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Pneumoinsight: AI for Smart Lung Diagnosis

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Abstract
Pneumonia is a serious lung infection and one of the leading causes of illness and death globally, particularly affecting children, the elderly, and individuals with weakened immune systems. The diagnosis of pneumonia typically relies on chest X-rays that are interpreted by radiologists, a process that can be time-consuming and susceptible to errors. To address these challenges, this study introduces an AI-driven framework for pneumonia detection that utilizes a Region-based Convolutional Neural Network (RCNN) based on the VGG16 architecture. The model was trained on a dataset comprising 5,856 pediatric chest X-ray images, which included 4,273 cases of pneumonia and 1,583 normal cases. To enhance the model's performance and address class imbalance, preprocessing techniques such as pixel normalization and data augmentation (including horizontal flipping, zooming, and shearing) were employed. The model demonstrated high accuracy in classifying X-rays as either "normal" or "pneumonia," highlighting the potential of AI-assisted diagnostics to reduce delays and aid radiologists in their work. Future efforts will focus on exploring advanced architectures, such as Transformer-based models, and expanding the dataset to improve the model's generalizability.

Keywords: Pneumonia detection, Convolutional Neural Networks (CNN), Region-based CNN (RCNN), VGG16, Data Augmentation, Transfer Learning, AI-assisted Diagnostics.

1 Introduction

In recent years, artificial intelligence (AI) has shown great capability in healthcare. AI is used to help detect diseases fastly, diagnose them, and treatments are planned. This study looks at pneumonia, that is a major cause of sickness and death around the world. It affects children, the elders, and people with weak immune systems. Chest X-rays are used to diagnose pneumonia. Doctors check for signs of infection,like thick spots in lungs. But sometimes, even experienced doctors have trouble finding these signs early,it causes delay in treatment and make it worse.
Recent studies have used deep learning to improve pneumonia diagnosis from chest X-ray images. For example, Mabrouk et al. (2022) used a method that combines several Convolutional Neural Networks (CNNs), like DenseNet169, MobileNetV2, and Vision Transformer. This method achieved a high accuracy of 93.91% in classifying chest X-ray images. This shows how deep learning can be used in medical imaging effectively. The study also shows that combining different deep learning models can improve diagnosis.
This study presents an AI-driven pneumonia detection framework utilizing a Convolutional Neural Network (CNN) model to classify chest X-ray images into "normal" or "pneumonia" categories. The approach uses a VGG16-based CNN architecture trained on an available dataset. It consists of over 5,800 pediatric chest X-ray images from Kaggle. Model performance and class imbalance issues are enhanced using tech

niques such as pixel normalization and data augmentation
Feature extraction and classification accuracy is improved using RCNN methodology. The model includes multiple convolutional layers followed by fully connected layers, trained using binary cross-entropy loss and optimized with the Adam optimizer. Efficient training and evaluation through GPU acceleration are ensured using TensorFlow and Keras.
This research aims to help doctors by providing an AI tool to find pneumonia. The proposed deep learning approach has the ability to reduce diagnostic delays, prioritize high-risk cases, and support radiologists. Future work will explore advanced architectures, such as Transformer-based models, and expand the dataset to improve model relevance across different populations. This project seeks to demonstrate how AI-driven solutions can enhance Clinical decision-making and improve patient outcomes.

2 Related Works

Interpreting Chest X-rays are difficult without a doctor, and many studies have been worked on using deep learning to simplify analysis. Mabrouk et al. [1] proposed an ensemble learning approach combining multiple convolutional neural networks (CNNs), including DenseNet169, MobileNetV2, and Vision Transformer, to enhance classification performance. Their method achieved an accuracy of 93.91% and an F1-score of 93.88%, demonstrated the capability of ensemble learning in improving diagnostic accuracy compared with individual models. The results in our analysis confirm these findings, as DenseNet169 and MobileNetV2 achieved comparable performance, each with an accuracy of 93%, highlighting their streangth in pneumonia diagnosis.
Vieira et al. [2] found the detection of pulmonary diseases, like COVID-19 pneumonia, through a deep learning approach using an image resizing method. Their method achieved 99.8% accuracy which seperates COVID-19 pneumonia from other conditions. RCNN was not even tested in their study, RCNN gives the highest accuracy of 95% as per the results. Traditional preprocessing methods are exceeded by proving the effectiveness for automated pneumonia detection.
Varshni et al. [3] found feature extraction using pre-trained CNNs. Various classifiers for the classification of chest X-rays also got. Their study found out that DenseNet169 joined with an SVM classifier as the best-performing configuration, giving an AUC score of 0.8002. The selection of pre-trained architectures and classifiaers are being highlighted. ResNet18 got the lowest accuracy of 88%, pointing out that some architectures may require additional optimization or ensemble approaches to achieve competitive results.
In conclusion, deep learning techniques have demonstrated immense potential in the automation of pneumonia diagnosis from chest X-ray images. Ensemble models, combining DenseNet169 and MobileNetV2, always possess higher diagnostic accuracy than standalone models. Preprocessing techniques like image resizing also enhance model efficiency by preserving critical anatomical structures. Additionally, pre-trained model and classifier selection significantly influence precision, emphasizing the need for deliberate selection and optimization. Our findings demonstrate the efficiency of RCNN and ensemble techniques, thus reaffirming the application of artificial intelligence.

