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Deep convolutional neural network (DCNN)-based model for pneumonia detection using chest x-ray images

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Abstract

In recent years, the integration of machine learning techniques within the medical field has shown promising results in aiding healthcare professionals in accurate diagnosis and treatment planning. This study focuses on developing and implementing a machine learning model tailored specifically for medical diagnosis, leveraging advancements in computer vision and deep learning algorithms. This research aims to design an efficient and accurate model capable of classifying medical images into distinct categories, enabling automated diagnosis and identification of various ailments and conditions. This study uses a dataset comprising 5,863 Chest X-ray images (JPEG) and 2 categories (Pneumonia/Normal) (anterior-posterior) selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou, obtained from Kaggle data repositories. Data Preprocessing was conducted to enhance image quality and extract relevant features, followed by implementing a deep convolutional neural networks (DCNNs) model using TensorFlow's Keras. Using pre-trained models such as Resnet, transfer learning techniques were employed to learn efficient features from large-scale datasets and optimize the model's performance with the limited medical data available. The results from the experimental analysis showed that after 9 epochs, the training and validation accuracies had steadily increased, achieving 95% and 75%, respectively. Overall, the model achieved 99.9% training accuracy across multiple epochs and an average validation accuracy of 75%. The model's performance and scalability highlight its potential for integration into clinical workflows. This could revolutionize healthcare by augmenting the diagnostic process and improving patient outcomes.

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Keywords: Machine learning, Pneumonia, Convolutional neural networks (CNN), Artificial intelligence, Pre-trained models

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1. Introduction

Pneumonia remains a significant public health concern globally, contributing to substantial morbidity and mortality. Pneumonia stands as a pivotal global health challenge, exerting a substantial burden on healthcare systems and communities worldwide. According to the World Health Organization (WHO), pneumonia accounts for a significant portion of infectious disease-related morbidity and mortality, particularly affecting vulnerable populations such as young children, the el-

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derly, and individuals with compromised immune systems [1]. Statistics from the Centers for Disease Control and Prevention (CDC) highlight the pervasive impact of pneumonia, indicating that it is one of the leading causes of hospitalization and mortality, resulting in millions of hospital visits and tens of thousands of deaths annually in the United States alone [2]. Moreover, in low- and middle-income countries, pneumonia remains a primary cause of death among children under five years old, contributing to nearly 15% of mortality in this age group [3, 4]. The economic burden of pneumonia is also substantial, encompassing direct medical costs, such as hospitalizations and treatments, and indirect costs arising from lost productivity and absenteeism due to illness. Studies estimate the economic impact of pneumonia to be billions of dollars globally each year [5].

Furthermore, the emergence of antimicrobial resistance poses a growing threat to pneumonia management and treatment efficacy. The inappropriate use of antibiotics, often driven by misdiagnosis or lack of timely identification of the causative agents, contributes to the escalation of resistance, complicating disease management and necessitating more comprehensive diagnostic strategies [1]. Timely and accurate diagnosis is pivotal in effective treatment and patient outcomes. The emergence of machine learning, particularly Convolutional Neural Networks (CNNs), has offered promising avenues for automating the detection of pneumonia from chest X-ray images [6]. Conventional methods for pneumonia diagnosis heavily rely on manual interpretation of medical imaging by trained radiologists [7, 8]. However, this process is time-consuming, subjective, and may suffer from interobserver variability. The advent of deep learning, specifically CNNs, has revolutionized medical image analysis by enabling automated feature extraction and classification, potentially enhancing diagnostic accuracy and efficiency. This paper aims to contribute to the existing body of research by introducing a refined machine learning-based framework tailored for pneumonia detection in chest X-ray images. Leveraging the advancements in CNN architectures and data augmentation techniques, the proposed model endeavors to achieve optimal accuracy, robustness, and interpretability, thus fostering improved diagnostic support for healthcare practitioners.

