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BRONCHOPNEUMONIA DETECTION USING NOVEL MULTILEVEL DEEP NEURAL NETWORK SCHEMA

Prasanna K.R[1]*, *Vijayakumar R*[2], *Joseph Durai Sevam*[3] and *Parthasarathy P*[4]

[1]Research Scholar, Bharat Institute of Higher Education and Research, Chennai, India
[2]Professor and Head, Lakshmi Narayana Institute of Medical Science, Puduchery, India
[3]Associate Professor, School of Business and Management, Christ Deemed to be University, Banglore, India
[4]Assistant Professor, ECE Department, PSNA College of Engineering and Technology, Dindigul, India

Abstract. Pneumonia is a dangerous disease that can occur in one or both lungs and is usually caused by a virus, fungus or bacteria. Respiratory syncytial virus (RSV) is the most common cause of pneumonia in children. With the development of pneumonia, it can be divided into four stages: congestion, red liver, gray liver and regression. In our work, we employ the most powerful tools and techniques such as VGG16, an object recognition and classification algorithm that can classify 1000 images in 1000 different groups with 92.7% accuracy. It is one of the popular algorithms designed for image classification and simple to use by means of transfer learning. Transfer learning (TL) is a technique in deep learning that spotlight on pre-learning the neural network and storing the knowledge gained while solving a problem and applying it to new and different information. In our work, the information gained by learning about 1000 different groups on Image Net can be used and strive to identify diseases.

1 Introduction

Pneumonia is a respiratory disease that affects the lungs. Pneumonia can cause the air sacs in the lungs, called alveoli, to fill with air when a person breathes. It can cause respiratory problems and pain. Pneumonia can be caused by bacteria, viruses, bacteria or their environmental influence. The diagnosis of lung cancer is usually made by a specialist with a chest X-ray (CXR).

Whenever possible, comparison of CXRs taken at different times in the patient and correlation by means of symptoms and medical history assist in diagnosis. Numerous factors, such as the patient's position and the intensity of the chest, can vary the appearance of the CXR, making interpretation difficult.

Pneumonia is a leading cause of death among children, claiming the lives of approximately 2,200 children annually, including over 800,000 children under the age of 5 and more than

* Corresponding author: sivanviji@gmail.com

153,000 newborns. This high mortality rate has prompted scientists and researchers to focus on improving pneumonia diagnosis methods. Various techniques have been developed, including radiology-based methods that utilize X-rays to identify lung diseases. While X-rays can provide comparable results for different diseases, distinguishing between pneumonia, cancer, or other conditions can be challenging, requiring advanced technology for more accurate and early detection. In recent years, computer engineering has emerged as a promising field in medical research, with machine learning and deep learning playing a crucial role in diagnosing lung diseases, including pneumonia.

CNNs are widely utilized in image classification tasks to extract relevant features, and their application has been extended to video analysis, enabling them to learn from large datasets. In this research, a novel approach for detecting lung disease sites is developed, leveraging injection, compression, and sparsely convolutional neural networks.

2 Literature Survey

Ratne et al. developed a Logistic Regression classifier for pneumonia diagnosis [1]. Another model [2] utilizes a dataset to assist physicians in diagnosing pneumonia based on chest X-ray images. The classification task is binary, with the outputs being either non-pneumonia or pneumonia. Ayan et al. [3] focused on pneumonia diagnosis using two well-known convolutional neural network models, namely Xception and Vgg16. Adaptive learning and optimization techniques were employed in their work. Test results demonstrated that the Vgg16 network outperformed the Xception network, achieving higher accuracy rates of 0.87% and 0.82% respectively. The system was trained using diagnostic information provided by pediatric respiratory specialists, which served as the gold standard. Black R E et al., [4] demonstrate the model and its effectiveness in reducing child mortality worldwide. The content of data collected through document analysis and semi-structured interviews in the Democratic Republic of Congo showed the same results. But according to the critics, according to the data collected during this investigation, it is clear that the program will achieve the set goals with the intention of doing it in advance.

The study introduces a convolutional neural network (CNN) architecture [5] identifying the spatial location of activations associated with lung disease detection. Computer-aided diagnostic systems [6] have been developed to address diagnostic challenges, and this research aims to explore various approaches in this field. Sequential antibiotic use is recommended for the treatment of lung disease. Deep CNNs [7] demonstrate great potential for diverse and complex data processing. The study focuses on skin classification using a CNN trained directly from images, using pixel and disease information as input. The CNN was trained on a dataset of 129,450 medical images, which is twice the size of the previous dataset, encompassing 2,032 different diseases. Early-stage manifestations of certain diseases may not be evident in X-ray findings, leading to delayed diagnosis. Interpreting chest X-rays for pneumonia diagnosis can be challenging due to a shortage of experienced radiologists [8].

