the form of pneumonia affecting the patient.

Applications of AI algorithms in pneumonia, including treatments, empirical antibiotic decisions, requirement prediction for mechanical ventilation, and outcome classification, have not yet been made. Most likely soon, the potential value of such inclusion will be investigated.

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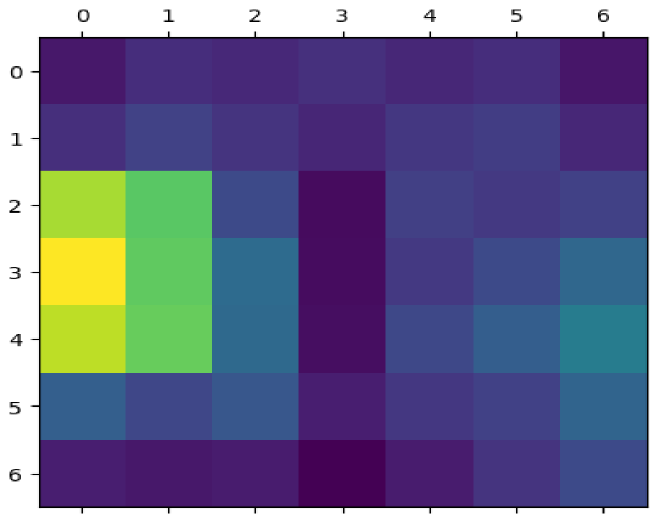

Fig. 11: GRAD-CAM Heatmap.

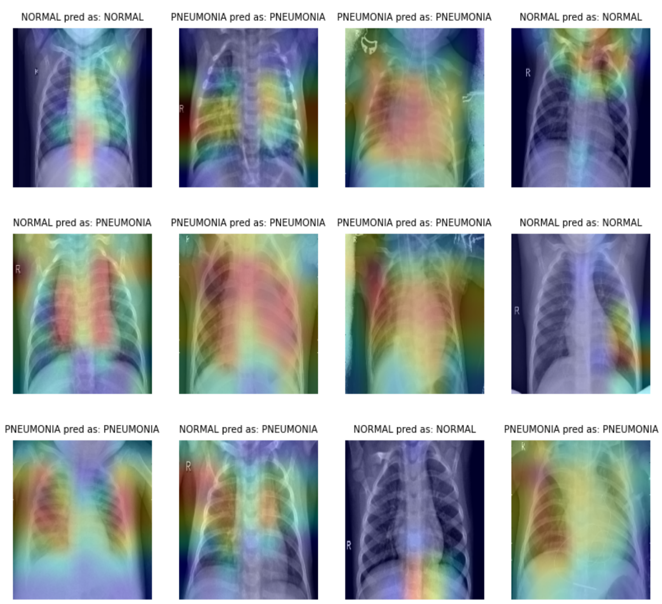

Fig. 12: GRAD-CAM interpretation on Densnet predictions.

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