The key contributions of this paper to the body of knowledge include:

1. Analysis of recent machine learning methods for pneumonia prediction;
2. Implement convolutional neural networks for pneumonia prediction using parameter optimization;
3. Evaluated the implemented method using various machine learning performance metrics for generalizability and training loss;
4. Extensive evaluation of various model parameters and detection speed to ensure efficiency.

2. Review of literature

Healthcare systems worldwide have encountered significant challenges due to a shortage of diagnostic support systems and healthcare professionals, especially in third-world countries where radiologists are more inclined to seek opportunities abroad or in first-world countries with better remuneration for healthcare workers. This scarcity is particularly acute in rural areas, exacerbating the difficulties faced by hospitals where the dearth of radiologists is more pronounced [9]. As a result, individual doctors bear a significant workload, often managing numerous cases, which can result in diagnostic errors. To mitigate this issue, there's a growing focus on the development of computer-aided diagnostic systems. These systems aim to support healthcare providers by assisting in the diagnosis process, especially in scenarios where access to specialized medical expertise is limited.

Research studies have focused on supporting tools to diagnose pneumonia accurately. According to a recent, Gilani [10] implemented a PERCH (Pneumonia Etiology Research for Child Health) project, an extensive multinational study on childhood pneumonia's etiology since the research initiatives were conducted by the Board on Science and Technology in International Development. Black *et al.* [11] opined that over a million children die of pneumonia annually. International organizations such as WHO [12] have reiterated the need for pneumonia detection systems to reduce the significant global mortality burden caused by pneumonia and outlined many guidelines for low-resource settings that concentrate on pneumonia in children under 5 years old. However, according to the submission of the Institute for Health Metrics and Evaluation [13], pneumonia remains a crucial concern for older children as well. Estimates from the Global Burden of Disease reveal that pneumonia contributes to approximately 7% of deaths in children aged 5-9 years.

Recent studies in pneumonia detection have put forward various research and diverse techniques using machine learning methods. These studies primarily utilize the Chest X-ray dataset. for instance, Feng *et al.* [14] utilized a dataset containing Chest X-ray images to create a model that captured the features specific for easy categorization of pneumonia images. The study implemented Long Short-term Memory Models (LSTMs) to determine the correlations among target labels. In their approach, Feng et al. adopted a 2D ConvNET as an image encoder for processing chest X-rays. To ensure a fair comparison, they employed an identical data split (70% for training, 10% for validation, and 20% for testing) since no standard split existed for the dataset. Their model exhibited noteworthy efficacy and feasibility, achieving an accuracy of 85%, when trained with the Reasoning Algorithm with boosting and discounting configuration. Another research by Rajpurkar *et al.* [15] employed the Chest X-ray14 dataset to create CheXNet, a 121-layer convolutional neural network. The research involved a comparison between CheXNet's performance and that of a radiologist, using the F1 metric. This comprehensive network was capable of identifying 14 different diseases, including pneumonia, from X-ray images. During its analysis of an X-ray image, the model not only provides the likelihood of pathology but also highlights specific areas within the image associated with the condition. The training set comprised 98,637 images (70%), the validation set included 6,351 images (20%), and the testing set comprised 430 images (10%). Ultimately, the model achieved an F1 score of 0.435, surpassing the radiologist's performance, which scored 0.387. though, this F1 score of 0.435 might roughly correspond to an accuracy in the same range, roughly around 43-50%.