3 Proposed System

The objective of this study is to classify patients as COVID-19 positive, pneumonia positive, or healthy using various learning methods. Machine learning (ML) refers to a technique that trains computers to perform tasks without explicit programming. ML can be categorized into different types based on the type of dataset used. Supervised machine learning involves labeled data, while unsupervised machine learning deals with unlabeled data. Deep learning is a subcategory of ML that focuses on neural networks. Deep learning methods such as deep belief networks, deep neural networks, convolutional neural networks, and CNNs have been successfully applied in computer vision and natural language processing tasks. The term "deep" in deep learning signifies the neural networks' resemblance to the human brain and its complex network of neurons, making them suitable for tasks that involve intricate learning processes.

The proper selection of machine learning techniques and data preprocessing steps is crucial when training a model. These steps involve various methods such as preprocessing, rescaling, and feature extraction to enhance the quality of the data. In this case, deep learning is the preferred approach as it utilizes nonlinear methods to extract features, reducing the reliance on manual feature selection. By utilizing layers, deep learning algorithms can hierarchically learn representations that best capture the underlying patterns in the data. Medical imaging, such as chest X-rays, can provide valuable information, particularly in cases of COVID-19 where bilateral, posteriorly distributed opacities or peripheral, multifocal opacities are commonly observed, typically located in the lower lobes of the lungs. However, relying solely on chest X-ray images can lead to confusion in diagnosing patients, as similar patterns may be present in various lung diseases. Therefore, careful examination and further testing are essential to ensure accurate diagnosis and appropriate treatment. Misdiagnosis can have serious consequences, including increased fear, costs, unnecessary exposure to COVID-19, and potential harm to patients.

In this study, the VGG16 architecture is utilized as a pre-trained feature extractor for extracting relevant features. VGG16 is a convolutional neural network (CNN) architecture that gained popularity after its success in the ILSVRC (ImageNet) competition in 2014. CNNs are widely recognized as highly effective models for image classification tasks. VGG16 specifically consists of 3x3 filter convolutions and employs max pooling and padding layers with 2x2 filters. The convolutional and pooling layers throughout the network share a similar structure. The architecture concludes with two fully connected layers connected to a SoftMax layer, which produces the final output probabilities. The name "VGG16" is derived from the fact that it comprises 16 layers, with approximately 138 million parameters, including different weights. In summary, VGG16 serves as a powerful feature extraction tool due to its well-designed CNN architecture and pre-trained weights, making it a suitable choice for the task at hand.