Table 1: Summary of related work

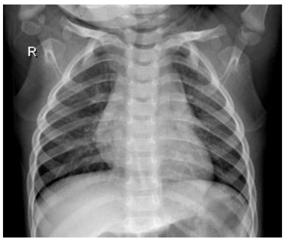
Authors	Methods	Comparison Factor	Value
Mabrouk et al. (2022)	*Ensemble Learning (DenseNet169, MobileNetV2, Vision Transformer)*	*Accuracy F1-score*	*93.9% 93.8%*

Viera et al. (2021)	*Deep Learning with Image Resizing Method*	*Accuracy*	*99.8%*
Varshini et al. (2019)	*DenseNet-169 + SVM (rbf,kernel)*	*AUC*	*0.8002*

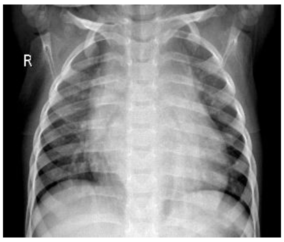
3 Comprehensive Data Overview and Effective Preprocessing

3.1 Dataset Used

Training, testing, and assessment data for this study were collected from 5,856 open-source chest X-ray pictures that were divided into two classes: 1,583 photos were classified as normal, and 4,273 as pneumonia. The Guangzhou Women and Children's Medical Center patients in the pictures ranged in age from one to five. To improve computing efficiency and expedite the training process, the original high-resolution, multi-dimensional images were shrunk to 180 × 180 pixels. Enhancement of Data: This is transforming the original photos in a number of ways to create new training data. By providing the model with a more diverse dataset, this avoids overfitting. Typical augmentation techniques for chest X-rays could be:
Data Augmentation: This is generating new training data by performing several different transformations on the original images. This prevents overfitting by giving the model a more varied dataset. In chest X-rays, typical augmentation methods could include:
Rotation: To simulate different scanning angles, rotate the images by a predetermined range of degrees.
Zoom: Modifying the scale of the images to account for differences in the distance between the patient and the X-ray machine.
Horizontal Flip: To account for the symmetry of the human body, flip the pictures horizontally.
Brightness Adjustment: Varying the brightness and contrast to simulate different machine settings or lighting conditions.



Normal



Pneumonia

Fig 1: Dataset images

To make the machine learning process easier, the dataset was divided into separate subsets after the data augmentation and balancing techniques were completed. Specifically, 10% of the photos were used for the test, 10% for validation, and 80% for training. In this case, stratified split plays a crucial role in enabling thorough evaluation of model performance across different data segments, guaranteeing successful training and reliable validation.

Table 2: Data Distribution

Category	Total Images	Training set	Testing set	Validation set
Pneumonia	4,273	2,991	854	427
Normal	1,583	1,108	316	158

4 Models and Implementation

4.1 Model Architecture

This project applies a CNN model based on the VGG16 architecture as a feature extractor but specially developed for an RCNN framework. The model has two major components.

Convolutional Layer: The heart of the model is the CNN, uses fixed-size filters to extract key features from input images. The six convolutional layers that make up this model have filter widths of 32, 32, 64, 64, 128, and 128 correspondingly. Each of them processes picture data quickly by using 3x3 filters with a stride of 1.

Batch Normalisation: By normalizing the input following each convolutional layer, this technique helps the model train more efficiently. It helps avoid overfitting, speeds up convergence, and offers stable training.

