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Research Article

Deep learning Models for Multi-class Pneumonia Detection with emphasis on Covid-19

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ABSTRACT

Pneumonia is a dangerous condition that can lead to death. Bacteria, fungi, or viruses are common causes of this condition, which can affect one or both lungs.

The x-ray scans can be used to identify this lung ailment. Pneumonia is a dangerous condition that can lead to death. Bacteria, fungi, or viruses are common causes of this condition, which can affect one or both lungs. The x-ray scans can be used to identify this lung ailment. This illness usually presents itself with a cloudy white structure on the chest x-rays. The Kaggle datasets used for chest X-rays contains a variety of images that are divided into 4 categories – "Normal", "Viral Pneumonia", "Bacterial Pneumoia", "Covid-19". A deep learning model will be developed that can truly tell us whether or not a person has pneumonia disease. The model will be able to accurately assess the illness severity by detecting the degree of this cloudiness with an automated pneumonia detection system. This project is based purely on 'Deep Learning' concepts and will be scalable in types of complications covered, model accuracy and utility convenience analysis/application. Statistical results obtained demonstrate that CNN models can be trained to analyze chest X-ray images, specifically to detect Pneumonia and even to differentiate between Covid-19 and Pneumonia. The attempt to differentiate between viral and bacterial pneumonia has been partially successful, and suggests that it is difficult to distinguish between them due to similar patterns on the X-rays. With the help of MobileNet Architecture is possible to scale this model, the results also suggest that it is also possible to differentiate between pneumonia and COVID-19, which present similarly on the x-rays, which most models fail to undertake. It is thus deduced that the lung damage is most similar in viral and bacterial pneumonia, but the pattern is different for lungs affected with Covid-19.

Keywords: Deep learning Models, Pneumonia Detection, Covid-19

INTRODUCTION

It is crucial to recognize pneumonia early and provide quick care to children since the severity of the infection can vary from mild to life-threatening. Viruses, bacteria, and fungus are all potential disease-causing agents.An automated pneumonia detection system, free from human error, can detect the disease at an early stage, potentially preventing delicate and significant treatment measures. The use of chest X-rays is a common diagnostic tool for pneumonia, allowing doctors to assess the extent and location of the infection. Pneumonia typically produces a patchy or opaque appearance on X-rays due to the infection in the air sacs of the lungs, while fluid in the layer between the lungs and chest wall, called pleural effusion, can also cause a cloudy appearance.

Our primary goal is to develop an advanced system that provides medical professionals with an efficient and effective tool for pneumonia diagnosis during medical treatment. Specifically, our focus is on creating an automated pneumonia detection system that accurately determines the extent of cloudiness in x-ray imagery, enabling the identification of infection severity with a high degree of precision. We aim to design a sophisticated and reliable system that can detect pneumonia disease patterns using various inputs, thereby significantly improving the medical expert's diagnosis. To achieve this, we have envisioned a cutting-edge system that utilizes convolutional neural networks to classify image data from x-ray imagery.

The capacity of our initiative to provide accurate and concise results indicating the presence or absence of pneumonia in an individual. Additionally, our system can easily be scaled to identify the specific type of pneumonia involved. Our project relies on 'Deep Learning' concepts, and it is scalable in terms of the types of complications it covers, model accuracy, and convenience of analysis/application. The analysis of chest X-ray images, notably for the detection of pneumonia, can benefit greatly from the employment of pre-trained CNN models in conjunction with supervised classifier methods, according to statistical findings. We are confident that our system will be a valuable asset for medical professionals in the diagnosis and treatment of pneumonia.

RELATED WORKS

We surveyed a plethora of systems and reviewed several papers published on Pneumonia and disease detection to recognize existing limitations and gain knowledge on optimal technologies and methodologies that are compatible with our proposed system and are able to effectively tackle our problem statement. Following is a review of the surveyed systems:

The task of perceiving viral pneumonia, non-viral pneumonia, and strong controls is framed in this paper as a one-class gathering based peculiarity ID issue. Hence, the CAAD model, which involves a typical part extractor, an inconsistency disclosure module, and a sureness assumption module, is proposed. The chief benefit of this procedure over equal portrayal is that all known examples of viral pneumonia are treated as irregularities to assist the one-class with demonstrating instead of unequivocally showing a couple of viral pneumonia classes.**[1]**

A chest x-ray examination is the diagnostic imaging approach that is used the most frequently to identify suspected cases of pneumonia. This study focuses on a computer-aided diagnostic approach for pneumonitis that is based on computed tomography (CXR) and has the potential to improve the accuracy of diagnosis. Several different edge detection and image segmentation methods have been utilized in order to segment the lung; however, none of these methods have provided a segmentation result that is considered to be promising. In order to efficiently identify the presence of pneumonia mists in chest X-rays, this work incorporates the Gaussian filter, which is a technique for increasing contrast using the CLAHE method.**[2]**

