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ENSEMBLED DEEP LEARNING METHOD FOR PNEUMONIA DETECTION

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ABSTRACT

With each incremental advancement in artificial intelligence, humanity is edging closer to the AI era, where AI will guide humans in exploring everything from basic mathematical calculations to uncovering the profound mysteries of the universe. Convolutional Neural Networks (CNNs) have emerged as a valuable tool in the medical field, but there is a growing demand for improved accuracy and efficiency. The availability of a suitable dataset is crucial for training artificial neural networks, in addition to optimizing the model architecture and employing appropriate optimization methods.

Early diagnosis of pneumonia is pivotal in ensuring effective treatment for this infection. Chest X-rays serve as a key diagnostic method for pneumonia. However, medical image analysis can be prone to errors when performed by inexperienced radiologists and can be time-consuming for experienced professionals. Furthermore, pneumonitis manifestations in X-rays can mimic other abnormalities, complicating the diagnosis. In this paper, we propose a deep-learning model for pneumonia detection that is ensembled with the Focal Loss function of the RetinaNet Model. Additionally, we address the significant challenges involved in developing neural networks for image processing tasks such as image classification, segmentation, and object detection.

Keywords: Convolution Neural Network, Deep Learning, Pneumonia, Ensemble, Retinanet, Focal Loss, Chest X-Ray, Radiology, Machine Learning, Image Classification, PACS.

I. INTRODUCTION

Pneumonia is an acute lower respiratory tract(LRT) infection commonly caused by viruses, bacteria, and fungi. Pneumonia can be classified into commonly acquired pneumonia(CAP), Hospital-acquired pneumonia, opportunistic pneumonia, and recurrent pneumonia[1]. Aspiration pneumonia represents 5–15% of all cases of CAP[2]. According to the 2019 Global Burden of Disease(GBD) study, 489 million people were affected by pneumonia and bronchiolitis. The most affected group by pneumonia was children below the age of 5 and adults aged more than 70[3]. According to the world health organization pneumonia accounted for 14% of the deaths of children aged below 5 in 2019 killing more than 7 lakh children[4]. The symptoms of pneumonia are cough, breathlessness, chest pain, sputum production, and fatigue[5][6]. With symptoms prevailing for more than 7 days, the radiographic test is essential for confirmation of the infection. Antibiotics are the most used therapy for pneumonia. However extreme cases of pneumonia-acquired patients need the therapy of beta-lactam[2].

Pneumonia is typically characterized by increased opacity in certain lung regions on CXR. This opacity is caused by lung inflammation and the presence of significant volumes of fluids in the affected areas[7]. However, there are potential complications that can affect the accuracy of pneumonia diagnosis using CXR. One such complication is pulmonary edema, which is often caused by cardiac issues, internal lung bleeding, lung cancer, or atelectasis. Pulmonary edema refers to the accumulation of fluid in the lungs, leading to increased opacity on CXR[8]. On the other hand, atelectasis refers to the collapse or shutdown of a part or the entire lung, resulting in decreased air content and increased opacity on CXR[9]. These complications can make it challenging to distinguish pneumonia from other conditions solely based on CXR findings. To overcome this challenge, it is important to have trained physicians and specialists who can interpret the CXRs and consider the patient's clinical history. Additionally, comparing CXRs taken at different time frames can aid in identifying changes in lung opacity, which can support an accurate diagnosis of pneumonia.