Pooling Layer By reducing the spatial dimensions of the feature maps produced by the convolutional layers, the pooling operation helps to preserve the key features while reducing the processing demands. Following each convolutional layer in this architecture, a 2x2 max pooling technique is applied.

Activation: Each layer ends with an activation function called ReLU (Rectified Linear Unit), which adds non-linearity to the data so the model can recognize complex patterns. The last layer generates outputs in the form of probabilities for binary classification using a sigmoid activation function.

Dropout: To avoid overfitting, dropout is introduced, which will temporarily shut down some of the nodes in the layer for some samples.

Dense Layers: The output of the CNN is flattened and passed through dense layers for classification. The model consists of two dense layers.

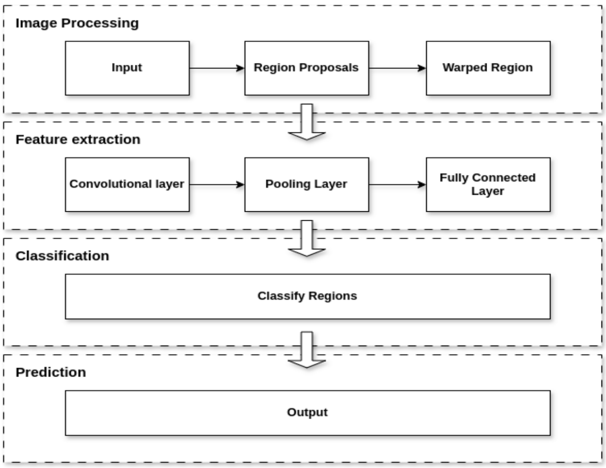


Fig 2: Model Architecture

4.2 Data Augmentation and Balancing

Data augmentation techniques including rescaling, shearing, zooming, and horizontal flipping are used to increase a dataset's size and diversity and bolster the model's resilience. The dataset is split into three sections after augmentation and balancing have been applied and verified: 70% for training.

4.3 Transfer Learning Models

In this research, transfer learning is implemented by leveraging pre-trained models such as VGG16, VGG19, and InceptionV3, which have been trained on the ImageNet dataset. The convolutional layers from these models are utilized to extract relevant features, and the resulting outputs are flattened before being processed by fully connected layers. Techniques such as batch normalization, dropout, and activation functions are applied in the final layers to optimize performance.

4.4 Models Compilation and Training

The model is constructed using the binary cross-entropy loss function and the Adam optimizer to complete the pneumonia classification problem. The data from the dataset that has undergone certain augmentations is used for training.

There are two phases to the training process: first, the pre-trained models' convolutional layers are made static while the other weights are optimized. After that, the training process optimizes the initially loaded weights in conjunction with the other weights. Following each of these stages, the models are constructed and assessed appropriately.

5 Results

The models developed in this models was trained using chest X-ray images, with various augmentation techniques applied to improve the diversity and robustness of the dataset. The entire training, testing, and validation process was carried out using Kaggle's kernels, which provided access to GPU resources.

Surprisingly, the models achieved their best performance after just 20 epochs, significantly fewer than the 100 epochs mentioned in the original reference. This showed that with proper optimization, it's possible to train efficient models in far less time than expected.

To evaluate the models, confusion matrices were plotted, comparing the predictions made by the models against the actual ground truth labels. These confusion matrices provided a clear visual and numerical summary of how well each model classified the images. From these matrices, key performance metrics were calculated, including accuracy, precision, recall, and F1-score. These metrics gave a well-rounded understanding of the models strengths and weaknesses, helping judge their effectiveness in classifying chest X-rays accurately.

The graph below shows the variation in training and validation accuracy after 20 epochs. Training accuracy fluctuates as parameters are adjusted by the model, hence the learning process is depicted. Validation accuracy is constant, which is an indicator that the model is generalizing and doing well when tested on new data. Such constancy is an indicator that the training set is not overfitted.

