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DEVELOPMENT OF A PNEUMONIA DETECTION SYSTEM USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT
Pneumonia is one of the world's most lethal and life-threatening diseases today, affecting people of all ages. Early proactive treatment can significantly reduce the likelihood of death from this illness and also prevent circumstances from worsening. Chest X-rays imaging has been one of the most well-liked and well-known clinical approaches. However, diagnosing the condition using X-rays has become increasingly challenging due to pneumonia resembling other lung disorders. As a result, this study developed a system to detect pneumonia disease in chest X-ray images using convolutional neural network-based approach. The datasets used for this study consists of 5856 chest X-ray images was obtained from Kaggle to train three pre-trained CNN architectures: VGG16, ResNet50, and MobileNetV3. The dataset was cleaned, preprocessed, and divided using the 80:20 data split ratio. Early stopping and learning rate reduction were applied to each model to prevent overfitting. The performance of each model was evaluated using accuracy, precision, recall, and f1-score on the test data. The VGG16 model outperformed others with 94% accuracy, 91% precision, 95% recall, and 93% f1-score. The MobileNetV3 model, which had the second-best performance, had an accuracy of 93%, precision of 90%, recall of 94%, and f1 score of 92%, while ResNet50 had 92% accuracy, 89% precision, 93% recall, and 91% f1-score. The best performing model of the three which is VGG16 was chosen and implemented on a web application. This system will serve as a tool for the medical practioners in detecting pneumonia earlier and accurately for proper treatment.

Keywords: Artificial Intelligence, Convolutional Neural Network, Deep Learning, MobileNetV3, Pneumonia, ResNet50, MobileNetV3.

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1. INTRODUCTION

Pneumonia is a respiratory infection that affects the lungs, and millions of individuals get infected each year, making it the third leading cause of death worldwide (World Health Organization (WHO), 2022; Mujahid *et al.*, 2022). Pneumonia is one of the most fatal and life-threatening diseases and the number one killer of children and the elderly worldwide (Yi *et al.*, 2021). According to Mujahid et al. (2022), pneumonia accounts for approximately 4 million deaths of children and the elderly each year. It caused 14% of deaths in children under five and 740,180 documented child fatalities in 2019 (WHO, 2022). Accelerated pneumonia diagnosis and prompt administration of the appropriate treatment can help a great deal to prevent patients' conditions from getting worse and potentially dying (Ibrahim *et al.*, 2021).

The best method for determining the location and severity of pneumonia is chest X-rays. These methods, however, leave room for the disease's incidence to be ambiguous and mistaken for another sickness (Gupta, 2021). A chest radiograph is produced by an X-ray, with the hard tissues, such as the bones, giving a dazzling color and the soft tissues producing a dark hue. In the chest cavity, which is brighter, patients with pneumonia display symptoms of fluid filling the lungs' air sacs. Brighter color may also be a sign of a number of conditions, such as cancer cells, enlarged blood vessels, and heart problems in the lung cavities. Effective chest X-ray image analysis requires experience and expertise from a doctor who specializes in radiology. The absence of diagnostic tools, the high cost of therapy, and the accessibility of experts are just a few of the drawbacks of human-assisted approaches to pneumonia detection (Yi *et al.,* 2021).

Convolutional neural networks (CNN), one of the most potent deep learning techniques, are frequently employed for object detection and image classification. CNN is a very reliable method for a variety of image and object recognition applications because of its hierarchical structure and potent automatic feature extraction capabilities from a picture. There are numerous CNN architectures that have been useful in creating algorithms. LeNet, AlexNet (Krizhevsky *et al*., 2012, VGGNet (Simonyan and Zisserman, 2014), Xception (Chollet, 2016), GoogLeNet (Huang *et al*.,2017), ResNet (He *et al*., 2016) and ZFNet are examples of the CNN architectures.

Computer-aided diagnostic (CAD) technologies have been developed during the past few decades to extract meaningful information from X-rays (Alsharif *et al*., 2021; Ibrahim *et* al, 2021). These CAD systems, however, were unable to reach a level of relevance that would have allowed them to determine the types of illnesses or diseases visible in an X-ray. Consequently, their usefulness was limited to providing clinicians with visualization functionality to aid in decision-making. In this study, a computer-aided method of diagnosing pneumonia detection system capable of detecting and classifying chest X-ray images into cases with and without pneumonia using the best performing CNN architecture out of the following three CNN architectures VGG16, ResNet50, and MobileNetV3 was developed. This would improve the effectiveness and validity of clinical services as well as make an accurate diagnosis of the disease readily available, quick, and affordable.

2. RELATED WORKS

In recent time, exploration of Machine learning (ML) algorithms in detecting pneumonia diseases has gained attention in research area of medical image classification. A lot of studies have tried to address the problem of classifying images with high accuracy. However, implementing the results to build a system are not common. Therefore, this study after comparing the three popular CNN architectures performance in detecting pneumonia still went further to use the results of the best performing model out of the three to build a simple system. This developed system could detect and classify X-ray images of the chest into cases with and without pneumonia.

Sharma and Guleria (2023), utilized a deep learning (DL) model using VGG16 for detecting and classifying pneumonia using two CXR image datasets. For the first dataset, the VGG16 using Neural Networks (NN) yields accuracy of 92.15%, recall of 0.9308, precision of 0.9428, and F1-Score of 0.937. Another CXR dataset with 6,436 images of pneumonia, normal, and covid-19 was used in the experiment using NN and VGG16. Accuracy, recall, precision, and F1-score for the second dataset are 95.4%, 0.954, 0.954, and 0.954, respectively. The study's findings show that for both datasets, VGG16 with NN performs better than VGG16 with Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF), and Naive Bayes (NB).

Sharma *et al.*, (2022) used CNN and deep learning techniques to detect COVID-19-induced pneumonia from chest X-rays. Transfer learning with fine-tuning ensures that the proposed work successfully classifies COVID-19-induced pneumonia, regular pneumonia, and normal conditions. The experimental results were promising in terms of precision, recall, F1 score, specificity, false omission rate, false negative rate, false positive rate, and false discovery rate with a COVID-19-induced pneumonia detection accuracy of 98%.