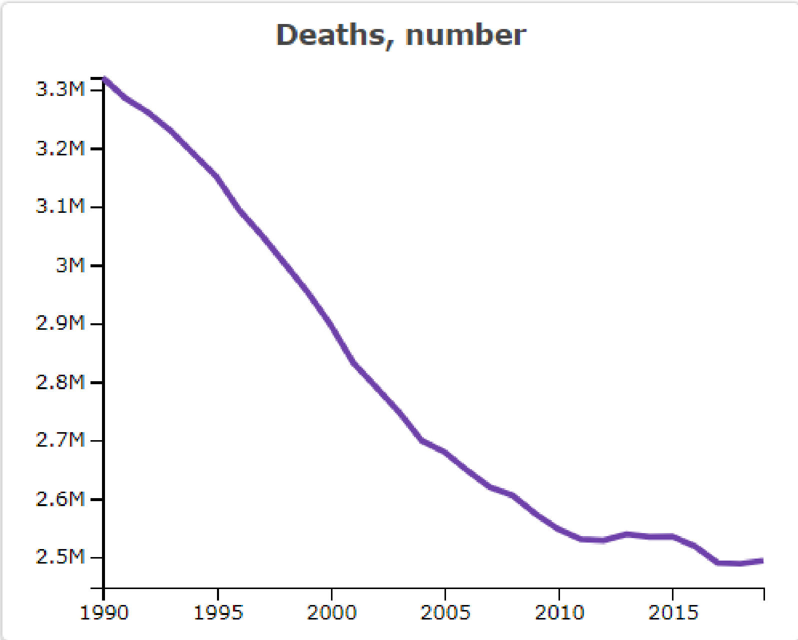

Figure 1: Total Number of Deaths from Lower Respiratory Disease from 1990 to 2019[3]

Deep learning is a class of machine learning methods that have shown success in computer vision tasks. Unlike traditional methods, deep learning learns image features automatically without the need for manual feature extraction. Convolutional neural networks (CNNs) are the core of deep learning for imaging and consist of multilayered artificial neural networks with weighted connections that are adjusted through exposure to training data. Ensemble learning combines several individual deep learning models to obtain better generalization performance[10]. Recognition of images using deep learning techniques, specifically convolutional neural networks (CNNs), has garnered significant interest due to its exceptional performance, and it holds great importance in the clinical management of patients[11]. Cheng et. al.[12] discusses terminology, data requirements, recent trends in CNN design, and important considerations such as training, validation, performance metrics, visualization, and future directions. Understanding these concepts can help radiologists comprehend the advancements of deep learning in medical imaging and support their adoption in clinical practice.

In the current study, a deep-learning model is developed with an ensemble technique for the detection of pneumonia using chest X-rays. The proposed model uses the focal loss[13] method for image loss reduction. The model comprises convolution layers and max pool layers with stride 2. The Adam optimizer[14] has been used and the output layer is activated with a softmax activation function.

II. LITERATURE SURVEY

Prior studies have investigated the use of machine learning and heat maps to detect pneumonia in chest X-rays[15]. Heat maps are visual representations of temperature or infrared radiation changes over an area or time. Additionally, computerized lung sound analysis has been utilized to differentiate between normal lung pathology and pulmonary diseases.

In recent times, several artificial intelligence-based solutions have been proposed to address various medical problems. Convolutional neural networks (CNNs) have been particularly successful in tackling a wide range of medical applications, including breast cancer detection, brain tumor detection and segmentation, disease classification in X-ray images, and more[16].

In previous research, there has been a focus on utilizing advanced deep learning frameworks, specifically convolutional neural networks (CNNs), to tackle the challenges associated with a pneumonia diagnosis. Recent studies have predominantly centered around pneumonia detection using modern CNN architectures that are deeper and more intricate compared to traditional architectures with only a few layers. Examples of such architectures include VGGNet proposed by Simonyan and Zisserman[17], as well as ResNet proposed by He et.

al.[18]. For instance, Kermany et al[19] conducted a comprehensive study using a deep CNN to address both treatable blinding retinal diseases and pneumonia in patients. However, a notable challenge with these deep CNN architectures lies in the complexity of training all the layers, as it can be time-consuming and computationally demanding.

In their contribution, Wang et al. [20] introduced a new dataset called ChestX-ray8, which consists of frontal X-ray images from 32,717 patients, totaling 108,948 images. They achieved promising outcomes by employing a deep CNN for analysis. Additionally, they noted that this dataset has the potential for expansion by incorporating additional disease labels. They split X-ray images into six types of patches and used ResNet to classify six patches and recognize lung nodules. They used rotation, translation, and scaling techniques for data augmentation.