Chandra *et al.* [16] introduced a transfer-learning approach for pneumonia detection, using five distinct models: AlexNet, InceptionV3, ResNet18, DenseNet121, and GoogLeNet. Among these models, AlexNet, trained for 200 iterations, achieved an AUC value of 0.9783. However, it was the ResNet18 model that displayed the most impressive performance, achieving an ROC AUC of 0.9936 alongside a testing accuracy of 94.23%, surpassing the other models in the study. Remarkably, when the results from all five models were combined, the collective outcome demonstrated a substantial ROC AUC of 0.9934, coupled with a testing accuracy of 96.39% and notably high sensitivity, reaching 99.62%. This ensemble approach yielded superior performance compared to the individual models, indicating the efficacy of leveraging multiple models for enhanced pneumonia detection from medical images. Also, Togacar *et al.* [17] introduced a deep feature using model CNN models such as AlexNet, VGG-16, and VGG-19 with different parameters, ranging from 100 to 1000. These models were structured using a minimum redundancy and maximum relevance algorithm to extract features. The extracted features were then fed into additional models, such as K-nearest neighbors, linear discriminant analysis, support vector machine, and linear regression. The culmination of this methodology resulted in an impressive accuracy rate of 99.41%. This indicates the robustness and effectiveness of their approach in leveraging deep-feature CNNs in conjunction with secondary models for highly accurate pneumonia detection from medical images.

3. Methodology

Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou obtained from the Kaggle dataset (https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia) and were first collected in Kermany *et al.* [18]. The dataset was organized into 3 folders (train, test, validation) and contains subfolders for each image category (Pneumonia/Normal). All chest X-ray imaging was performed as part of patients' routine clinical care. There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).

In this research method, a Convolutional Neural Network (CNN) model was constructed leveraging TensorFlow's Keras API. The initial layer comprised a 2D convolutional structure with 32 filters, each spanning a 3x3 size and employing the ReLU activation function. To accommodate our dataset, initial input images were standardized to a height and width of 64 pixels, forming a dimension of 64x64 pixels, with 3 color channels (RGB), establishing an input_shape = (64, 64, 3). Subsequently, it traverses three residual blocks, with each block comprising convolutional layers, batch normalization layers, and a shortcut connection, also known as identity mapping or skip connections, which circumvents one or more layers in the block. Finally, the max pooling block, comprising 62 pooling layers, calculates the maximum value across each of the 32 channels. Subsequently, the fully-connected block generates the probabilities indicating the presence or absence of tremors. Figure 1 illustrates the structure of the convolutional neural network (CNN) from convolution to Max pooling. The model commenced with convolutional and pooling layers, allowing feature extraction, followed by a sequence of flattening and dense layers tailored for classification. We introduced a fully connected (dense) layer, hosting 128 neurons and employing ReLU activation. A visual representation of this architecture is shown in Figure 2, depicting the schematic of our DCNN-Based Pneumonia Detection model. Recall, the image input of 64 x 64 passes through 3 Residual blocks or skip connections. The Residual blocks fundamental components of deep neural networks and each of these consists of convolutional and batch-normalization layers. The basic structure that defines the residual blocks of the model is the input tensor; the Main path, containing convolutional layers and activation function (ReLU); shortcut connections that provide an identity mapping of the input tensor; and Merge Operation that which combines the output of the main path and the shortcut connection using an element-wise addition operation. Mathematically, the Residual blocks can be defined as:

$$Output = ReLU\,(Conv\,(Input) + Input), \tag{1}$$

where $ReLU$ – is the Activation function (Rectified Linear Unit activation function), $Conv$ - the main path convolutional layer, and $Input$ (X) - Input tensor.

There was an initial input tensor (X) to, which transformation (T) was applied by the convolutional layers of the blocks, the generated output F(X) of the residual blocks is therefore calculated as:

$$F(X) \; = T(X) \; + \; X. \tag{2}$$

So, the combined mathematical model of the DCNN residual blocks is defined as follows:

$$F(X) \;\; = \;\; ReLU\,(W_2 \, . \, ReLU\,(W_1 \, . \, X \, . \, B_1) + \; B_2) + X, \tag{3}$$

where W_1 and W_2 are the weights metrics of the convolutional layers, and B_1 and B_2 are the bias victors.