Chest X-ray pneumonia diagnosis is carried out by variants of CNN, including VGG19, InceptionResNetV2, DenseNet201, and Xception. The entire procedure is presented, including dataset selection, dataset processing, and chest X-ray pneumonia identification. Chest X-ray pneumonia detection using convolutional neural networks (CNNs) can enhance both training speed and detection accuracy, achieving a maximum accuracy of 94.20% in experimental results. **[3]**

The result shows that Coronavirus and Coronavirus versus Pneumonia were precisely identified. The exactness of Coronavirus versus Ordinary is higher than Coronavirus versus Pneumonia among the two. This approach is equipped for identifying Coronavirus, Pneumonia, and its subtypes, like bacterial or viral Pneumonia, with 80% precision. The recommended model's capacity to distinguish Coronavirus, bacterial pneumonia, and viral pneumonia supports fast determination and assists with separating Coronavirus from various kinds of pneumonia, making it simpler to apply the right medicines. However the low accuracy is a drawback.**[4]**

The suggested strategy was evaluated with the use of two pneumonia X-beam datasets that are accessible to the general public. A five-fold cross-approval approach was utilized by the Radiological Society of North America (RSNA), which was conducted independently. The suggested method achieved accuracy rates of 98.81% and 86.85% on the two datasets, and awareness rates of 98.80% and 87.02%, respectively, on the two datasets. We were able to get outcomes that were superior to those achieved by cutting-edge procedures, and our plan surpassed traditionally utilized business processes. A factual analysis was performed on the datasets using McNemar's and ANOVA tests, which allowed for the demonstration of the efficiency of the approach.**[5]**

The usefulness of utilizing CNN models that have already been trained as feature extractors is investigated in this study. followed by various classifiers, to categorize chest X-rays as normal or abnormal. Statistical analysis indicates that combining pre-trained CNNs with supervised classifiers can be highly effective for assessing chest X-ray images, especially in detecting pneumonia.**[6]**

This paper introduces deep learning models designed to accurately detect pneumonia in lungs using chest X-ray images, providing tools that medical professionals could apply in clinical pneumonia treatment. The models progressively incorporate one to four convolutional layers, with For the first model, the accuracy rate was 89.74%, for the second model it was 85.26%, for the third model it was 92.31%, and for the fourth model it was 91.67%. After applying dropout regularization to the second, third, and fourth models, the overfitting that occurs in the fully linked layers is reduced.**[7]** In order to solve the problem of image-based pneumonia classification, the authors of this paper have researched, developed, deployed, and evaluated customized convolutional neural networks. ResNet-50 and DenseNet-161 models were used to build a special deep network architecture and improve pneumonia classification accuracy overall. Additionally, the suggested models were assessed using data augmentation in addition to conventional datasets**.[8]** The goal is to automatically distinguish between viral and bacterial pneumonia using digital x-ray images. Before explaining the authors' method, it provides a full description of the advancements made in the proper detection of pneumonia. Four different pre-trained deep convolutional neural networks (CNNs)—AlexNet, ResNet18, DenseNet201, and SqueezeNet—were used to perform transfer learning. After preprocessing, 5247 chest x-rays of healthy individuals, germs, and viruses underwent training for a classification task based on transfer learning.**[9]**

To precisely distinguish and analyze Coronavirus from chest CT filters, this examination proposes a changed AI (ML) strategy that consolidates profound learning (DL) methods for highlight extraction and notable classifiers. At the point when 2000 elements were separated involving GoogleNet and ResNet18 as well as the help vector machine (SVM) classifier, the best typical exactness accomplished was 99.9%. When contrasted with comparative methodologies revealed in the current writing utilizing the equivalent datasets or different datasets of practically identical size, the outcomes delivered using the changed ML process were higher; subsequently, this study is viewed as adding to the collection of existing information.**[10]**

DATASET DESCRIPTION

Three Kaggle datasets are used:

1. Chest X-Ray Images (Pneumonia) – binary classes (normal and pneumonic), which has 1583 images of normal chest x-rays, and 4273 images of pneumonia x-rays. [11]
2. 3 Kinds of Pneumonia - which contains four classes, normal x-ray (3270 images), pneumonia-bacterial (3001 images), pneumonia-viral (1656) and COVID-19 (1281 images). [12]
3. Chest X-ray (COVID-19 & Pneumonia) – includes normal, pneumonia, and COVID-19 images. It contains 6432 images in total. Out of these, 4273 belong to Pneumonia, 1583 are normal, and 576 are of covid-19. The test data set contains 1288 images and the training data set has 5144 images. [13]

These datasets undergo preprocessing steps like resizing, normalization, and data augmentation to ensure high model performance. Data augmentation techniques such as horizontal flips, rotations, and brightness adjustments, artificially expand the dataset, helping prevent overfitting and improving robustness. This preprocessing pipeline enhances model accuracy and usability.