In the study of Kundu, Rohit et. al.[21], a computer-aided diagnosis system was developed using deep transfer learning and an ensemble of three convolutional neural network models: GoogLeNet, ResNet-18, and DenseNet-121. A weighted average ensemble technique was employed, with weights determined using a novel approach based on evaluation metrics. The proposed method was evaluated on two publicly available pneumonia X-ray datasets, achieving high accuracy and sensitivity rates outperforming state-of-the-art methods. Statistical analyses confirmed the robustness of the approach.

Habib, Nahida, et. al.[22] in their work, train two deep Convolutional Neural Networks (CNNs), CheXNet and VGG-19, to extract features from the X-ray images, which are then ensembled for classification. To address data irregularities, different sampling techniques are applied to the ensembled feature vector. Machine Learning (ML) classification techniques such as Random Forest, Adaptive Boosting, and K-Nearest Neighbors are used for classification. The Random Forest method demonstrates better performance metrics compared to others, achieving 98.93% accurate prediction on the standard dataset.

Ko, Heewon, et. al.[23] ensemble Mask R-CNN[24] and RetinaNet[13] models to detect lung opacity in the chest x-ray. They adopted the top-performing classifier from the multiple tests they ran with the suitable ratio of weights.

Sirazitdinov et al.[25] used a combination of two models, namely, masks R-CNN and RetinaNet to form a deep ensemble version for the detection and localization of pneumonia. They suggested Average Precision (mAP) for localization state-of-the-art pathology and similar precision, recall, and F1-ratings of 0.758, 0.793, and 0.775.

III. PROPOSED ARCHITECTURE

The designing of the CNN architecture starts with the collection of the chest x-ray dataset, preprocessing and augmenting the dataset, construction, and ensembling of the custom model, testing and evaluating the ensembled model, and the final step is the prediction step.

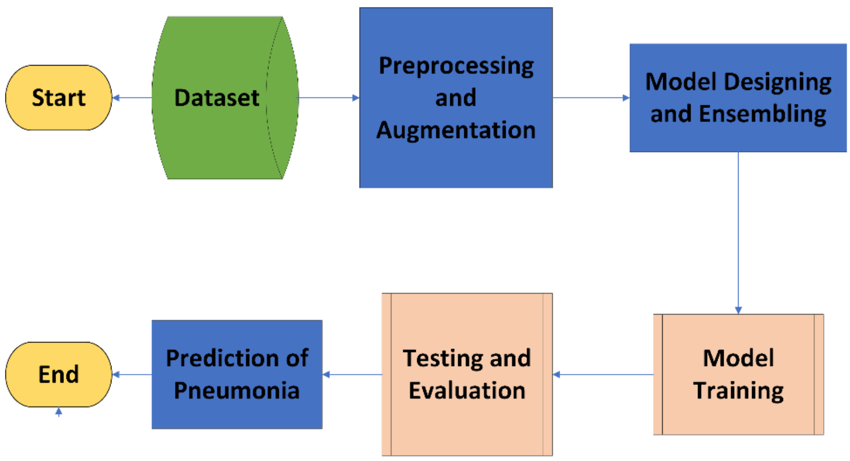

Figure 2: Design Process of the CNN Architecture

Dataset

We have used two different datasets, the first one being chest X-ray images contributed by Kermany et. al[26] on Mendeley Data on 1 June 2018. The dataset is available on Kaggle. The total number of images in the dataset

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is 5836, divided into groups specifying testing, training, and validation set. A further division based on pneumonia and normal chest X-rays is done on the images.