To address internal covariate shift, accelerate training, and stabilize our training process, we introduced batch normalization (BN). Mathematically, batch normalization applies a normalization process at the conclusion of each training iteration to adjust the parameters of the normalizing flow, aiming to approximate the true posterior distribution within the model. This adjustment facilitates faster convergence of the model and enhances its performance on test data. Two main methods to perform normalization is either to scale it to a range from 0 to 1, which is the most straightforward method, also known as the Min – Max normalization, using the following formula:

$$\widehat{X} \; = \; \frac{X - Min}{Max \; - \; Min}, \tag{4}$$

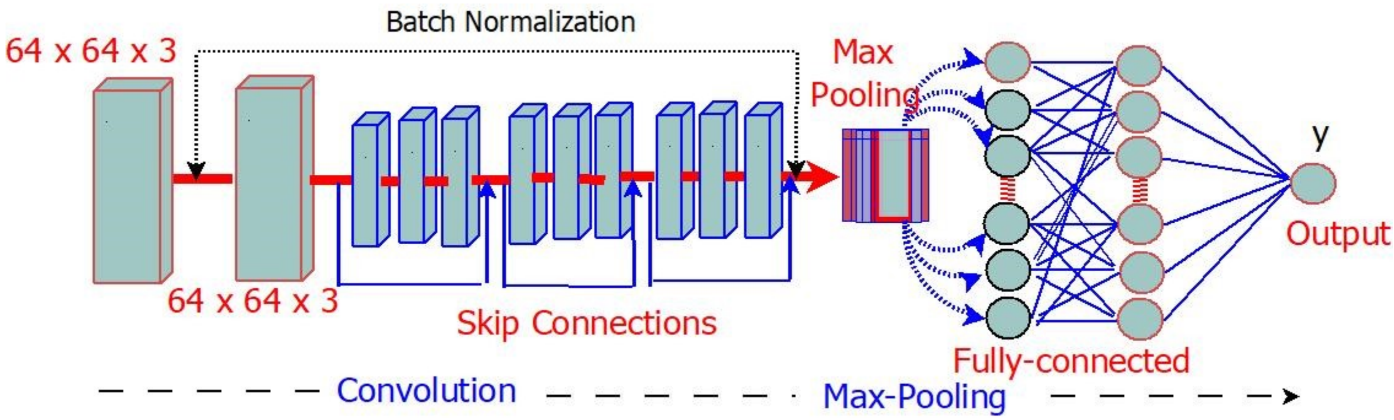

Figure 1. The structure of the DCNN pneumonia detector system.

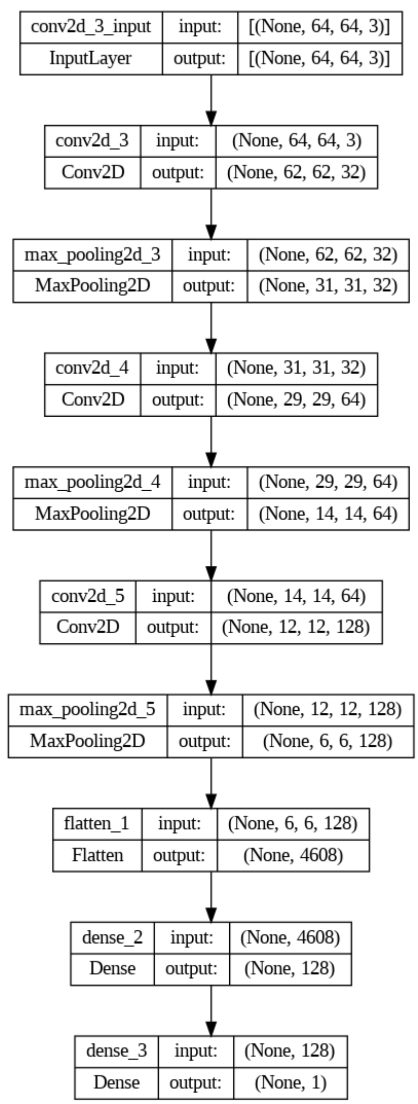

Figure 2. The model architecture of the DCNN-Based pneumonia detection.

where $\widehat{X}$ – is the Normalized value, X – is the value to be normalized, Min – is the minimum value, and Max – is the Maximum value.

