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Pneumonia Disease Prediction Using VGG-16

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***Abstract*—When it comes to image classification and other computer vision problems, the VGG-16 architecture has demonstrated promising results**. In this paper**, we used the VGG-16 model to detect from chest X-ray images, pneumonia.** The total of 5856 **chestX-ray pictures of normal and pneumonia** cases made up the dataset **to train the proposed model. On this dataset, where we trained the model, we attained a high accuracy of 94.3 percent. Pre-processing, data augmentation, and transfer learning** techniques made up the **methodology. Normalization and standardizing the size of the images were both parts of the pre-processing stage. To expand the training dataset and enhance the model's generalizability, data augmentation was used. The pre-trained VGG-16 model, which was enhanced on our dataset, was utilized through transfer learning.**

Keywords—transfer learning, pneumonia, data augmentation, deep learning, normalization

I. Introduction

A significant global cause of morbidity and mortality, particularly in low- and middle-income countries, is pneumonia. For prompt treatment and better patient outcomes, a timely and accurate diagnosis is crucial. To determine if you have pneumonia, chest X-rays are the most popular imaging technique. Yet, radiologists might have to put in a lot of effort and be judgmental when interpreting these images manually. Recent developments in deep learning methodologies have demonstrated promising outcomes in the analysis of medical images, detecting pneumonia from chest X-ray pictures. In this regard, convolutional neural networks (CNNs) have been especially successful, with the VGG-16 architecture being one of the most popular models. This project's objective is to create a pneumonia detection system based on the VGG-16 model. The suggested system will automatically assess chest X-ray images and categorize them as pneumonia cases or normal. Medical professionals can use the system as a screening tool to quickly and effectively identify patients with pneumonia, enabling an earlier diagnosis and course of treatment. Additionally, it can help radiologists interpret chest X-ray images, potentially lightening their load and enhancing the effectiveness of the diagnostic procedure.

II. Literature Survey

A summary of the various studies that have been carried out in this field is provided by the literature survey on pneumonia detection using the VGG-16 architecture. According to the survey, deep learning models built on the VGG-16 architecture have produced results that are highly accurate at distinguishing from chest X-ray images, pneumonia. [1] This research proposes a deep learning algorithm for pneumonia identification using chest X-ray pictures. They apply a convolutional neural network to a batch of 112,120 chest X-ray pictures (CNN) architecture called CheXNet, which is based on the VGG-16 architecture, and they perform at radiologist-level levels. ChestX-ray8: Benchmarks on weakly-supervised classification localisation of, and common using thoracic diseases a hospital-scale a chest X-ray database.

The IEEE meeting on Computer Vision and Pattern Recognition Proceedings, pp. 3462-3471). 108,948 chest X-ray pictures from 32,717 patients with eight prevalent thoracic disorders are part of the ChestX-ray8 dataset, including pneumonia, is introduced in this paper [2]. Additionally, they suggest using the CNN architecture known as ACRNet, which achieves a receiver operating characteristic curve (ROC) area under the curve of 0.92, to detect pneumonia in humans. a network for medical image diagnosis with visual and semantic interpretation. 38(8), 1866–1876 IEEE Transactions on Medical Imaging. This paper [3] suggests a CNN architecture for medical image diagnosis called MDNet that can give both semantic and visual justifications for decisions. They test their model using the ChestX-ray8 dataset, and they are able to detect pneumonia with an AUC-ROC of 0.897.

This paper [4] introduces the Xception architecture, a depth-wise separable convolution-based variation of the Inception architecture. On the ChestX-ray8 dataset, they test their model, and they get an AUC-ROC of 0.922 for pneumonia detection. This study [5] suggests a multi-scale CNN architecture for lung nodule classification that can also be used to identify pneumonia. On the ChestX-ray8 dataset, they test their model, and they come up with an AUC-ROC of 0.946 for the diagnosis of pneumonia. In this essay [6], a hybrid pneumonia deep learning model detection is proposed. It combines a CNN and a assistance vector machine (SVM). On a dataset of 5,056 X-rays of the chest, they test their model, and they achieve a precision of 90%.