PROPOSED WORK

The goal is to classify chest x-ray pictures using CNN architecture in order to determine whether or not a person has pneumonia. Three CNN models will be developed, one for binary classification, one for multiclass classification between normal, Covid-19, bacterial, and viral pneumonia, as well as one that uses MobileNet Architecture to differentiate between normal pictures, Covid-19, and pneumonia. This study investigates three models with differing objectives:

1. **Binary Classification Model**: This model classifies X-rays into "normal" or "pneumonic" categories, providing a straightforward and rapid method for detecting pneumonia.

2. **Multiclass Classification Model**: A CNN model that provides precise illness detection necessary for focused therapy by distinguishing between bacterial, viral, COVID-19, and normal pneumonia.

3. **MobileNetV2-based Model**: This model uses the MobileNetV2 architecture to classify chest X-rays into pneumonia, COVID-19, and normal categories, with an emphasis on computational efficiency, making it suitable for real-time use in low-resource settings.

The CNN architecture employed in this study, shown in Fig. 1, consists of components such as convolutional layers, pooling layer, and fully connected layers. These elements form a powerful feature extraction pipeline well-suited for medical imaging due to their robustness in identifying intricate patterns in images.

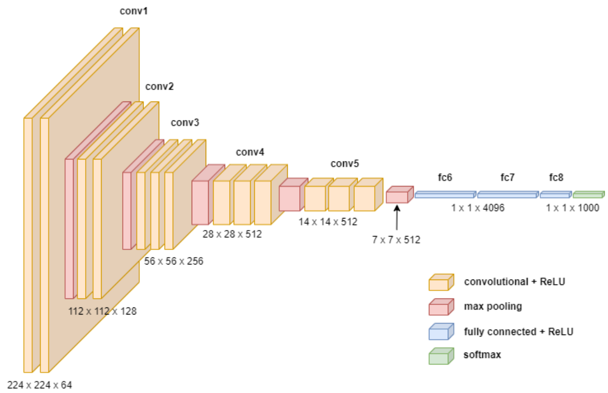

Fig. 1. CNN architecture

Convolutional Layers: Convolutional layers apply a set of filters (kernels) to each image to extract low- and high-level features, essential for understanding visual structures within X-rays. The convolution operation, defined as:

$$h_{i,j}^{(l)} = \sigma\left(\sum_{m,n} w_{m,n}^{(l)} x_{i+m,j+n}^{(l-1)} + b^{(l)}\right)$$

Where the $h_{i,j}^{(l)}$ is the output at layer l, and $x_{i,j}^{(l-1)}$ represents the input from the previous layer, $w_{m,n}^{(l)}$ is the convolutional filter, and $b^{(l)}$ is the bias term, aids in capturing the unique textural and structural patterns in X-ray images, crucial for differentiating between healthy and diseased lungs. The layers can identify complex shapes and textures, such as patchy infiltrates and nodules associated with various forms of pneumonia.

Pooling Layers: Pooling layers downsample the feature maps, effectively reducing data dimensionality while preserving essential information. Max pooling, commonly used in CNNs, is defined as: $y_{pool} = \max\{y_{i,j}^{conv}\}$ where $y_{i,j}^{conv}$ is the output of the convolutional layer within a region. This downsampling reduces the number of computations, enhancing processing efficiency, and mitigates the risk of overfitting by discarding less relevant information. Pooling contributes to robustness in classification, as the model becomes less sensitive to small positional changes in image features.

After convolution and pooling, the features are flattened and passed to fully connected layers, which provide a final mapping to the predicted class. By producing a probability distribution over the target classes, the fully connected layers enable precise classification, crucial for reliable diagnosis in medical applications. The binary classification model leverages these CNN benefits to create a simple yet effective approach for differentiating normal from pneumonic X-rays. This model serves as the foundation for developing more complex classification models in the study. Using convolutional neural networks (CNNs), the multiclass model can distinguish between four types of pneumonia: common, bacterial, viral, and COVID-19. This model uses additional convolutional layers and a softmax activation function, allowing for multi-class predictions essential for a more granular understanding of each patient's condition. The softmax function is mathematically represented as:

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Where z_i represents the logits for class *i* out of K classes. This function ensures a probabilistic output across the four classes, crucial for confident, interpretable predictions. The multiclass model, therefore, offers a granular diagnosis by distinguishing between bacterial and viral pneumonia from COVID-19 and healthy states, the model supports clinicians in delivering targeted treatment. It performs automated differentiation and aids as manual analysis of X-rays for multiple conditions is time-intensive and prone to human error. Automated classification allows for faster, more accurate diagnoses, especially in high-stress environments like emergency rooms. This model's structure allows it to handle multiple disease classes, expanding its utility in diverse clinical settings, where quick differentiation between infections is often necessary.