Kundu *et al*. (2021) suggested employing an ensembled model comprising three GoogLeNet, ResNet-18, and DenseNet-121 convolutional neural network models to automatically identify pneumonia. On the first dataset, the model had an accuracy rate of 98.81%, a sensitivity rate of 98.80%, a precision rate of 98.82%, and a f1-score of 98.79% after being trained and assessed on two chest X-ray image datasets. On the second, a five-fold cross-validation technique produced an accuracy rate of 86.86%, a sensitivity rate of 87.02%, a precision rate of 86.89%, and a f1-score of 86.95%.

In order to diagnose pneumonia quickly and affordably, Masud *et al*. (2021) suggested adopting machine learning-based diagnosis techniques. The researchers completed a three-class classification of pneumonia in this study (bacterial, viral, and normal) using features based on the examination of chest radiographs and information from image samples. They employed a deep learning architecture to extract statistical features from the chest X-ray pictures as well as global features, and they also used the image augmentation technique to balance the dataset's sample sizes. The two groupings of features were combined, and the final classification was performed using a random forest classifier. Additionally, feature selection was done in order to locate the most pertinent traits. The random forest classifier achieved a classification accuracy rate of 86.3% and an F1 score of 86.03%.

Meng *et al.,(*2021) researched using feature extraction, feature clustering, and dimensionality reduction algorithms to enhance classification outcomes while lowering computing complexity in the model training process. They used a classifier created by machine learning that combined RF, SVM, Naive Bayes, and KNN models. They compared their performance to the three other deep learning classifiers MobileNet, Xception, and ResNet. Among the suggested deep learning models, their classification accuracy score of 76.4% was the highest.

Chandra and Verma (2020) investigated the detection of pneumonia using ROI (Region of Interest) images of features, using five machine learning algorithms Multilayer Perceptron, Random Forest, Sequential Minimal Optimisation (SMO), Logistic Regression, and Classification through Regression were assessed. The ChestX-ray14 dataset was used in the study which has 412 chest X-ray pictures with 206 pneumonic and 206 normal patients. Results revealed that the suggested method had a high accuracy of 95.39% with the multilayer perceptron and 95.6% with the logistic regression classifier.

Using a CNN model and an ensemble learning model (combination of three CNN models), Darici *et al*. (2020) suggested using chest X-ray images to perform binary (pneumonia and healthy) and multiclass (viral, bacterial, and healthy) classification of pneumonia disease. Accuracy, precision, recall, and F1 score were used to assess the performance of both models. For binary classification, both models obtained an accuracy of 95%, while for multiclass classification, the average accuracy for the bespoke model and ensemble model, respectively, was 78% and 75%. For the multi-class classification, the ensemble model scored 77%, 75%, and 75%, compared to the CNN model's 80%, 78%, and 78% average precision, recall, and f1 scores.

3.MATERIALS AND METHODS

This section introduces the method used for pneumonia disease detection in Chest X-ray images along with the dataset used for the experiment.

3.1 Datasets Description

The dataset was obtained from Kaggle.com. The images of the dataset obtained from Kaggle were observed to be of different dimensions and were organized into three folders - training, test, and validation datasets. The dataset contained 5,856 chest X-ray images split into two categories, normal (chest X-ray images without pneumonia) and pneumonia (chest X-ray images with pneumonia). As illustrated in Table 1, the dataset contained a total of 5856 images, with 1,583 X-ray images representing cases without pneumonia and 4,273 images of X-rays representing cases with pneumonia. The dataset is a publicly accessible dataset: containing JPEG images only. Figure 1 shows the dataset. Description.

Table 1: Description of the dataset among the two classes

S/N	Class label	Number of images
1	Normal	1583
2	Pneumonia	4273
Total		5856

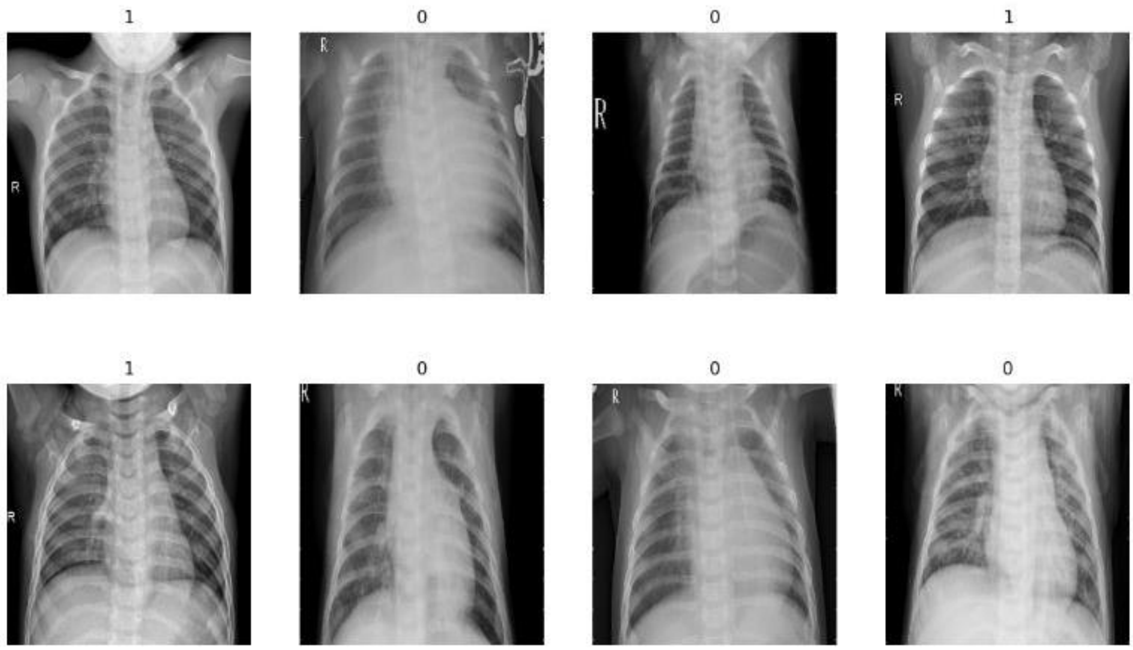

Figure 1: Sample images in the dataset (Kaggle)

