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AUTOMATED PNEUMONIA IDENTIFICATION THROUGH CNN-BASED ANALYSIS

S.Aadarsh[1], V.Kiran satya[2] , P.Lal john basha [3]
[1,2,3]*ECE, RVRJCCE, INDIA*
E-mail: samudralaaadarsh@gmail.com[1]
E-mail: kiransatya2003@gmail.com[2]
E-mail: pathanlaljohn2003@gmail.com[3]

Abstract

Pneumonia, a condition caused by infectious agents such as bacteria, viruses, fungi, or parasites, results in lung infections and the accumulation of pus in affected tissues. Incorrect diagnosis or improper treatment can significantly impact a patient's quality of life. This project focuses on the precise identification and categorization of pneumonia-afflicted patients through the analysis of their chest X-rays. Leveraging advancements in deep learning, healthcare experts can make more accurate diagnostic decisions for various illnesses. This study presents an innovative approach utilizing Convolutional Neural Networks (CNN) to predict and distinguish between patients affected by pneumonia and those who are not, based on chest X-ray images. The methodology involves a series of convolutional and max pooling layers activated using the ReLU activation function. Subsequently, the processed data is passed through dense layers, culminating in the activation of the output neuron through the sigmoidal function. During the training process, the model exhibits increasing accuracy and decreasing loss, demonstrating its effectiveness. To prevent overfitting, data augmentation techniques are applied before model fitting. These strategies collectively enhance the robustness and reliability of the deep learning models, resulting in accurate and persuasive detection of pneumonia from chest X-ray images.

Keywords:
Pneumonia, CNN, VGG-16, VGG-19, Chest X-rays, Classification, Deeep learning, Data augmenatation, ReLU, softmax.

1. INTRODUCTION

Pneumonia is a global health concern with high impact. Its diagnosis is challenging due to complex medical imaging data. Recent advancements in deep learning, specifically Convolutional Neural Networks (CNNs), have transformed medical image analysis. Our paper presents a novel method for pneumonia detection using these networks. We specifically use VGG-16 and VGG-19, known for their effectiveness in image classification, to automate disease detection and diagnosis.

The application of VGG-16 and VGG-19 in our method allows for a more accurate and efficient diagnosis process. This approach significantly reduces the time taken for diagnosis, enabling quicker treatment. It also minimizes human error, enhancing the overall reliability of the diagnosis. Ultimately, our method aims to improve patient outcomes in pneumonia treatment.The motivation behind this project stems from the pressing need for reliable and efficient methods of pneumonia detection to assist healthcare professionals in making timely and accurate diagnostic decisions. Traditional methods of pneumonia diagnosis, such as manual interpretation of chest X-rays, are labor-intensive, prone to subjective interpretation, and may lead to inconsistencies in diagnosis. By harnessing the capabilities of deep learning, we aim to enhance the efficiency and accuracy of pneumonia detection from chest X-ray images.

The VGG-16 and VGG-19 architectures, originally proposed by Simonyan and Zisserman in 2014, are characterized by their deep structures comprising 16 and 19 convolutional and fully connected layers, respectively. With their remarkable ability to learn hierarchical features from images, VGG-16 and VGG-19 have demonstrated exceptional performance in various image classification tasks, including those in the medical domain.In this study, we adapt both the VGG-16 and VGG-19 architectures for pneumonia detection by training the models on a dataset of chest X-ray images annotated for pneumonia presence. Through rigorous experimentation and evaluation, we demonstrate the effectiveness of our approach in accurately identifying pneumonia-afflicted patients, thereby facilitating prompt intervention and treatment. The contributions of this paper lie not only in the application of deep learning techniques for pneumonia detection but also in the exploration of the potential of the VGG-16 and VGG-19 architectures in medical image analysis. By providing reliable and automated methods for pneumonia detection, our approach has the potential to significantly improve patient outcomes and alleviate the burden on healthcare systems.

2. RELATED WORK

2.1 Traditional Methods for Pneumonia DetectionManual

Interpretation of Chest X-rays: Historically, pneumonia detection relied on manual interpretation of chest X-ray images by trained radiologists. While this method has been the gold standard, it is subjective, labor-intensive, and prone to inter-observer variability.