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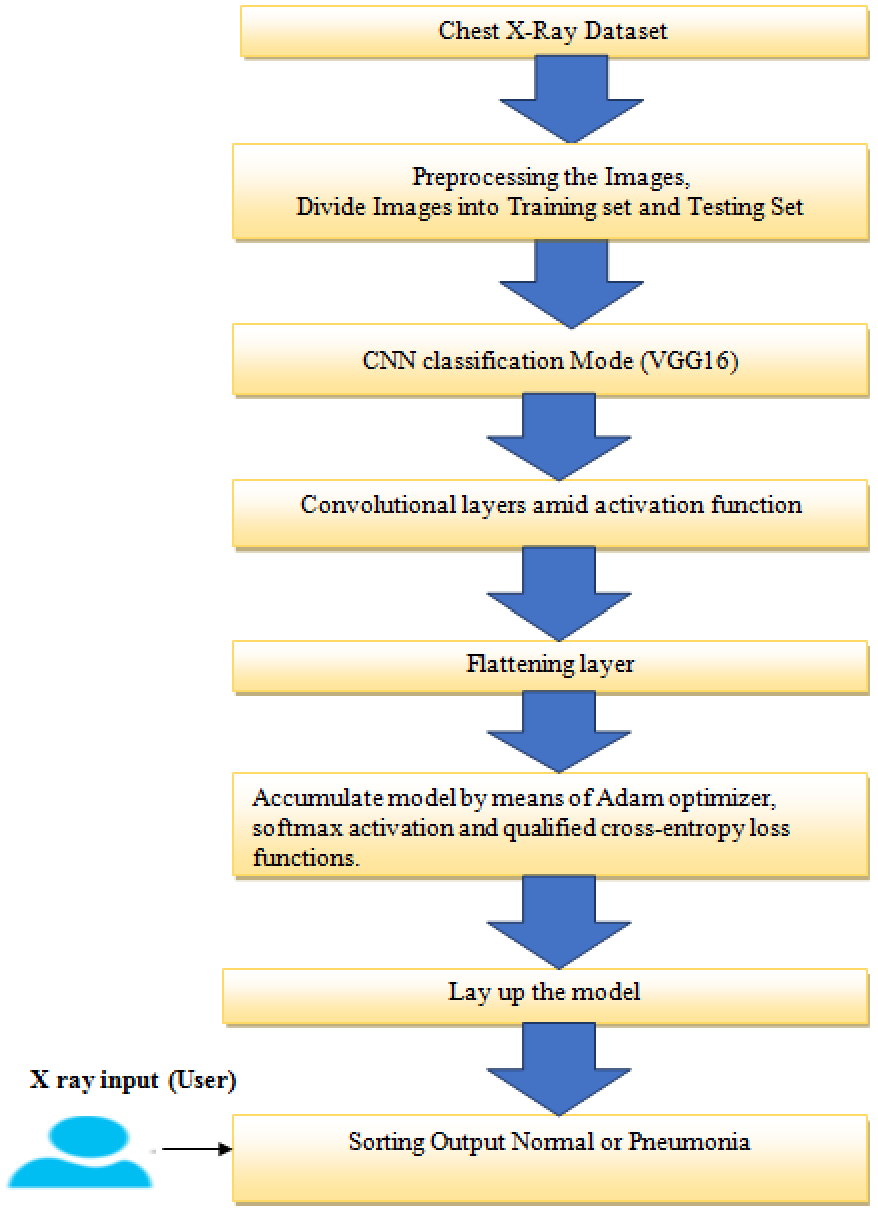

Fig.1. A Flowchart of our proposed method

5 Performance Analysis

The performance of two models, ResNet50 and Composite Scale ResNet50, was evaluated based on accuracy, recall, and precision scores. Accuracy represents the ratio of correct predictions to the total number of predictions, indicating how well the model predicts the true labels.

Accuracy= (TP+TN)/ (TP+TF+FP+FN)

Precision=TP/ (TP+FP)

Recall=TP/ (TP+FN)

To assess the performance of the models, confusion matrices were generated for ResNet50 and Composite Scale ResNet50.

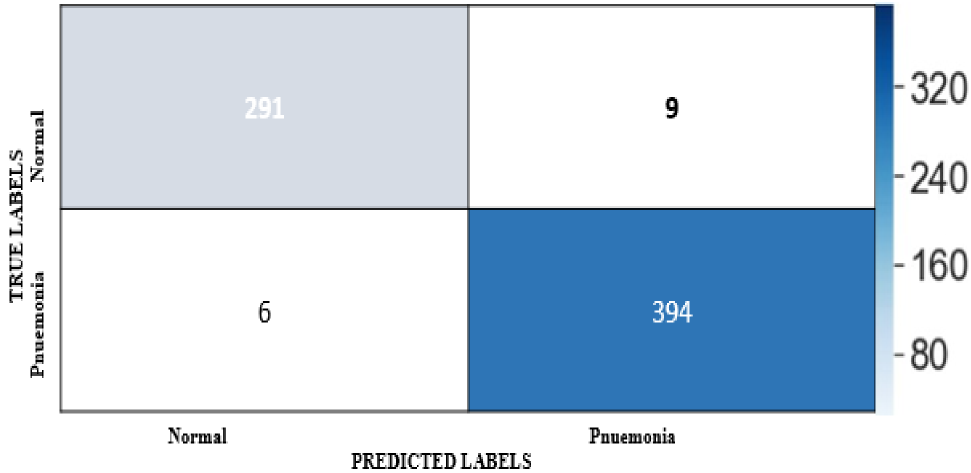

Fig.2. Confusion matrix for the proposed compound scaled ResNet50 architecture over the testing dataset**.**

F1 = (2∗Precision∗Recall)/ (Precision Recall)

The ResNet50 model has an F1 score of 99.50 and the hybrid ResNet50 model has an F1 score of 99.71. The AUC curve was also plotted. Integration of the ResNet50 architecture provides higher AUC scores. The results also show that similar images learned by the deep neural network can be initialized with good weights when trained on the Image Net dataset. Transfer learning works when there are differences. Therefore, it is better to start with weights from a model that fits the data distribution, rather than starting with extreme weights. It can moreover be perceived so as to the assortment used in the work is sufficient for outspreading the model and refining the show of the model.