3.2 Methodology

The model development process is categorized into several parts: data collection, preprocessing, training, testing, classification, and pneumonia prediction, as shown in Figure 2. The data preprocessing is done for balancing and normalizing the data, this technique is used to set the data in a normalized form between a range of [0-255]. The Keras image preprocessing package ImageDataGenerator was used to apply image augmentation to the training and validation data. Using picture augmentation does not affect the goal class of the images, but it does provide a different perspective for capturing many potential real-life classification tasks, such as a degree of heterogeneity in the dataset and improving model generalization on unseen data.

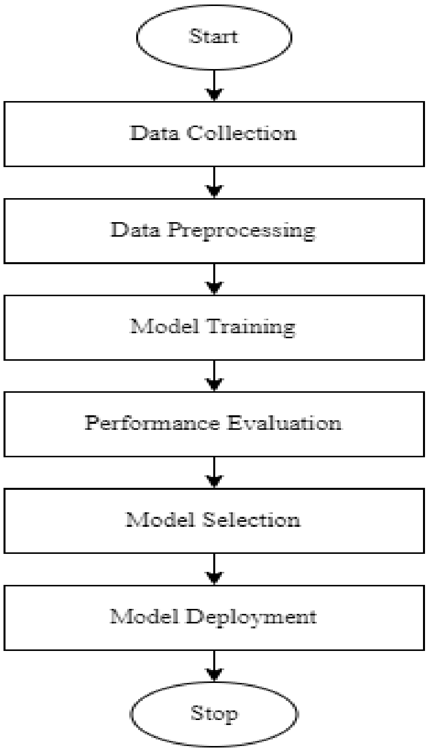

Figure 1: Process Overview

The enhanced training and validation dataset was used to train the three chosen models, which includes the VGG16, ResNet50, and MobileNetV3 CNN models. Each model was initialized and compiled for binary classification. The VGG16, ResNet50, and MobileNetV3 architectures are summarised in Figures 3, 4, and 5 respectively, and each figure displays the number of parameters and the output forms of each layer.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 flatten_1 (Flatten)         (None, 25088)             0

 batch_normalization (BatchN  (None, 25088)            100352
 ormalization)

 dense (Dense)               (None, 128)               3211392

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 18,026,561
Trainable params: 3,261,697
Non-trainable params: 14,764,864
_________________________________________________________________
```

Figure 3: VGG16 model summary

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 7, 7, 2048)        23587712

 flatten_2 (Flatten)         (None, 100352)            0

 batch_normalization_1 (Batc  (None, 100352)           401408
 hNormalization)

 dense_2 (Dense)             (None, 128)               12845184

 dropout_1 (Dropout)         (None, 128)               0

 dense_3 (Dense)             (None, 1)                 129

=================================================================
Total params: 36,834,433
Trainable params: 13,046,017
Non-trainable params: 23,788,416
_________________________________________________________________
```

Figure 4: ResNet50 model summary

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 MobilenetV3small (Functiona  (None, 7, 7, 576)        939120
 l)

 flatten_3 (Flatten)         (None, 28224)             0

 batch_normalization_2 (Batc  (None, 28224)            112896
 hNormalization)