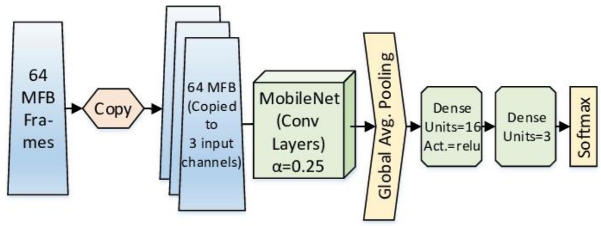

Fig.2. MobileNet architecture

MobileNetV2, shown in Fig. 2, is a streamlined Google's CNN architecture is designed to attain high accuracy while minimizing computing expense, rendering it appropriate for mobile and embedded applications.This architecture is ideal for X-ray image classification, especially in low-resource environments or on devices with limited processing power, such as mobile diagnostic units.

Depthwise Separable Convolutions: In contrast to conventional convolutions, depthwise separable convolutions partition the process into depthwise and pointwise convolutions, hence reducing computing expenses. The operation is defined as:

$$Y_{out}(x, y, k) = \sum_{i,j} X(x + i, y + j, k) \cdot W(i, j, k)$$

where $Y_{out}(x,y,k)$ is the depthwise-convolved output, X is the input, and W is the depthwise filter. This efficient design makes MobileNetV2 lightweight and suitable for real-time applications, enhancing responsiveness in critical settings.

MobileNet utilizes depthwise detachable convolutions, which separate the spatial sifting and channel-wise sifting tasks, bringing about a critical decrease in the quantity of boundaries and calculations required. It likewise utilizes a procedure called "bottleneck plan," which lessens the quantity of directs in the moderate layers to additionally diminish the calculation cost. The engineering comprises a progression of depthwise distinct convolution layers compared to non linear activation functions such as Relu which are used in CNN, trailed by a worldwide normal pooling layer and a completely associated layer. It additionally incorporates skip associations, which further develop angle streams and assist with forestalling the evaporating inclination issue.

MobileNet comes in a few variations, including MobileNet V1, V2, and V3, each with various enhancements for various use cases. In our proposed work, we will be using MobileNet V2 architecture. Generally speaking, MobileNet is an amazing decision for versatile and installed gadgets, where computational assets and memory are restricted.

To evaluate the models' efficiency, a comparative analysis of CNN and MobileNetV2 models will assess their accuracy, computational efficiency, and deployment suitability for low-resource settings. Evaluation metrics include:

- **Accuracy**: Indicates the proportion of images that are correctly classified.
- **Precision, Recall, and F1 Score**: Offer insights into each model's sensitivity and specificity, which are essential in medical diagnostics.
- **Confusion Matrix**: Displays true positives, false positives, true negatives, and false negatives, highlighting each model's strengths and areas needing improvement.

RESULTS

For binary classification of X-Rays into Pneumonic and Normal :

We trained the given data by creating our sequential CNN model. We have our initial convolutional layer with 32 filters and stride of 1. The activation function used is ReLu (Rectified Linear Unit) and the shape for the input to be 150 x 150. Using the mean and standard deviation of the most recent batch of inputs, the layer will perform batch normalization, which will normalize the output. We will perform max pooling on the given output of the layer to extract the important features from the data. We will add 4 more such layers with varying weights. Eventually we will flatten the data in an array and perform the dense function using the sigmoid activation function. Finally we will compile the model using rmsprop optimization, and set loss as binary-cross entropy for binary classification. We have divided the given data and trained it in a batch size of 32 for 10 epochs.

After processing the accuracy given to us is 96.41% on the training set. When the model is evaluated on the testing data the accuracy turned out to be 92.15%.

Figures 3a and 3b illustrate the Gradio interface developed for pneumonia detection. Table 1 provides an estimation of the precision, recall, F1-score, and accuracy of our model.Precision is defined as the ratio of True Positives to the total number of Positives. The accuracy of our model was 94% for pneumonia prediction and 90% for normal image prediction. Recall quantifies the model's accuracy in recognizing True Positives. The recall for pneumonia is 94%, whereas for normal images it is 89%.