Rule-Based Systems: Some early attempts at automated

pneumonia detection involved rule-based systems that Analyzed specific radiographic features associated with pneumonia, such as consolidations and infiltrates. However, these methods often lacked robustness and generalizability.

2.2 Deep Learning Approaches for Pneumonia

DetectionCNN-Based Approaches: With the advent of deep learning, there has been a surge in research exploring the application of CNNs for pneumonia detection. Rajpurkar et al. (2017) introduced CheXNet, a CNN trained on a large dataset of chest X-ray images, achieving state-of-the-art performance in pneumonia detection.

Multi-Task Learning: Li et al. (2018) proposed a multi-task learning framework for pneumonia detection that simultaneously predicted the presence of pneumonia and other thoracic diseases. Their approach demonstrated improved performance compared to single-task models.

Attention Mechanisms: Zhang et al. (2019) introduced an attention-guided CNN for pneumonia detection, which dynamically weighted the importance of different regions in the chest X-ray images. Their method improved localization accuracy and model interpretability.

3. METHODOLOGY

3.1 Data Description

The chest X-ray dataset used in this study was sourced from Kaggle, a popular platform for hosting datasets and machine learning competitions. The dataset comprises a collection of chest X-ray images annotated for the presence or absence of pneumonia. It includes images obtained from both pediatric and adult patients, covering a wide range of demographics and disease presentations. There are 5,863 X-ray images . We have then split the dataset by 80:20 training and testing ratio.

3.2 Process flow

In this phase, chest X-ray pictures are gathered and resized to 224 by 224 pixels, which is the usual size. This guarantees uniformity in the input dimensions for the processing stages that follow.The chest X-ray image dataset is divided into a training set and a testing set in this stage. The CNN model is trained on the training set, and its performance is assessed on the testing set.Choosing a pre-trained CNN architecture, like VGG16 or VGG19, is the first step in creating the classification model. These models are good at extracting features from photos because they have been pre-trained on huge datasets like ImageNet. The VGG16/VGG19 CNN architecture that was chosen has several convolutional layers. A collection of filters is applied by each convolutional layer to the input images in order to extract information at various spatial hierarchies. To add non-linearity to the model, activation functions such as the Rectified Linear Unit (ReLU) are added after every convolution process.The feature maps are flattened into a 1-dimensional vector after the convolutional layers. Connecting the convolutional layers to the fully linked layers requires this step.One or more fully connected layers pass through the flattened features. The retrieved features are mapped by these layers to the final output classes (pneumonia or normal). In order to provide non-linearity and enable the model to recognize intricate patterns in the data, activation functions such as ReLU are utilized.