 dense_4 (Dense)             (None, 128)               3612800

 dropout_2 (Dropout)         (None, 128)               0

 dense_5 (Dense)             (None, 1)                 129

=================================================================
Total params: 4,664,945
Trainable params: 3,669,377
Non-trainable params: 995,568
_________________________________________________________________
```

Figure 5: MobileNetV3 model summary

3.2.1 Data Cleaning and Preprocessing

The data preprocessing is done for balancing and normalizing the data, this technique is used to set the data in a normalized form between a range of [0-255]. The whole dataset was loaded from the three original folders (training, test, and validation) in which the images were arranged, but the images had to be reorganized because the split ratio did not follow the 80:20 ratio. The dataset was loaded, and because the photos had different sizes, they were adjusted to create uniformity and improve the performance of the models. The photos were read in the desired color space (RGB - Red-Blue-Green color scheme) and reshaped to ensure they were in the right format to be fed into the models. The images in the dataset were also subjected to image normalization, which involves dividing each pixel value by the maximum pixel value in order to normalize the image pixel values to a common range, such as [0, 1], which aids in improved convergence during training. A Keras image augmentation tool called ImageDataGenerator was also utilized to increase the training and validation dataset. Additional training samples were produced using ImageDataGenerator augmentation methods such as rotation, zooming, flipping, and scaling to prevent the CNN models from overfitting on the training and validation data and guarantee that they generalize properly on unknown test data.

3.2.2 VGG16

The study utilized the VGG-16 CNN design, is a 16-layer convolutional neural network developed by Simonyan and Zisserman in 2014. The network consists of 13 convolutional layers, 2 fully connected layers, and 1 SoftMax classifier. The first and second convolutional layers receive RGB images, with the output transferred to the max pooling layer. The third and fourth layers have 124 feature kernel filters, reducing the output to 56x56x128. The final layer is a max pooling layer with a stride of 1, and the final layer is a SoftMax output layer.

3.2.3 ResNet50

ResNet, a deep convolutional neural network (CNN) model, was used in a study to train extremely deep neural networks with over 150 layers. ResNet designs come in various forms, such as ResNet-34, ResNet-50, and ResNet-101, all identified by the number of convolutional and fully connected layers they contain. ResNet-50 is a profound 50-layer convolutional neural network with 48 convolutional layers, one MaxPool layer, and one average pool layer. The network uses input images with 224x224x3 dimensions and uses a layering pattern of 12 layers, 12 layers, and 18 layers. The final blocks consist of 512, 512, and 2048 kernels, resulting in nine layers. The average pooling layer and fully linked layer with n nodes are produced using a SoftMax function.