We can see that the accuracy of the entire model is 92%. In the confusion matrix (Fig. 7) there were 25 such cases where the image belonged to the normal class but was classified as pneumonic, and 24 cases for vice versa.

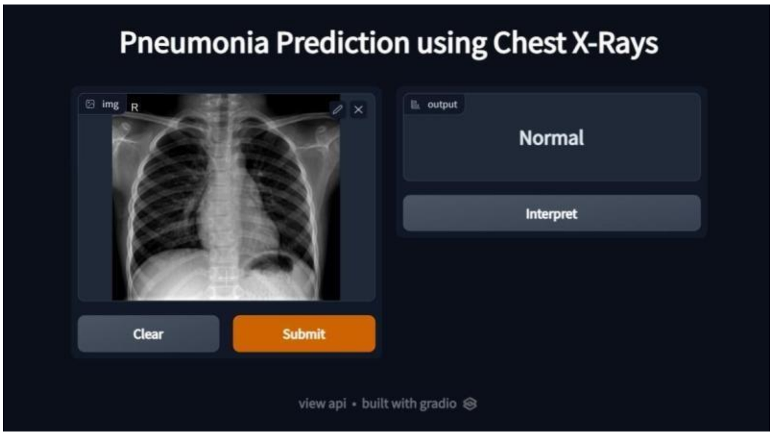

Fig 3.a Binary Classification using CNN(Normal X-Ray

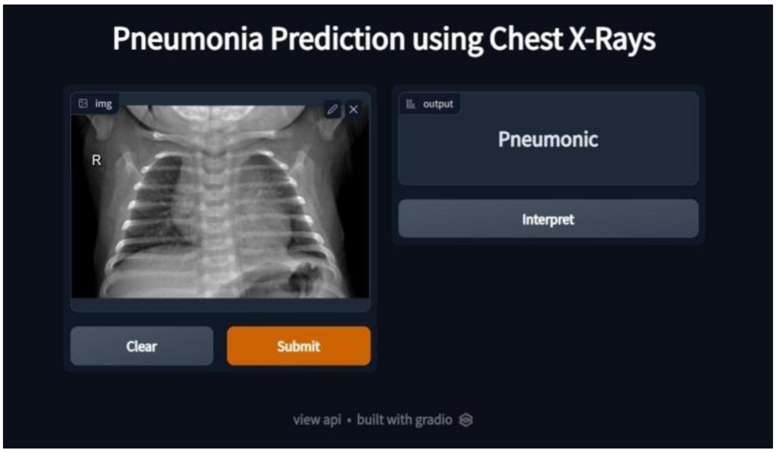

Fig 3.b Binary Classification using CNN(Pneumonic X-Ray)

Table 1 Classification Report including precision, recall,

f1-score and support performance metrics.

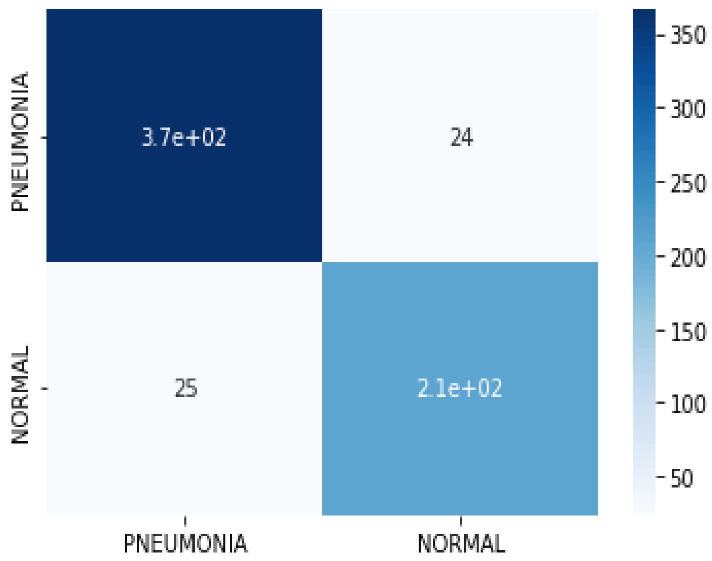

Fig 4. X-rays are classified as either normal or pneumonic using a confusion matrix.

Fig. 4 shows the confusion matrix for binary classification of X-Ray into normal and pneumonic X-Rays.