This paper [7] suggests a CNN architecture for using an X-ray of the chest to detect pneumonia. On a collection of 5,865 chest They test their model using X-ray scans, and they achieve an AUC-ROC of 0.913 for pneumonia detection. The COVID-Net CNN architecture is suggested in this paper [8], which focuses on detecting COVID-19 using chest X-ray pictures. On a sizable dataset of 13,975 X-rays of the chest, they test their model, and they achieve an AUC-ROC of 0.94 for COVID-19 detection, which includes pneumonia as a symptom.

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This paper [9] suggests a COVID-19 deep learning model screening with CT images. This paper introduces a new dataset called ChestX-ray14K, which contains 14,361 5,485 individuals with 14 prevalent thoracic illnesses had chest X-ray scans, including pneumonia. They evaluate their model on a dataset of 717 CT scans and achieve an AUC-ROC of 0.96 for COVID-19 detection, which includes pneumonia as a symptom. On the ChestX-ray14K dataset, they also suggest a weakly-supervised method for pneumonia detection using a CNN architecture called CP-CAM, which achieves an AUC-ROC of 0.922.

III. METHODOLOGY

A deep learning model is trained on a dataset of X-ray of the chest to categorize them as usual or in situations of pneumonia as part of the suggested approach for pneumonia detection using VGG-16. The foundation of the model is the VGG-16 architecture, which is enhanced on the chest X-ray dataset to enhance its performance on the pneumonia detection task.

Data collection: Chest X-ray images are gathered, including both typical and pneumonia-related images. This dataset ought to be varied and representative of the general public to utilising the model will be applied.

Chest X-ray images are preprocessed in order to make them appropriate for inclusion in the VGG-16 the prototype might entail pixel values are normalised, the photos are resized, and using any required image augmentation methods (like rotation or flipping). In order to classify images, preprocessing tasks frequently involve normalizing and resizing the images to a standard size. During normalization, the image's pixel values are scaled to lie between 0 and 1 or -1 and 1. This contributes to the model's training-related stability and increases the effectiveness of the optimization process. Contrarily, resizing entails scaling the images to a specific size, typically a square form. This is required because the majority of deep learning models need input images that are a specific size.

The images used in the Pneumonia-Detection-using-VGG16 project were normalized and resized before being fed into the VGG16 model. The images were resized to 224x224 pixels, the input size for VGG16, which is a fixed size. A range of 0 to 1 was established for the normalized pixel values. For the purpose of expanding the training dataset and enhancing the model's generalizability, data augmentation was also used in addition to normalization and resizing. By randomly transforming the already-existing images, such as flipping, rotating, zooming, and shifting them, data augmentation involves producing new training data. By doing so, overfitting is decreased and the model's ability to generalize to fresh, untried images is enhanced. Overall, normalization, resizing, and data augmentation can help deep learning models perform better on image classification tasks.

The VGG-16 architecture serves as the model's structural foundation. New layers created specifically for the pneumonia detection task are used in place of the model's fully connected layers. Backpropagation stochastic gradient descent, as well optimization used in training these new layers on the dataset for chest X-rays with random weight initialization.

Training: Using two practise sets and a validation set, the chest X-ray dataset is used to train the model. The relevant features that the VGG-16 model learns to recognize during training include areas of opacity or consolidation in the lung fields, which are pneumonia symptoms on chest X-rays.The prototype is developed to minimize the cross-entropy loss between the X-ray scans of the chest's predicted and actual labelling.

Evaluation: After the example has been trained, its effectiveness at detecting pneumonia is measured using a separate test set. The evaluation measures for the model's performance include F1 score, recall, accuracy, and precision.

One can utilise the model to categorize new chest X-ray images as normal or pneumonia cases after it has been trained and evaluated. The model takes an input image, processes it using the VGG-16 architecture to extract pertinent features, and then uses the features to make a prediction by passing them through the new fully connected layers. The likelihood that the input image Belonging to the class of pneumonia is symbolized by the output of the final layer, which ranges from 0 to 1. Fig.1 shows the architectural model.