3.2.4 MobileNetV3

This study uses MobileNetV3, a deep neural network architecture used in image classification. It extracts image features through multiple convolution layers, reducing parameters and increasing efficiency. The architecture consists of multiple blocks, including a bottleneck layer, 1x1 convolutional layer, depth wise separable convolutional layer, squeeze and excitation layer, module for channel-wise feature recalibration, and expansion layer. The final layers consist of fully linked layers, the SoftMax output layer, and global average pooling layer, with the SoftMax function applied to provide output probabilities.

4. Results and Discussion

The pretrained CNN models were tested for 30 epochs. The experiments were carried out on ratio combinations of 80: 20, wherein 80% of the total images were for training purposes and 20 for testing and validation. This paper discusses the results obtained on the 80: 20 ratio, as it is the most efficient one when compared with the other two ratios and was performed on the Google collaboratory platform with the GPU runtime as provided. Further, along with the performance, the detections are displayed using a confusion matrix, and the classification reports along with the pneumonia are shown.

VGG16 Model: The VGG16 model achieved an accuracy of 94%, 91% precision,95% recall, and 93% f1 score. The model's confusion matrix and classification report based on its performance in classifying each class is depicted in Figure 6 and Figure 7, respectively.

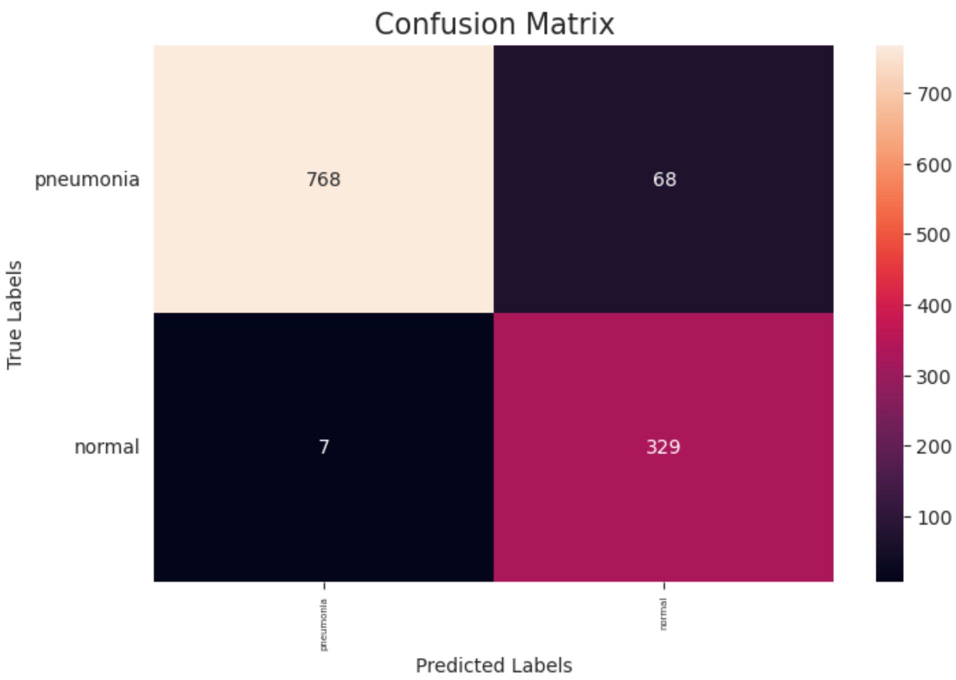

Figure 6: VGG16 confusion matrix

	precision	recall	f1-score	support
Pneumonia (0)	0.99	0.92	0.95	836
Normal (1)	0.83	0.98	0.90	336
accuracy			0.94	1172
macro avg	0.91	0.95	0.93	1172
weighted avg	0.94	0.94	0.94	1172

Figure 7: VGG16 classification report

The training and validation accuracy and loss graphs shown in Figure 8 below give a visual representation of how the learning performance of the model varies with the number of epochs. The performance of VGG16 model has been found better for the prediction of pneumonia, in which various performance metrics have been calculated with the least value of error as shown in figure 8 (right). The figure shows no significant divergent differences between the training and validation accuracies in the model. This depicts that the fact that there is no overfitting in the developed model.

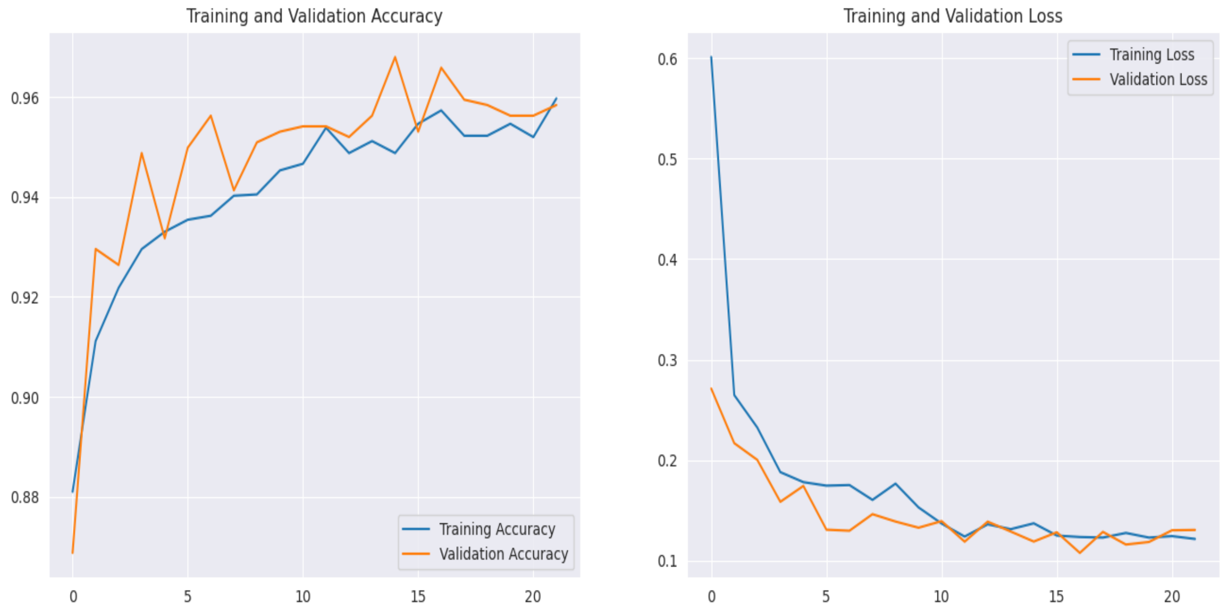

Figure 8: VGG16 model accuracy (left) and loss (right) graph

ResNet50 Model: The ResNet50 model achieved an accuracy of 92%, 89% precision, 93% recall, and 91% f1 score. The model's confusion matrix and classification report based on its performance in classifying each class is depicted in Figures 9 and 10, respectively.

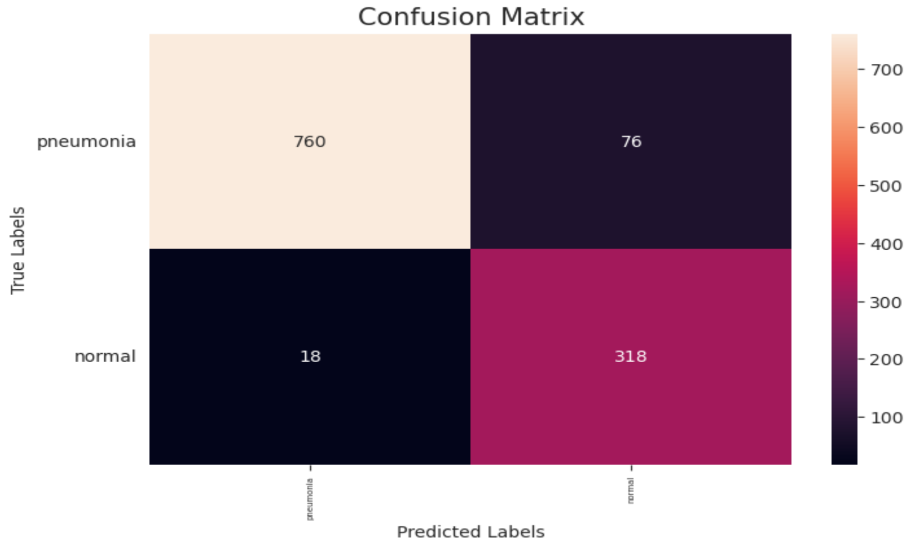

Figure 9: ResNet50 confusion matrix

	precision	recall	f1-score	support
Pneumonia (0)	0.98	0.91	0.94	836