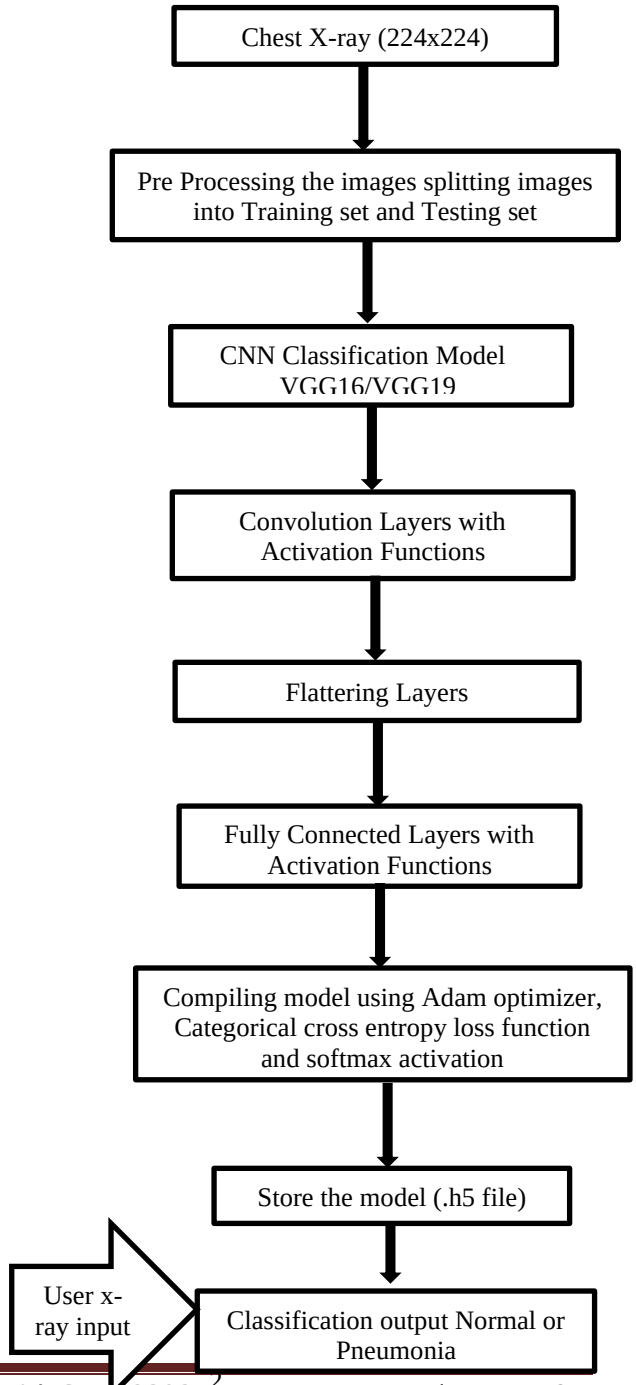

Fig: process flow of the proposed method

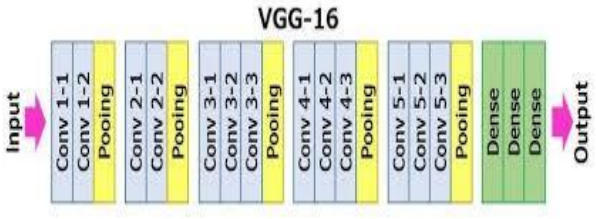

Fig: VGG 16 Architecture

The Adam optimizer, an adaptive learning rate optimization technique, is used to assemble the model. For multi-class classification problems, the categorical cross-entropy loss function is utilized as the loss function. The output layer uses softmax activation to transform the unprocessed model outputs into probabilities for every class.The model is saved in a.h5 file format after it has been trained. This eliminates the requirement for retraining and makes it simple to load and use the model again for classification jobs.An X-ray image of the chest is supplied by the user to the trained model during inference.After processing the input X-ray picture, the trained model applies its learnt features and classification decision boundaries to predict if the image is normal or displays signs of pneumonia**.**

3.3 VGG Architecture

VGG16 and VGG19 are deep convolutional neural network designs that the University of Oxford's Visual Geometry Group (VGG) has suggested. VGG19 expands this design with 19 weight layers, while VGG16 has 16 weight layers, consisting of 13 convolutional layers and 3 fully linked layers. These models provide state-of-the-art performance on several benchmark datasets and are well known for their simplicity and efficacy in picture classification tasks. The uniform architecture of VGG networks, which includes max-pooling layers and tiny 3x3 convolutional filters, despite their depth, has contributed to their popularity and broad use in the deep learning field.

3.4 Data Augementation

To enhance the diversity of the dataset and mitigate overfitting, data augmentation techniques such as random rotation, horizontal flipping, and zooming were applied to generate additional training samples.

Hyperparameters for Data Augmentation	Values
Rescale	1./255
Shear Range	0.2
Zoom Range	0.2
Horizontal flip	True

Table 1 image Augmentation settings

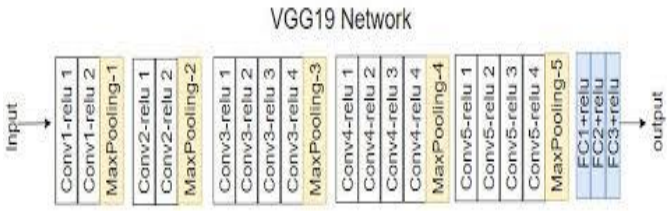

Fig : VGG 19 Architecture

3.5 Input for the Proposed Method

These are the input images that are given to the CNN model for pneumonia detection.