The other technique is to force the data points to have a mean of 0 and a standard deviation of 1, called the Z – score

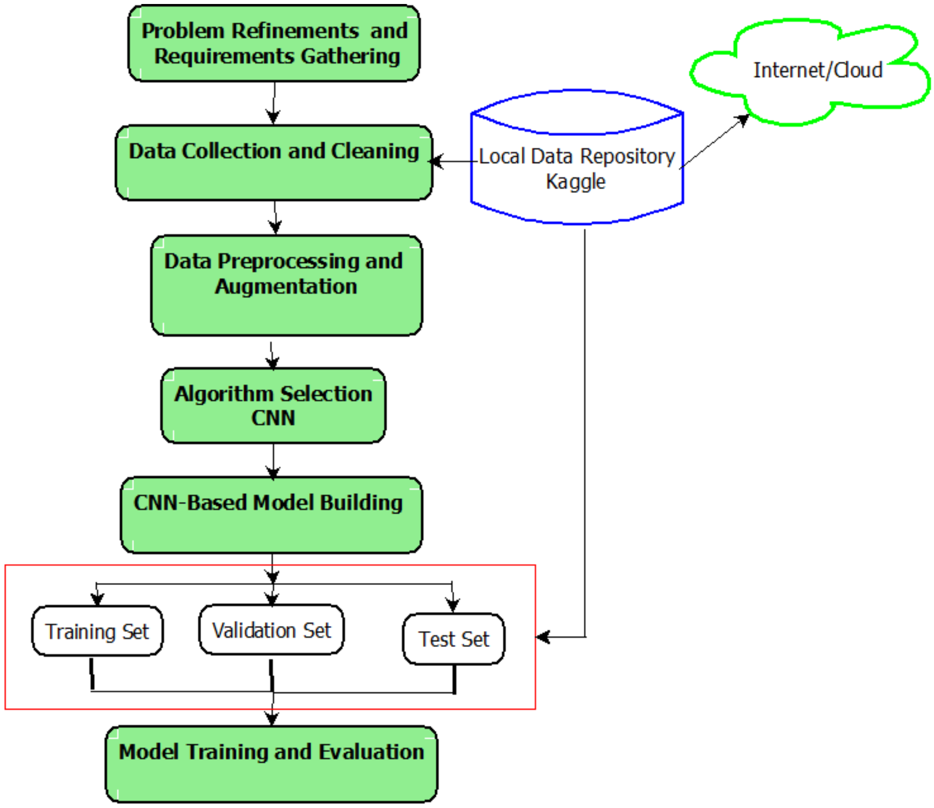

Figure 3. The structure/dataflow diagram of the CNN model.

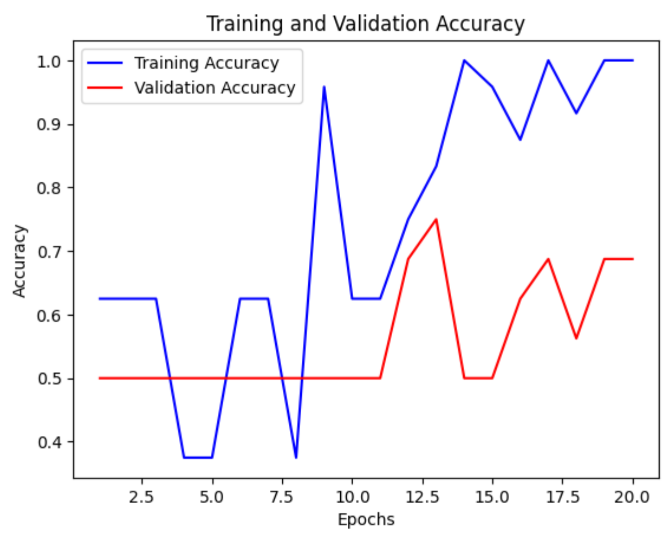

Figure 4. Comparison of training set and validation accuracies across different numbers of epochs.