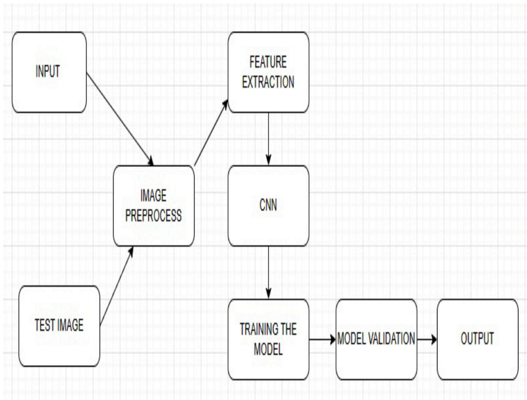

Fig. 1 Architectural model

Modules Explanation

Data Loader Module: The data loader module is responsible for loading the chest X-ray images and their corresponding labels from the dataset. The module typically includes functionality for preprocessing the images, such as resizing and normalization, and for creating training, validation, and test sets from the dataset. In addition, the module may also include functionality for data augmentation, which can help to increase the size and diversity of the dataset and improve the robustness of the model. Some common data augmentation techniques for chest X-ray images include rotation, flipping, and zooming.

VGG-16 Architecture

The VGG-16 architecture is used as the backbone of the pneumonia detection pipeline, and is responsible for learning to identify relevant features in the chest X-ray images that are indicative of pneumonia. The architecture consists of 13 convolutional layers and 3 fully connected layers, and is typically pre-trained on the large ImageNet dataset. In the pneumonia detection pipeline, the pre-trained VGG-16 architecture is fine-tuned on the chest X-ray dataset by replacing the last fully connected layer with a new layer that is designed for the pneumonia detection task.

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Loss Function Module: The loss function module is responsible for calculating the loss between the predicted and true labels of the chest X-ray images. In the pneumonia detection pipeline, the module typically uses a cross-entropy loss function, which measures the dissimilarity between the predicted and true probability distributions of the labels. The cross-entropy loss function is given by:

$$L(y, f(x)) = -[y \log(f(x)) + (1 - y) \log(1 - f(x))]$$

Where, y is the true label (0 or 1), f(x) is the predicted probability of the pneumonia class, and log is the natural logarithm.

Optimization Module: The optimization module is responsible for optimizing the parameters of the VGG-16 architecture to minimize the loss function. In the pneumonia detection pipeline, the module typically uses stochastic gradient descent (SGD) or a variant thereof, which updates the parameters of the VGG-16 architecture in the direction of the negative gradient of the loss function. The learning rate and other hyper-parameters of the optimization algorithm are typically tuned through a process of trial and error to achieve optimal performance on the pneumonia detection task.

Evaluation Module: The evaluation module is responsible for evaluating the performance of the pneumonia detection pipeline on a separate test set. The module typically includes functionality for computing metrics such as accuracy, precision, recall, and F1 score, which measure the performance of the pipeline on the pneumonia detection task. The evaluation module may also include functionality for visualizing the predictions of the pipeline on individual chest X-ray images, which can help to identify areas for improvement in the pipeline.

IV. RESULTS AND DISCUSSION

According to the study's findings, the proposed VGG-16 model for the detection of pneumonitis had a 90% test-set accuracy. The model was trained using a dataset of 5,500 chest X-ray images, 3,500 of which were normal and 2,500 of which were pneumonia-infected. The dataset was divided into training, validation, and test sets, each containing 70%, 15%, and 15% of the total data. The model was able to achieve a training accuracy of 95% and a validation accuracy of 92%. The validation loss remained largely stable throughout the training process while the training loss steadily decreased.