Normal Images: Represent healthy lung conditions with clear lung fields and absence of pathological findings, indicating no signs of infection or inflammation.

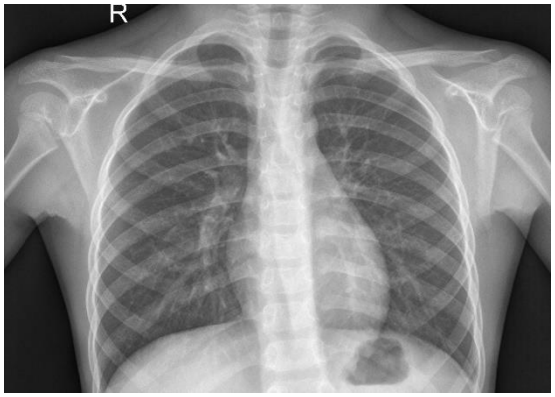

Fig: Normal Chest X-Ray

Pneumonia Images: Depict various abnormalities including opacities, consolidations, and infiltrates, indicating inflammation and infection within the lung tissue, crucial for training and evaluating pneumonia detection models.

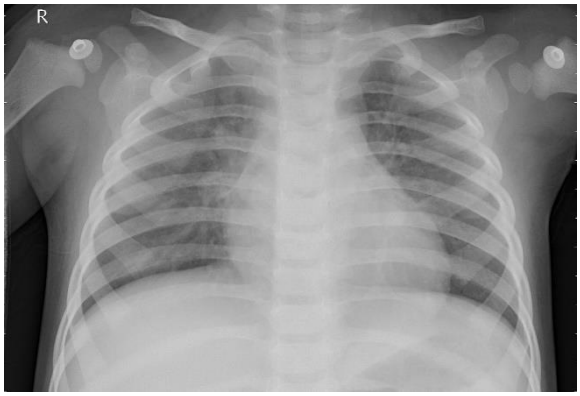

Fig: pneumonia Chest X-Ray

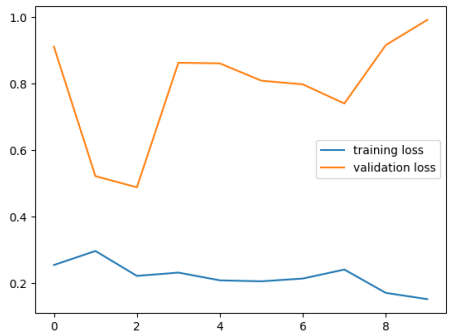

Fig: Training and Validation Loss graph of VGG 16

The above picture shows line graph that shows the loss of training and validation over a series of epochs during a machine learning model's training process The salient features are as follows:
The blue line represents training loss.The orange line represents validation loss.During model training, the training loss and validation loss are shown on the graph.Training loss varies a lot; it starts just below 1.0, drops to about 0.6, peaks again around 1.0, and ends slightly above 0.8.Validation loss is still comparatively constant, averaging 0. 2.Epochs are represented by the x-axis, which runs from 0 to just past 8.Loss values are plotted on the y-axis and range from 0 to 1.0.

3.6 Formulae used for the model

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

2. Loss $= -\frac{1}{N}\sum_{i=1}^{N} = \sum_{j=0}^{c} = y_{i\,j}\log(p_{i\,j})$

4. EXPERIMENTAL RESULTS

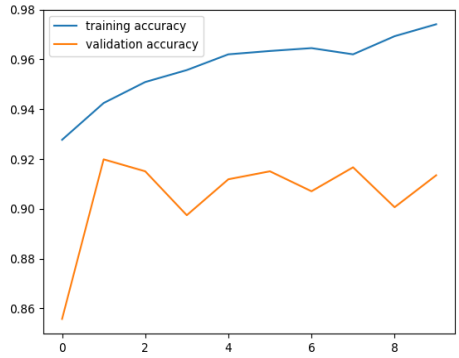

Fig: Training and Validation Accuracy graph of VGG 16

The above picture shows line graph that shows the accuracy of training and validation over a series of epochs during a machine learning model's training process The salient features are as follows:
The blue line represents training accuracy.The orange line represents validation accuracy.Training accuracy steadily increases from approximately 86% to 98% across epochs.Validation accuracy fluctuates but generally improves, ranging from around 86% to 98%.The x-axis represents epochs, and the y-axis represents accuracy.Overall, the model demonstrates convergence and generalization.