Table 1: Distribution of Dataset for First Dataset

Category	Training	Validation	Testing
Normal	1341	234	234
Pneumonia	3875	390	390
Total	5216	624	624

The other dataset used is the labeled dataset of the chest X-ray images and patient metadata publicly provided by the US National Institutes of Health Clinical Center [27]. This database comprises frontal-view X-ray images from 26684 unique patients in dicom format. Each image is labeled either 'Normal' representing healthy patients, 'Lung Opacity' having the presence of a fuzzy cloud or white and diagnosed with pneumonia, or 'No Lung Opacity/Not Normal' data with a visible cloud but without a diagnosis of pneumonia. The target values 0 or 1 indicate whether pneumonia is diagnosed or not.

Table 2: Distribution of the second dataset according to different classes and targets.

Class	Target	Patients
Lung opacity	1	9555
No Lung Opacity/ Not Normal	0	11821
Normal	0	8851

Figure 3: Sample Image from First Dataset

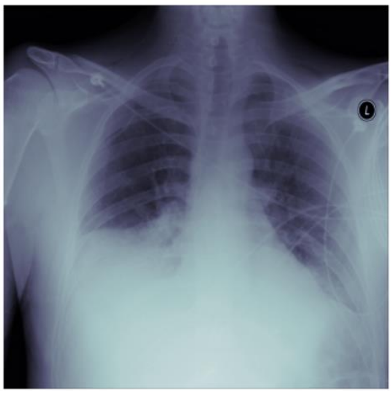

Figure 4: Sample Image from Second Dataset

Preprocessing and augmentation of images

Images from the first dataset were already available in the distribution of testing, training, and validation set therefore they were subjected to augmenting techniques like flipping, shifting, and zooming. The images were resized, and the pixels were divided by 255 so that the pixels could be in floating point numbers between 0 and 1.

The data from the second dataset was first split into Train/ Validation/ Test classes with a ratio of 80:10:10. Augmentation techniques like resize, flipping, brightness multiplication, and linear contrast were implemented on the dataset. Some training set images were subjected to Gaussian noise, blur, and additive noise. The validation and test set were only subjected to resize process.

IV. MODEL DESIGN AND ENSEMBLING

Artificial Neural Networks (ANNs) are computational systems inspired by biological nervous systems, consisting of interconnected nodes or neurons that collectively learn from input to optimize output[28]. Convolutional Neural Networks (CNNs) are a type of ANN that comprises self-optimizing neurons[28]. Modern deep learning models often utilize CNN-based algorithms, which consist of input, output, and hidden layers. The hidden layers include a convolutional layer that processes neuron outputs from local regions of the input, a pooling layer that reduces parameters by downsampling spatial dimensions, and fully connected layers that

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generate scores for image classification[29]. The connectivity between neurons in convolutional layers allows the network to extract low-level features in hidden layers and combine them into high-level features in subsequent layers. The pooling layer, commonly using max pooling, reduces the complexity of representations while preserving information[28]. Activation functions are essential in CNNs as they map the activated neurons using non-linear functions, enhancing the network's ability to solve non-linear problems. Common activation functions include sigmoid, tanh, softplus, and ReLU. The model uses both the ReLU[30] and softmax activation functions in different layers[31].

Equation 1: Equation for softmax function[30]

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Ensemble learning, also referred to as an ensemble model, is the process of combining predictions from multiple models to form a final prediction. This approach utilizes several models and employs techniques such as averaging or voting to create an ensemble model that outperforms any individual model[10]. Ensemble methods consist of bagging, boosting, and stacking with applications in healthcare, speech, image classification, forecasting, and others[10].

Our model uses features of the RetinaNet model which is the focal loss function for the reduction of loss of training data while the model is trained on well-classified samples[13]. The Focal Loss function is utilized in tasks such as object detection to tackle class imbalance during training. It introduces a modulating term to the cross-entropy loss, allowing the model to focus on challenging misclassified examples. This dynamic scaling factor adjusts the cross-entropy loss, gradually diminishing its impact as the model's confidence in the correct class grows. By automatically reducing the contribution of easy examples during training, the Focal Loss function quickly directs the model's attention toward more difficult examples.