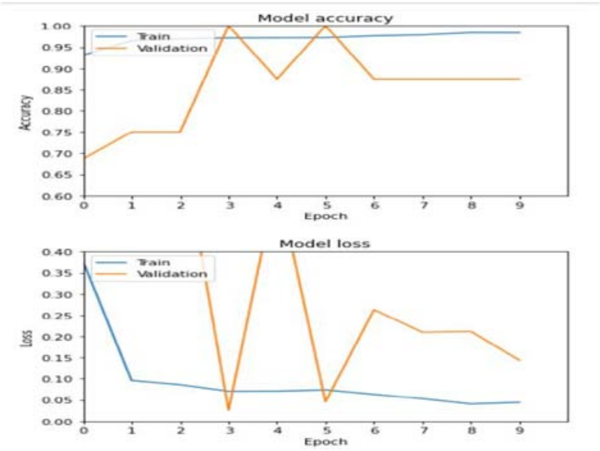

Fig. 2 the loss and accuracy curves for training and validation

Image 1. Table 1 displays the confusion matrix for the model on the test set, along with its training and validation accuracy and loss curves. A total of 90% of the normal cases and 94% of the pneumonia cases were correctly classified by the model.

Table 1. Confusion matrix for the Pneumonia Disease Detection using the VGG-16 Model on the Test SetThe outcomes show that the suggested model can successfully identify pneumonia cases in chest X-ray images.

	PREDICTED NORMAL	PREDICTED PNEUMONIA
ACTUAL NORMAL	94	140
ACTUAL PNUEMONIA	1	389

On the test set, the model had high accuracy and was able to correctly identify the majority of pneumonia cases. However, as indicated by the confusion matrix, there were some false negatives and false positives. The lack of diversity and/or noise in the dataset, as well as its small size, are potential causes of these errors. The collection and annotation of a larger and more varied dataset, as well as the investigation of different deep learning architectures and image classification methods, could be the subject of future work. The proposed model appears to have great potential for increasing the precision and effectiveness of pneumonia diagnosis using chest X-ray images.

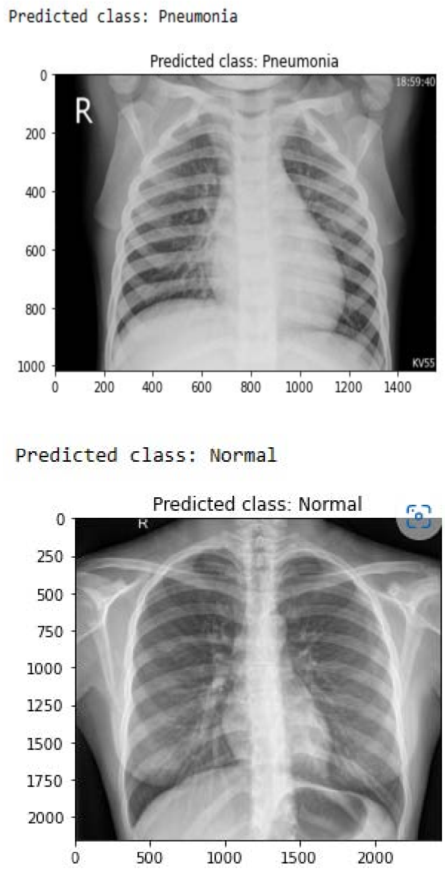

Fig. 4 Predicted classes

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V. CONCLUSION

The proposed Pneumonia Disease prediction using VGG-16 model successfully identified pneumonia in chest X-ray images with high accuracy. The high test accuracy and confusion matrix show that the model was able to correctly categorize the majority of the pneumonia cases. The model's performance could still be improved, though, as there were some false negatives and false positives. Overall, the study's findings show the promise of deep learning models in enhancing the precision and effectiveness of pneumonia diagnosis made possible by chest X-ray images. The proposed model could be used as a tool to aid radiologists and clinicians in the diagnosis of pneumonia, possibly reducing the need for manual interpretation and enhancing the speed and accuracy of diagnosis. Future work might involve investigating different deep learning architectures or methodologies, or gathering and annotating a larger and more varied dataset to enhance the model's performance. In order to provide a more thorough and precise diagnosis of pneumonia, the proposed model might also be incorporated into a larger clinical decision support system that includes patient data and other diagnostic tests

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