Normal (1)	0.81	0.95	0.87	336
accuracy			0.92	1172
macro avg	0.89	0.93	0.91	1172
weighted avg	0.93	0.92	0.92	1172

Figure 10: ResNet50 classification report

The training and validation accuracy and loss graphs of ResNet50 are shown in Figure 11. The figure also shows no significant divergent differences between the training and validation accuracies in the model.

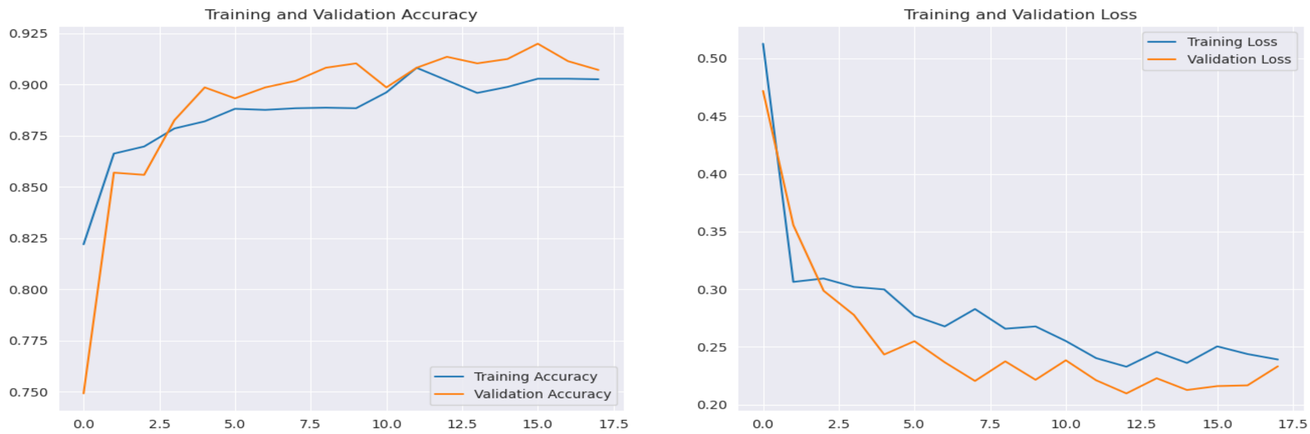

Figure 11: ResNet50 model accuracy (left) and loss (right) graph

MobileNetV3 Model: The MobileNetV3 model achieved an accuracy of 93%, 90% precision, 94% recall, and 92% f1 score. The model's confusion matrix and classification report based on its performance in classifying each class is depicted in Figures 12 and 13, respectively.

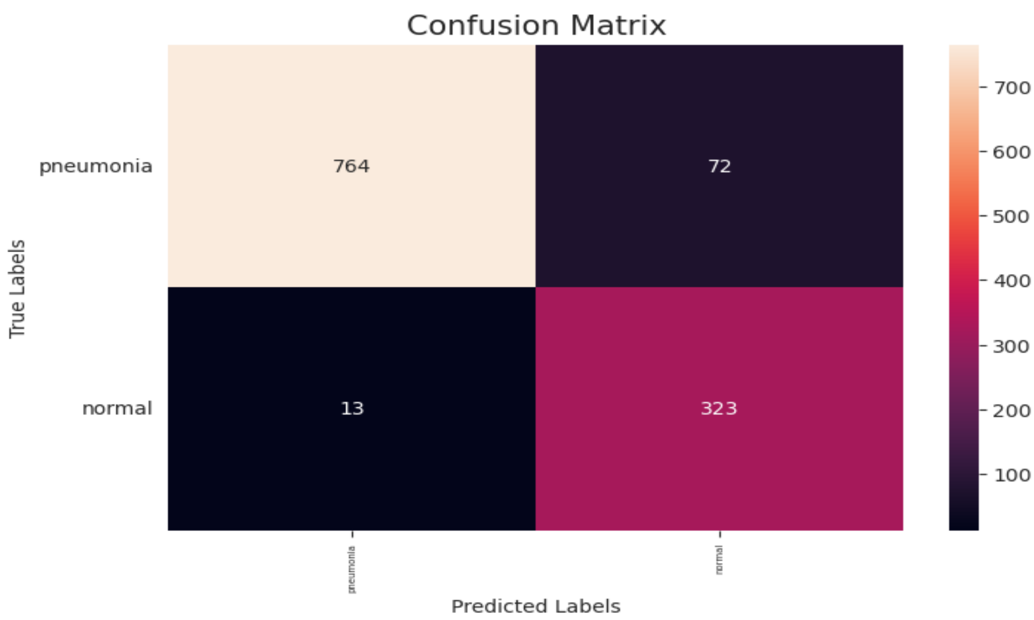

Figure 12: MobileNetV3 confusion matrix

	precision	recall	f1-score	support
Pneumonia (0)	0.98	0.91	0.95	836
Normal (1)	0.82	0.96	0.88	336
accuracy			0.93	1172
macro avg	0.90	0.94	0.92	1172
weighted avg	0.94	0.93	0.93	1172

Figure 13: MobileNetV3 classification report

4.2 Model Deployment

Considering the results obtained from the evaluation of each model as shown in Table 2, it was observed that there was a slight difference in the performance of the CNN models. Overall, the VGG16 model was observed to perform the best, followed by the MobileNetV3 and, lastly, the ResNet50. Hence, the VGG16 model was selected as the model for deployment.

Table 2: Summary of the performance evaluation result

S/N	Model	Accuracy	Precision	Recall	F1-Score
1	VGG16	94%	91%	95%	93%
2	ResNet50	92%	89%	93%	91%
3	MobileNetV3	93%	90%	94%	92%

The VGG16 model was saved using TensorFlow and deployed on a web application that allows the upload of chest X-ray images and then provides a diagnosis for classifying whether uploaded X-ray images are normal or contain pneumonia. Figure 14 shows the website when the user visits the web application initially. When a user visits the web application, they must upload the X-ray image for which they want to obtain inference. After uploading the X-ray image, the users must click on the predict button to gain inference from the VGG16 model deployed on the web application. Once the "Predict" button has been clicked, the input image is sent to the model, the model makes its prediction, and the inference is sent to the user. Figures 15 and 16, respectively, depict the website when the model predicts that the image uploaded is "Normal" or contains "Pneumonia."

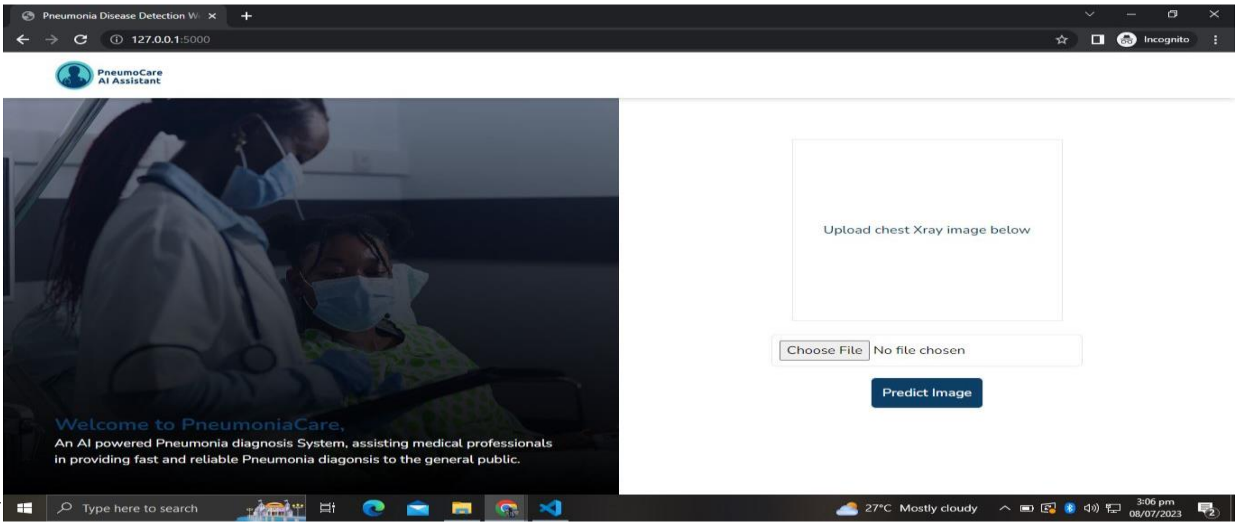

Figure 14: The web application in which the VGG16 model was deployed

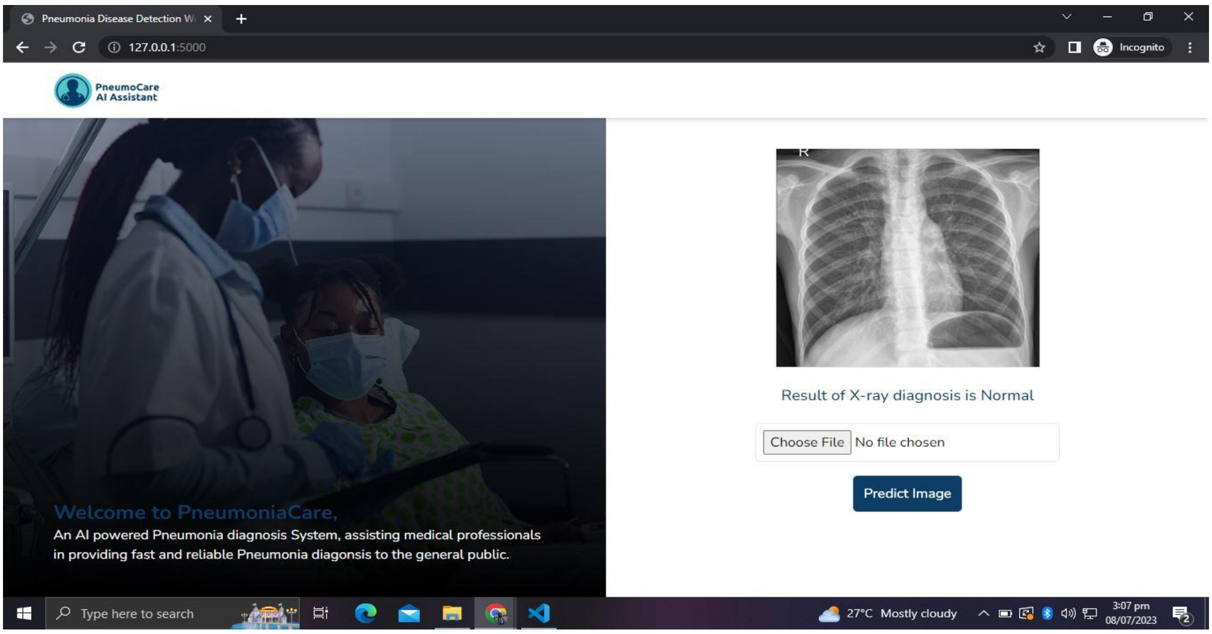

Figure 15: The web application when the model predicts a normal case

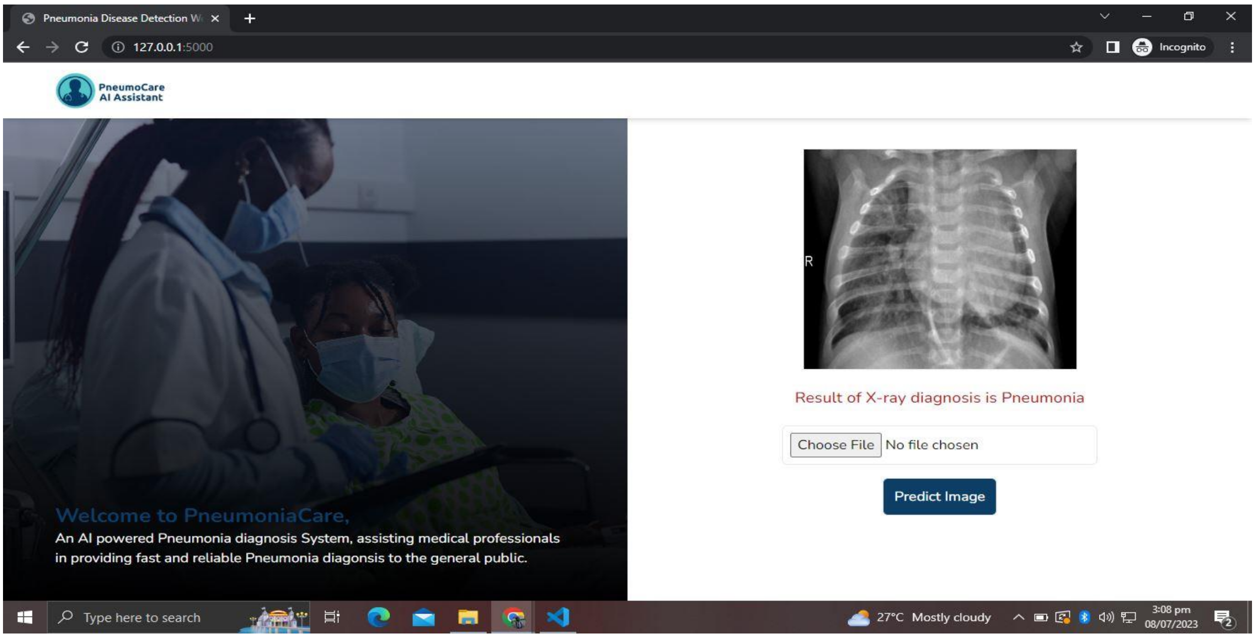

Figure 16: The web application when the model predicts a case of pneumonia

5.0 CONCLUSION