6. RESULTS

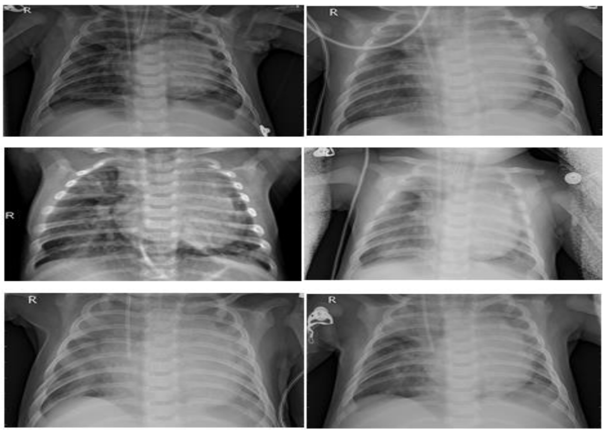

Fig.3. Pneumonia Affected Samples

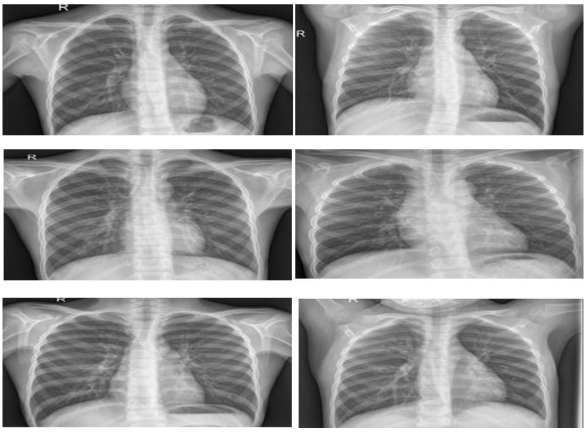

Fig.4. Normal Samples

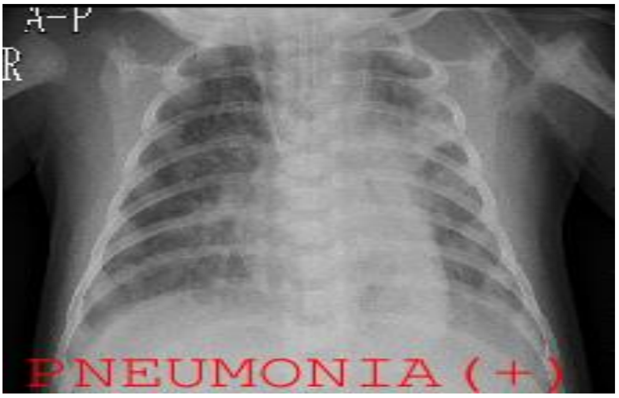

Fig.5. Pneumonia Positive

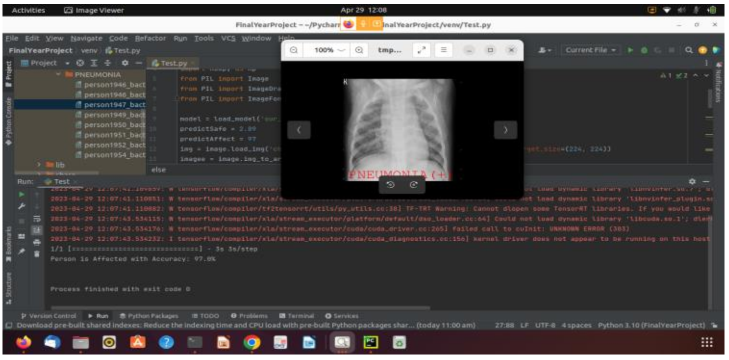

Fig.6. Pneumonia Positive Sample Output

Fig.7. Pneumonia Negative

7. CONCLUSION

This study proposes an algorithm to enhance computer-assisted diagnosis of pneumonia, a life-threatening disease with a high mortality rate in elderly patients. The proposed deep neural network architecture is more complex but offers improved accuracy. The model incorporates composite scaling to achieve optimal performance. Data augmentation and transfer learning techniques are employed to address limited data availability. Various metrics such as recall, accuracy, and precision are calculated to evaluate the model's performance. The model achieves an impressive accuracy of 98.14%, with an AUC score of 99.71 and an F1 score of 98.3. Discrepancies between training and testing results are also examined, with the model achieving an accuracy of 96.76%. Future studies could extend this work to encompass the description and classification of chest X-ray images related to lung cancer and pneumonia.

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