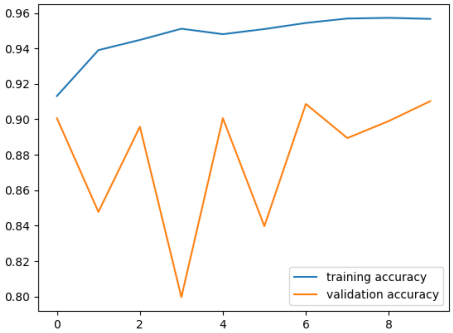

Fig: Training and validation Accuracy graph of VGG 19

The above picture shows line graph that shows the accuracy of training and validation over a series of epochs during a machine learning model's training process. The salient features are as follows:
The blue line represents training accuracy.The orange line represents validation accuracy. The x-axis likely represents the number of epochs or iterations through the training data .The y-axis ranges from 0.80 to 0.96, indicating the accuracy score. The blue line (training accuracy) starts high and remains relatively stable

throughout, suggesting consistent performance during training.The orange line (validation accuracy) shows more fluctuation, indicating variability in how well the model generalizes to new data.

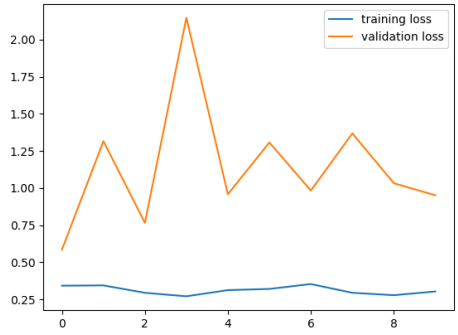

Fig: Training and Validation Loss graph of VGG19

The above picture shows line graph that shows the loss of training and validation over a series of epochs during a machine learning model's training process The salient features are as follows:
The blue line represents training loss.The orange line represents validation loss. The x-axis represents the number of epochs, ranging from 0 to just before 10.The y-axis represents the loss, with values ranging from 0 to slightly above 2. The blue line starts high and steadily decreases as the number of epochs increases. This indicates that the model is learning from the training data. At epoch 0, the orange line begins lower than the blue line, but it varies greatly and generally tends to rise.The orange line gets thinner as the number of epochs goes up.

No of epochs	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
2	0.9425	0.2968	0.9199	0.5218
4	0.9557	0.2318	0.8974	0.8628
6	0.9634	0.2056	0.9151	0.8088
8	0.9620	0.2409	0.9167	0.7402
10	0.9741	0.1520	0.9135	0.9917

Table 2 Performance of the Deep Learning Model VGG16

No of epochs	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
2	0.9390	0.3445	0.8478	1.3161
4	0.9511	0.2712	0.7997	2.1485
6	0.9509	0.3208	0.8397	1.3076
8	0.9569	0.2947	0.8894	1.3690
10	0.9567	0.3036	0.9103	0.9517

Table 3 Performance of the Deep Learning Model VGG19

The performances of the VGG16 and VGG19 deep learning models are shown in the two table above.

5. conclusion

As a result, it can be said that the VGG16 and VGG19 deep learning model combined with the previous proposal accurately diagnoses pneumonia based on chest X-rays. The model's loss is kept to a minimum during training, and accuracy rises in tandem with each epoch stage to produce unique classifications of individuals with and without pneumonia. The stages of data augmentation and preparation aid in preventing overfitting, which keeps the performance of convolutional and deep neural networks stable and guarantees consistent outcomes. The suggested combined VGG16 and VGG19 model, which has less convolutional layers, accurately predicts whether a particular chest X-ray sample is normal or indicates pneumonia. In the medical field, this is very beneficial for accurately and promptly diagnosing patients' pneumonia. Early diagnosis is crucial for preserving a person's life since it guarantees prompt and efficient patient care. Because there are more convolution layers in the VGG19 model than in the VGG16, it performs better.

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