Equation 2: Equation for focal loss

$$FL(p_t) = -\alpha_t(1 - p_t)^{\gamma} \log(p_t)$$

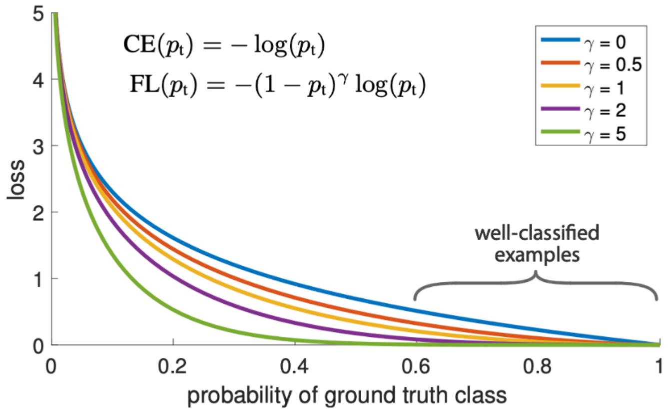

Figure 3: Effect of addition of factor to standard cross entropy

The optimization algorithm used to minimize the difference between the predictions made by the model and ground-level values we have used the Adam algorithm[14] which is a first-order iterative optimization algorithm for finding local minima of a differentiable function.

V. METHODOLOGY

Various studies in the literature have explored the utilization of manually crafted features for the detection of pneumonia in chest X-rays. Additionally, there have been several investigations into the application of deep learning techniques for pneumonia detection in pediatric chest X-rays. A limited number of researchers have attempted to provide a descriptive understanding of their model's learned patterns, internal computations, and predictions, offering qualitative explanations for their findings[32].

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This study focuses on image data, specifically pattern identification and classification tasks. To efficiently handle the image processing tasks, a suitable hardware system is required. In this project, Python Programming Language was utilized. However, it is important to note that normal laptops or systems may not have sufficient processing power to smoothly handle the model-building process. To address this limitation, the initial hardware acceleration was employed using a dedicated memory GeForce GTX 1050. The system utilized for this research includes an Intel 9th Gen i5 processor with a clock speed of 2.40. The final training of the model was done on Google Colab where the available resources were Intel Xeon CPU @2.20 GHz, 13 GB RAM, Tesla K80 accelerator, and 12 GB GDDR5 VRAM.

The necessary Python libraries have been imported to facilitate the implementation of the model's coding structure. One of the key libraries utilized is Keras[33], which offers a wide range of functions for convolutional neural networks (CNNs). The image data has been appropriately labeled and augmented. The model architecture comprises five convolutional blocks, each consisting of convolutional layers, a max-pooling layer, and batch normalization. Additionally, a flattened layer is followed by four fully connected layers. Dropout layers have been incorporated to mitigate overfitting [34].