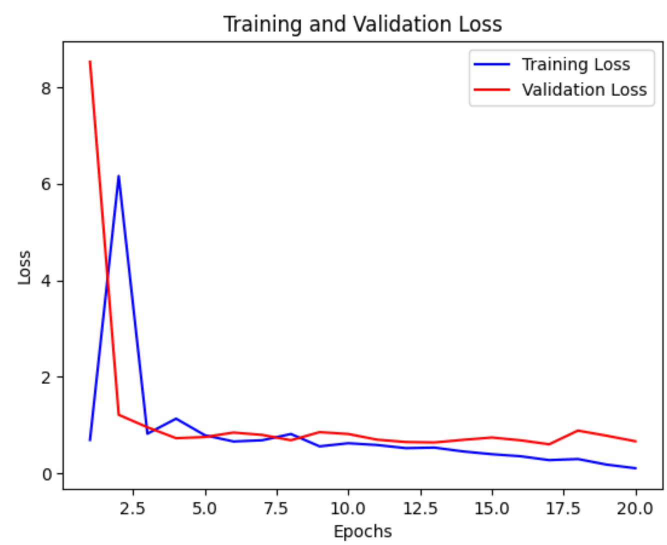

Figure 5. Comparison between the training loss and validation loss.

normalization, using the following formula:

$$\widehat{X} = \frac{X - Meam}{Standard\ Deviation}. \tag{5}$$

For the batch normalization,

$$\widehat{X} = \left(\frac{X - Meam}{Standard\ Deviation} \cdot \alpha \right) + \beta, \tag{6}$$

where:

$$\mu_\beta = \frac{1}{n} \sum_{i=1}^{n} X_i, \tag{7}$$

called the batch mean, and

$$\delta_\beta^2 = \frac{1}{n} \sum_{i=1}^{n} (X_i + \mu_\beta), \tag{8}$$

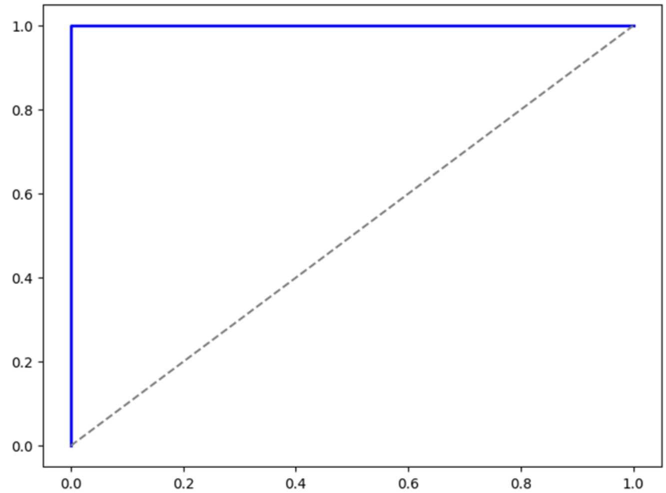

Figure 6. ROC-AUC of the model.

called the batch variance.

The scaled and shifted activation is:

$$Y_i = Y\hat{X}_i + \beta, \tag{9}$$

where Y and β are the parameters learned by the neural network.

Therefore, the full mathematical model of the DCNN's Batch Normalization is formulated as follows:

$$\widehat{X} = \frac{X_i - \mu_\beta}{\sqrt{\delta_\beta^2 + e}}. \tag{10}$$

Finally, to decrease the spatial dimensions of feature maps and computational complexity, and to perfectly regulate overfitting, we introduced Max pooling, which is a down-sampling operation frequently utilized in Convolutional Neural Networks (CNNs) to reduce the spatial dimensions of feature maps. A 6 x 6 max pool size was deployed.