In this paper, a pneumonia detection system that could detect and classify X-ray images of the chest into cases with and without pneumonia was developed. The ResNet50, MobileNetV3, and VGG16 CNN architectures were trained using augmented training and validation datasets, early stopping and learning rate reduction techniques were applied to ensure that the models could not overfit. The accuracy, recall, f1-score, and precision performance metrics were used to compare the three models' performance, and results showed that the VGG16 model performed the best at detecting and classifying chest X-ray images into cases with and without pneumonia. The VGG16 model had the highest accuracy, precision, recall, and f1 score with 94%, 83%, 98%, and 90%, respectively. The MobileNetV3 model, which performed second best, achieved an accuracy of 93%, precision of 82%, recall of 96%, and f1 score of 88%, while the ResNet50 model achieved an accuracy of 92%, precision of 81%, recall of 95%, and f1 score of 87%. Hence, the VGG16 model was saved using TensorFlow and deployed on a web application to provide a means for X-ray image diagnosis of pneumonia, eliminating the challenges faced by the manual diagnosis of pneumonia.

6.0 REFERENCES

[1] Ahmad J, Saudagar A., Malik K.,Ahmad W., Khan M.,Hasanat M., AlTameem A., AlKhathami M., Sajjad M.,(2022). Disease Progression Detection via Deep Sequence Learning of Successive Radiographic Scans. International journal of environmental research and public health. 19(1):480

[2] Alsenan, A., Youssef, B. B., & Alhichri, H. (2022). MobileUNetV3—A Combined UNet and MobileNetV3 Architecture for Spinal Cord Gray Matter Segmentation. *Electronics*, 2022(11), 1-24. https://doi.org/10.3390/electronics11152388

[3] Alsharif, R., Al-Issa, Y., Alqudah, A. M., Qasmieh, I. A., Mustafa, W. A., & Alquran, H. (2021). PneumoniaNet: Automated Detection and Classification of Pediatric Pneumonia Using Chest X-ray Images and CNN Approach. *Electronics*, *10*(2949), 1-13. https://doi.org/10.3390/electronics10232949

[4] Bhatti, A. T., Umer, M., Adil, S. F., Ebrahim, M., Nawaz, D., & Ahmed, F. (2018). Explicit Content Detection System: An Approach towards a Safe and Ethical Environment. Applied Computational Intelligence and Soft Computing, 2018(2), 1-13. https://doi.org/10.1155/2018/1463546.

[5] Chandra, T. B., & Verma, K. (2020). Pneumonia Detection on Chest X-Ray Using Machine Learning Paradigm. Conference: Proceedings of 3rd international conference on computer vision and image processing, 1022, 21–33. 10.1007/978-981-32-9088-4_3

[6] Darici, M. B., Dokur, Z., & Olmez, T. (2020). Pneumonia Detection and Classification Using Deep Learning on Chest X-Ray Images. *International Journal Of Intelligent Systems And Applications In Engineering*, *8*(4), 177–183.

[7] Dhankhar, P. (2019). ResNet-50 and VGG-16 for recognizing Facial Emotions. International Journal of Innovations in Engineering and Technology (IJIET), 13(4), 126-130. http://dx.doi.org/10.21172/ijiet.134.18

[8] Gupta, P., & Meshram, S. (2022). Skin Lesion Detection using VGG-16 and ResNet-50 based Hybrid CNN Model. International Journal of Creative Research Thoughts (IJCRT), 10(6), 934-941.