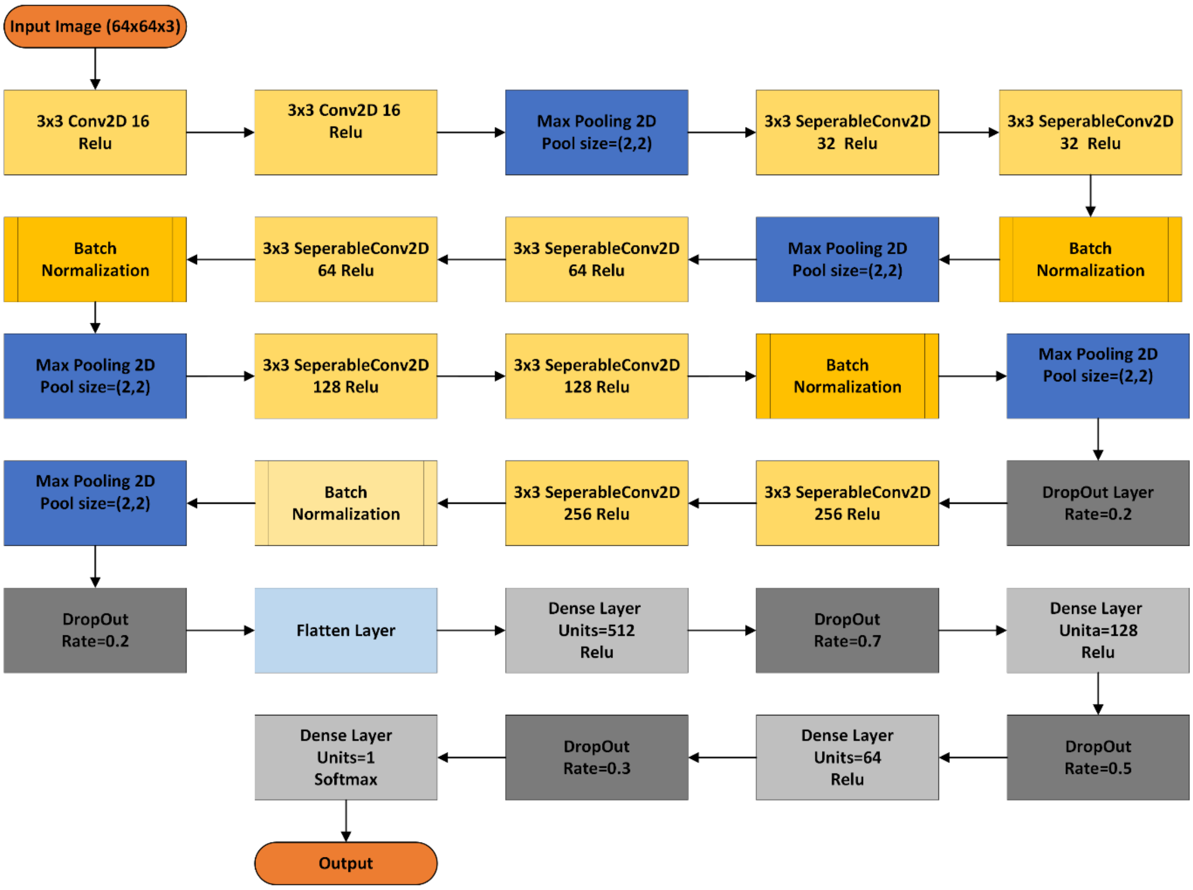

Figure 4: Architecture of the custom CNN

Throughout the model, the rectified linear unit (ReLU) activation function is employed, except for the last layer where a softmax function is used, considering the problem falls under binary classification. The optimization algorithm used is Adam, and the loss function employed is focal loss. Prior to training the model, callbacks such as model checkpoints and early stopping are defined. A separable convolution layer is utilized to decompose a convolution kernel into two smaller kernels. This layer first performs depth-wise convolution and then point-wise convolution. Batch normalization is employed to standardize the inputs to a layer, ensuring that the activation values neither become too high nor too low.

VI. MODEL EVALUATION AND RESULTS

The ensemble model is first trained on the dataset contributed by Kermany et. al[26] with the activation function at the output layer being the sigmoid function. The training accuracy comes out to be 71.10% with a

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training loss of 0%. Then the model is trained on the second dataset[27] with a change in the activation function from sigmoid to softmax at the output layer. An increase of 3% is observed in training accuracy which is 74.35% and no significant change in the training loss. The loss is negligible due to the use of the focal loss function. In the testing phase of the model, the accuracy and precision are evaluated at 62.5% with a recall value of 100%, and the F1 score stands out at 76.92%.