Multiclass Classification Model Results -

We split our data images into training and testing sets, with with a 80-20 split. Next, we have created our convolutional neural network model, with six layers. The first layer is the input layer which has 128 filters and uses the 'ReLu' activation function. We will then be max pooling the outputs. Ultimately, we will employ the flatten layer to generate a one-dimensional array and the dense layer to categorize photos. The model is constructed with the 'adam' optimizer, with categorical cross-entropy as the loss function for multiclass classification.

. We will fit the training data on the model with a batch size of 32 and 20 epochs. On the testing data the accuracy turned out to be 83% only. It was found that the model failed to classify between the viral and bacterial samples correctly.

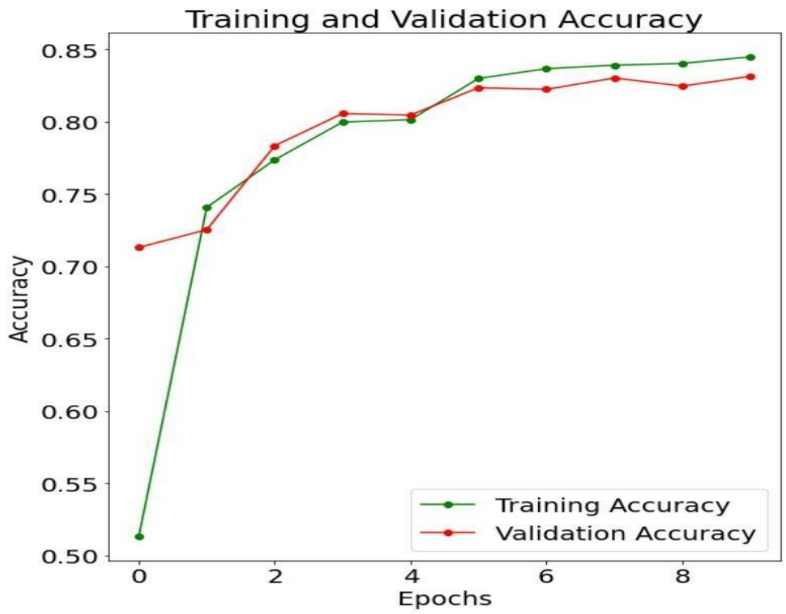

Fig. 5a : Training and Validation Accuracy over Epochs

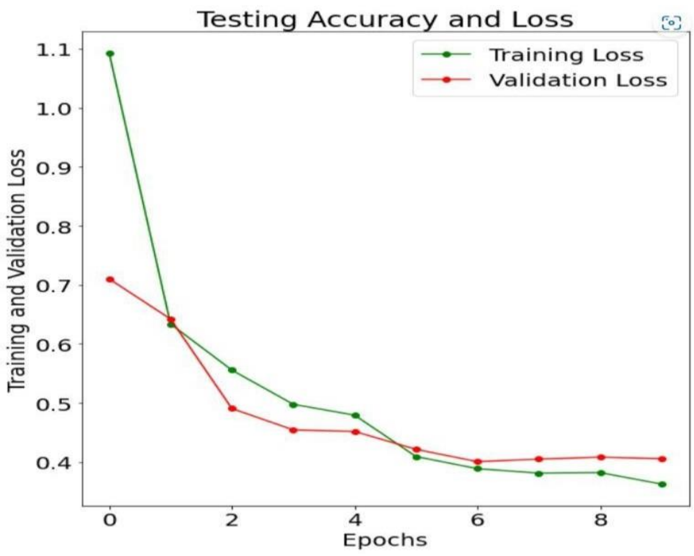

Fig. 5b : Testing accuracy and loss over Epochs

Fig. 5a shows the training and validation accuracy and fig. 5b shows testing accuracy and loss over epochs.

Table 2. Classification Report including precision, recall,

f1-score and support performance metrics.

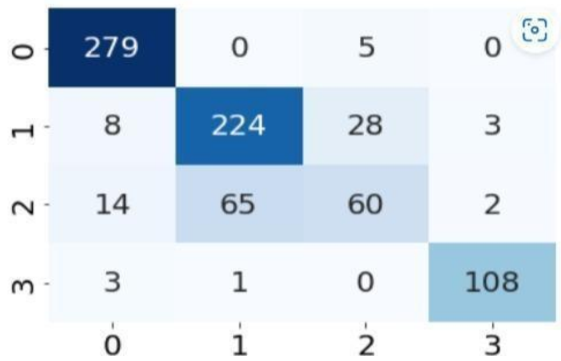

Fig. 6 Confusion Matrix for multiclass classification of X-ray images.

Fig 6. is the confusion matrix for multiclass classification, where the class 0 is normal x-rays, class 1 is viral pneumonia, class 2 is bacterial pneumonia and finally, class 3 is Covid-19.