4. Implementation of the proposed method

4.1. Dataset and data preparation

Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou obtained from the Kaggle dataset (www.Kaggle.com). The dataset is organized into 3 folders (train, test, validation) and contains subfolders for each image category (Pneumonia/Normal). All chest X-ray imaging was performed as part of patients' routine clinical care. There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal). The breakdown of the datasets includes a training set of 1342 samples of Normal images and 3876 samples of Pneumonia images; a Test set of 234 Normal images and 390 samples of Pneumonia images; and validation sets of 8 samples each of Normal and Pneumonia images, respectively. The goal is to use a simple model to classify x-ray images using convolutional neural networks (CNNs). The process of the model follows the data flow diagram/structure in Figure 3.

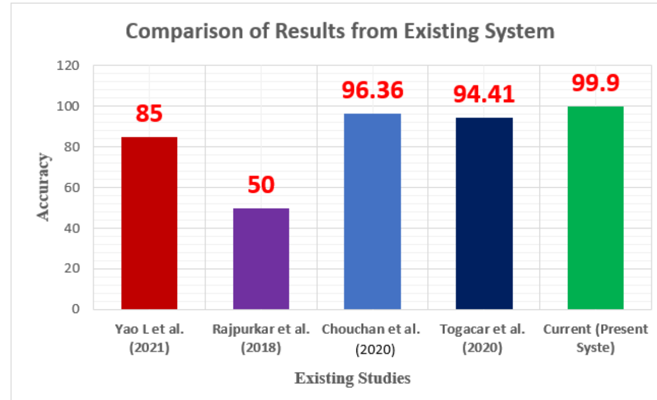

Figure 7. Comparison of the current system's result with the existing system.

4.2. Experimental design

This process outlines a common approach for building and evaluating deep learning models for image classification tasks.

1. Dataset Description: The original dataset consists of 5,863 X-ray images in JPEG format categorized into Pneumonia and Normal cases.
2. Data Splitting: The dataset was divided into training, testing, and validation sets. An 80-20 stratified split was applied to the training set to create a separate validation set.
3. Model Building: Using TensorFlow's Keras, a convolutional neural network (CNN) model was constructed, beginning with a base using ImageDataGenerator for data augmentation and then adding layers like Global Average Pooling (GAP), Flatten, Conv2D, MaxPooling2D, Dense, and Dropout.
4. Training and Evaluation: The model was trained on the training dataset and evaluated on the validation set to measure its performance and potentially fine-tune the model.
5. Performance Analysis: Metrics such as accuracy, were used to evaluate the model's performance on the validation and training sets.

Accuracy, in the context of machine learning and classification tasks, represents the ratio of correctly predicted instances to the total number of instances in a dataset. It's a fundamental metric used to evaluate the performance of a classification model. Mathematically, accuracy is calculated as:

$$Accuracy = \frac{Number\ of\ Correct\ Prediction}{Total\ Number\ of\ \ Predictions}$$

$$= \frac{True_{positive} + True_{negative}}{True_{positive} + True_{negative} + False_{positive} + False_{negative}}$$

$$= \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

Table 1. Training and validation accuracies.

Number of epochs (%)	Training accuracy (%)	Validation accuracy (%)
1	62	50
2	62	50
3	62	50
4	37	50
5	37	50
6	62	50
7	50	50
8	50	50
9	83	50
10	50	50
11	50	50
12	50	75
13	33	75
14	100	50
15	83	50
16	15	50
17	100	75
18	67	25
19	100	75
20	100	75

Table 2. Training and validation loss.