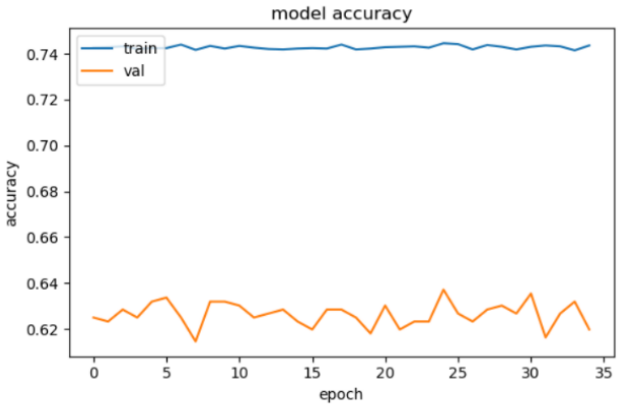

Figure 7: Model Accuracy Graph over Time

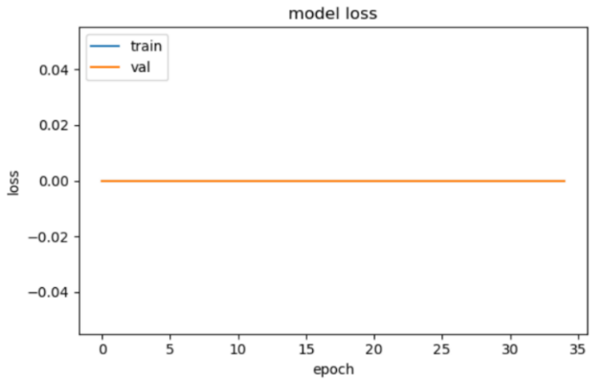

Figure 8: Model Loss Graph over Time

Figure 7 and Figure 8 represent the testing accuracy and testing loss over time. The model was compiled with a total of 35 epochs with the best model attaining at the 25th epoch with an accuracy of 74.36% which is comparable to[25].

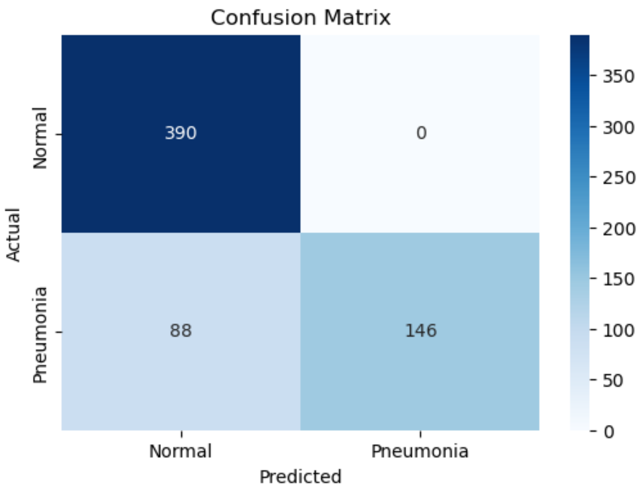

Figure 9: Confusion matrix for the compiled model

Another way of representing the results of the model is to build a confusion matrix [29]. The Y-axis of the confusion matrix holds the predicted values, while the X-axis holds the true values. The confusion matrix for our latest experiment is shown in Figure 9.

VII. CONCLUSION

This paper presents an exploration of deep-learning neural networks to support radiologists in the early detection of pneumonia, a leading cause of global mortality. While the proposed model demonstrates notable accuracy for the given set of more than 25 thousand images, there is room for improvement and fine-tuning. The use of different ensemble methods and encoders in the model is required to be worked upon. Ensembling methods like bagging and boosting have shown promising results. With the proper design of more sophisticated and efficient models through which the data can be trained with accuracy improvement is required to be studied upon. Research is needed to establish proper labeling and storage protocols for chest X-rays. Additionally, advancements in technology can facilitate the development of modern Picture Archiving and Communication Systems (PACS) for organized storage and retrieval of chest X-ray databases.

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As computer systems continue to advance in processing capabilities each year, it is crucial to develop models that efficiently utilize these resources. In addition to pneumonia detection, it is important to design experiments on CNN architecture that can be applied to various other diseases.

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