For multiclass classification of X-Rays into Pneumonia, Normal and Covid-19 With CNN MobileNet;

We have a dataset of 5144 images with 3 classes: Normal X-ray (1583 images), Pneumonia (4273 images), COVID-19 (576 images). We have split the images into training and testing sets in a 80-20 ratio.

Convolutional neural networks (CNNs) such as MobileNet are specialized for mobile and embedded devices. We will fit the training data on the model with a batch size of 32 and 10 epochs. On the testing data the accuracy turned out to be 91%. The training accuracy was found to be 94%.

Due to the similar nature of white cloudy patches in chest areas, it was expected that the results would not be accurate and would lead to misidentification of the two classes. However, we have successfully implemented a model, which classifies not only between normal and pneumonic x-rays, but also considers the possibility of covid-19. This model can also be incorporated in medical devices, to upload a copy of X-rays to differentiate between the two, which on a preliminary look, a doctor may not be able to distinguish.

Fig 7. MobileNetV2 Model Output

Fig.7 is the output of a dataset being tested on MobileNet architecture.

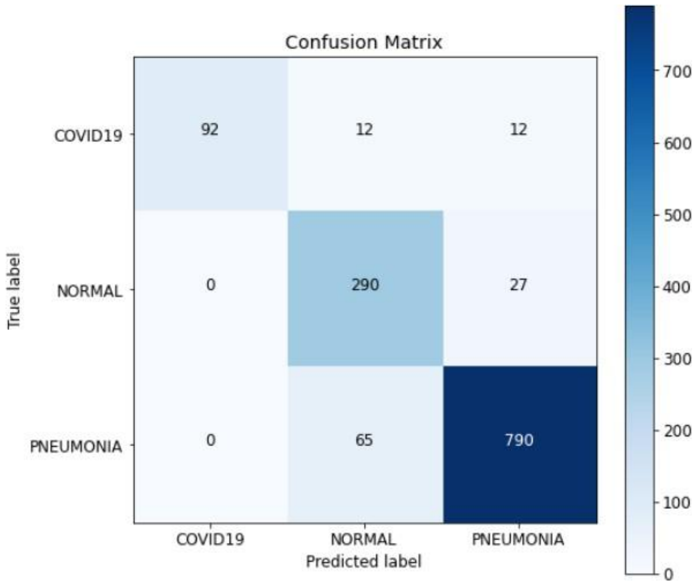

Fig. 8 Confusion Matrix for MobileNet V2 classification of X-ray images.

Fig. 8 Displays the confusion matrix for MobileNetV2 classification of X-ray pictures depicting Covid-19, pneumonia, and healthy lungs.