[9] Gupta, P., (2021). Pneumonia Detection Using Convolutional Neural Networks, International Journal for Modern Trends in Science and Technology, 7(1), pp77-80.

[10] He, K., Zhang, X.,Ren, S., & Sun, J.,(2016).Deep residual learning for image recognition, *Proceedings of the IEEE conference on computer vision and pattern recognition*,770778. https://doi.org/10.1155/2022/7474304

[11] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K., (2017).Densely Connected Convolutional Networks, *CVPR*, 1, 3.

[12] Ibrahim, A. U., Ozsoz, M., Serte, F., Al-Turjman, & Yakoi, P. S. (2021). Pneumonia classification using deep learning from chest X-ray images during COVID-19. *Cognitive Computation*, 1-13. https://doi.org/10.1007/s12559-020-09787-5

[13] Krizhevsky, A., Sutskever, I., & Hinton, G. E.(2012). Imagenet classification with deep convolutional neural networks, *Advances in neural information processing systems*, pp10971105

[14] Kundu, R., Das, R., Geem, Z. W., Han, G. T., & Sarkar, R. (2021). Pneumonia detection in chest X-ray images using an ensemble of deep learning models. *Plos One*, *16*(9), 1-16. 10.1371/journal.pone.0256630

[15] Masud, M., Nahid, A., Sikder, N., Rubaiee, S., Ahmed, A., & Anand, D. (2021). A Pneumonia Diagnosis Scheme Based on Hybrid Features Extracted from Chest Radiographs Using an Ensemble Learning Algorithm. Journal of Healthcare Engineering, 2021(2), 1–11. DOI:10.1155/2021/8862089

[16] Meng, Z., Meng, L., & Tomiyama, H. (2021). Pneumonia Diagnosis on Chest X-Rays with Machine Learning. Procedia Computer Science, 187, 42-51. DOI: 10.1016/j.procs.2021.04.032

[17] Mujahid, M., Rustam, F., Álvarez, R., Mazón, J. L. V., & Díez, T. (2022). Pneumonia Classification from X-ray Images with Inception-V3 and Convolutional Neural Network. *Diagnostics*, *12*(5), 1-16. 10.3390/diagnostics12051280

[18] Sharma, K., Jain, D.,Singh, T.,Saurabh, P.,Bisen, H.,Sahu, N.,Mishra, J.,Rahman, H.,(2022). Computational Intelligence and Neuroscience Deep Learning-Aided Automated Pneumonia Detection and Classification Using CXR Scans,1687-5265.

[19] Sharma, S., Guleria, K., (2023). A Deep Learning based model for the Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks, Procedia Computer Science,218,357-366, https://doi.org/10.1016/j.procs.2023.01.018.

[20] Simonyan, K., & Zisserman, A.,(2014). Very deep convolutional networks for large-scale image recognition

[21] Tammina, S. (2019). Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images. International Journal of Scientific and Research Publications (IJSRP), 8(10), 143-150. DOI:10.29322/IJSRP.9.10.2019.9420

[22] World Health Organization (WHO). (2022, November 11). *Pneumonia in children*. World Health Organization (WHO). Retrieved December 2, 2022, from https://www.who.int/news-room/fact-sheets/detail/pneumonia

[23] Yu, X., Wang, H., & Zhang, D. (2020). CGNet: A graph-knowledge embedded convolutional neural network for detection of pneumonia, *Information Processing & Management*, *58*(1), 102411. https://doi.org/10.1016/j.ipm.2020.102411

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