Number of epochs (%)	Training accuracy (%)	Validation accuracy (%)
1	90	94
2	04	00
3	78	25
4	30	97
5	70	97
6	69	27
7	32	23
8	20	31
9	56	12
10	10	25
11	40	06
12	90	62
13	01	69
14	06	04
15	31	97
16	08	15
17	36	93
18	34	31
19	76	68
20	27	13

4.3. CNN model training process

Subsequently, we proceeded to load the images from their respective folders and prepare them for input into our models. Our initial step involved defining the data generators. Leveraging the Keras Image Data Generator, we not only rescaled the pixel values but also applied random transformation techniques for real-time data augmentation. We established three distinct generators for various purposes: val_datagen (val_datagen = ImageDataGenerator) solely for rescaling the validation sets; train_datagram (train_datagen = ImageDataGenerator) incorporating transformations to augment the training set; and test_datagram (test_datagen = ImageDataGenerator) responsible for rescaling and augmenting the test sets. Moving forward, we embarked on creating and training image classification models utilizing a customized CNN. This process embraced the transfer learning paradigm, employing a pre-trained model as a feature extractor. Our final method involved Fine Tuning, where all layers from the pre-trained model were 'frozen', retaining the weights computed during its training on the ImageNet dataset.

5. Results and discussion

In our experiment, we ran 20 epochs in the model training. After training the CNN model for 9 epochs, we observed a steady increase in both the training and validation accuracies. The training accuracy increased to 95%, while the validation accuracy reached 75%, indicating continuous learning and improvement. However, we observed that at the 14 17, 18, 19, and 20 epochs, while the training accuracy continued to rise to 100%, respectively, the validation accuracy plateaued at 50% and 68%, respectively. This suggests that the model's learning capability saturated after 14 and 17, 18, 19, and 20 epochs, respectively. Further training could lead to overfitting. So, stopping our training at this point prevents overfitting and ensures the model's best generalization. The training was therefore terminated at 20 epochs. The model achieved a perfect training accuracy of 100% and demonstrated a validation accuracy of 95%. Tables 1 and 2 represent training and validation accuracies, and training and validation loss, respectively. Figure 4 illustrates the comparison between the training set and validation accuracies across different numbers of epochs, while Figure 5 depicts the comparison between the training loss and validation loss. The ROC curve of the convolutional neural networks obtained during the training is shown in Figure 6. Training loss and validation loss are metrics used to evaluate a machine learning model's performance during the training and validation phases, respectively. They serve different purposes in assessing how well the model is learning and generalizing.

Striving for a balance between high training accuracy and consistent validation accuracy is crucial, and our main goal during analysis is to ensure a well-performing and generalizable model. From the table, both training and validation accuracy accuracies tend to increase from epoch 14 as the model learns.

Our goal is to minimize both training and validation loss. The training and validation loss tends to decrease intermittently as the model learns. balancing these losses is essential to ensure that the model performs well on both the training data and new, unseen data.at epoch 20 we terminated the training to avoid overfitting.

Once more, we conducted a comparative analysis between our current CNN-based Chest X-ray detection model and those presented by Yao L *et al.* [14], Rajpurkar *et al.* [15], Chouchan *et al.* [16], and Togacar *et al.* [8]. The study in Ref. [14] achieved 85% accuracy, while Ref. [15] attained 50% accuracy, Ref. [16] demonstrated 96.36% accuracy, and Ref. [8] reported 94.41% accuracy. Notably, our current research surpassed these prior studies, achieving a mean accuracy of 99.9%. Figure 7 elucidates the individual performance of each model for clarity.

6. Conclusion

In conclusion, our CNN-based model for Pneumonia detection utilizing Chest X-ray images demonstrates remarkable advancements in accuracy compared to existing studies. The results obtained signify a substantial stride forward in accurate Pneumonia detection from Chest X-ray images and convolutional neural networks. The success of our model highlights its potential for practical deployment in clinical settings, promising enhanced diagnostic capabilities and potentially contributing to improved healthcare outcomes for patients with Pneumonia.

However, further validation and testing in diverse clinical environments would be beneficial to ascertain its robustness and real-world applicability. Nigeria has a highly polluted environment, weak health systems, and premature birth. These are the major causes of pneumonia in both children and adults. The system will be extended to relevant health by using imaging systems integrated with local hospitals and analyzed with deep learning models. This will be deployed into the clinical environment.

Data Availability

The link to the dataset used in this study is provided here: https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia.

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