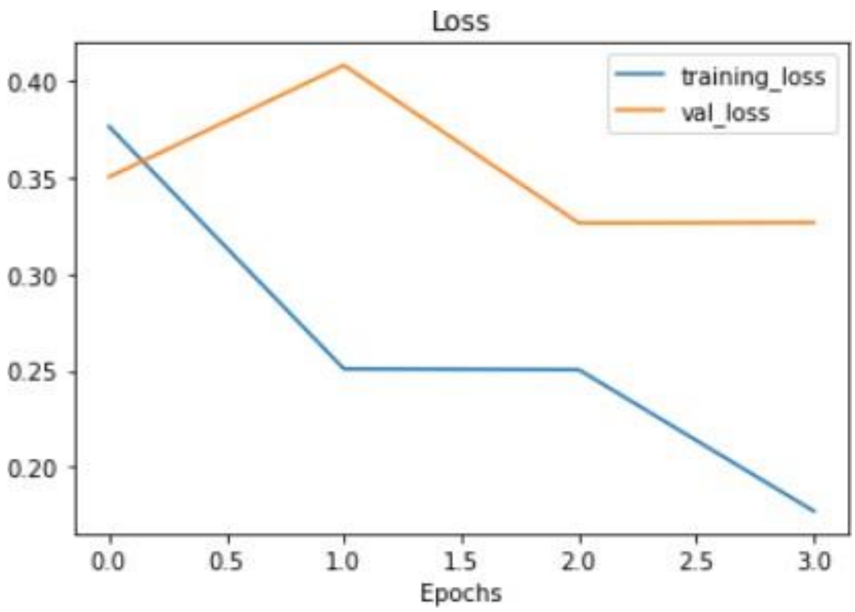

Fig. 9a: Testing and training datasets: Loss vs. Epochs

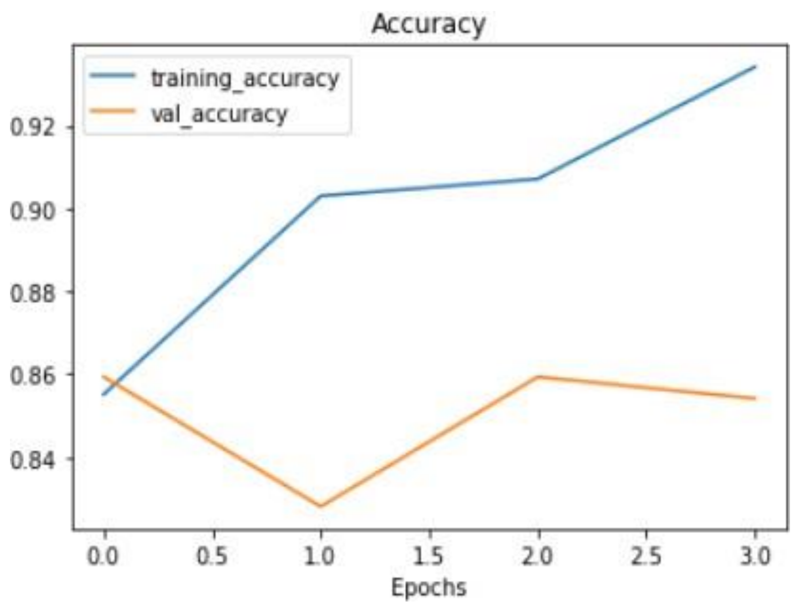

Fig. 9b Datasets for training and validation: Accuracy versus Epochs.

Fig. 9a and 9b shows the loss vs epochs and accuracy vs epochs graph for training and testing datasets.

CONCLUSION

Three CNN-based models were built to identify chest X-ray pictures for pneumonia and COVID-19 detection, attaining high accuracy standards across classification difficulties. The initial binary classification model for pneumonia and normal patients has 92% accuracy, making it useful for general pneumonia screening. The second model, with a multiclass classification between normal, COVID-19, viral pneumonia, and bacterial pneumonia, achieved 83% accuracy. While this model was able to distinguish COVID-19 effectively, it faced challenges in accurately differentiating between viral and bacterial pneumonia, which often have similar radiographic characteristics. Lastly, the third model, leveraging MobileNetV2 for mobile and computationally efficient deployment, yielded an accuracy of 91%, balancing performance with practicality for edge applications.

A novel aspect of this work lies in addressing the specific challenge of distinguishing COVID-19 from pneumonia, given their similar visual patterns on X-ray images. During the pandemic, the ability to accurately classify COVID-19 as distinct from other types of pneumonia became essential in clinical settings to prioritize and isolate cases. This work contributes to this ongoing need by providing an efficient, CNN-based approach that could assist radiologists in making rapid, more accurate diagnoses. Importantly, the integration of COVID-19 in the multiclass and MobileNetV2 models allows this research to support diagnostic differentiation with direct applicability to real-world health crises.

In summary, this work presents robust CNN models tailored for pneumonia and COVID-19 classification, contributing valuable insights and tools for improved diagnostic accuracy. By including COVID-19 among the categories, our models provide a crucial advancement in distinguishing between visually similar yet clinically distinct respiratory conditions.

While the models presented in this research demonstrate promising accuracy in classifying COVID-19 and pneumonia from chest X-ray images, there remain several avenues for future exploration to enhance both diagnostic accuracy and clinical applicability. First, integrating additional imaging modalities, such as CT scans, could improve differentiation, particularly between viral and bacterial pneumonia, by capturing more nuanced variations in lung patterns. Future models could also benefit from larger, more diverse datasets encompassing various age groups, demographics, and underlying conditions, ensuring broader generalizability and reducing potential biases.

Another promising direction is to explore hybrid models that combine CNNs with other techniques, such as attention mechanisms or transformer architectures, which could focus more specifically on regions of abnormality within X-ray images, potentially improving classification precision for visually similar classes. Additionally, real-time deployment on mobile and edge devices could be enhanced through further optimization of lightweight architectures like MobileNetV2, allowing for faster, on-site screening even in low-resource healthcare settings. Finally, expanding the system to provide probabilistic assessments or confidence scores may assist clinicians in understanding the degree of uncertainty in predictions, further enhancing the model's value in decision support.

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Data Sets -

[11] Chest X-Ray Images (Pneumonia) (kaggle.com) https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

[12] 3 kinds of Pneumonia (kaggle.com) https://www.kaggle.com/datasets/artyomkolas/3-kinds-of-pneumonia

[13] Chest X-ray (Covid-19 & Pneumonia) (kaggle.com) https://www.kaggle.com/datasets/prashant268/chest-xray-covid19-pneumonia