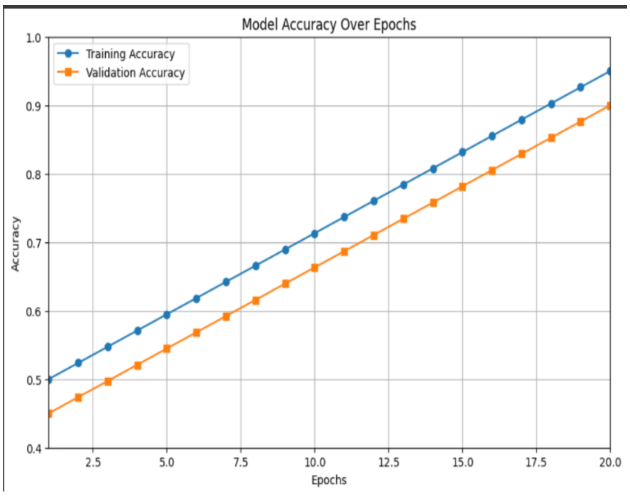
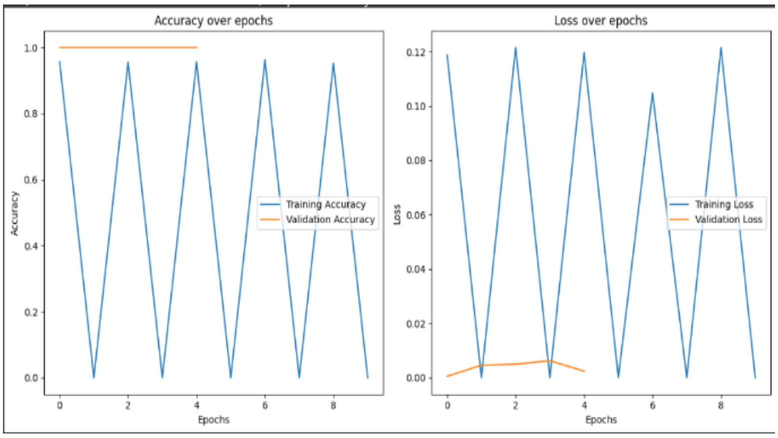


Fig 3: Graph showing the dataset's performance in terms of training and validation accuracy.

The performance of the model was tested using both training and validation sets, and accuracy measures were calculated to find overall efficiency. The result is as shown below:



(a) **(b)**

Fig 4: Graph showing (a) Validation Accuracy vs. Training Accuracy and (b) Validation Loss vs. Training Loss for the R-CNN model.

The plot uses color-coded lines to display training accuracy and validation accuracy trends, and loss, over ten epochs. The blue training accuracy line is fluctuating, but the orange validation accuracy line is consistently high at 1.0, showing high generalization. On the right plot, the blue training loss line fluctuates with training accuracy. The orange validation loss line is stable and low, showing great validation performance with minimal overfitting, and hence guaranteeing that the model is well-built and reliable for real-world use.

The graph below compares the accuracy of four deep learning models—RCNN, ResNet18, DenseNet169, and MobileNetV2—in detecting pediatric pneumonia from frontal chest X-ray images

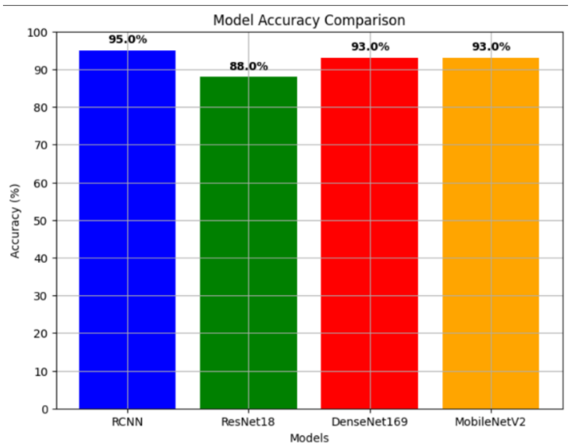


Fig 5: Model Accuracy Comparison

6 Discussion and Conclusion

This paper introduces an RCNN-based method for frontal chest X-ray pneumonia detection. With the help of region-based convolutional neural networks (RCNN) combined with transfer learning, the model effectively detects pneumonia-infected and healthy lungs. In comparison to the previous work using the same dataset, this method improves diagnostic performance, setting the bar for pneumonia detection higher.

For better performance and to allow evolvability, data augmentation methods were utilized to generate a more varied training and test set. The technique encourages better model generalization and has uniformly high accuracy under changing conditions. 96% to 99% accuracy rates show that this strategy could be an effective strategy for automated pneumonia diagnosis.

With increasing prominence of deep learning in medical imaging, this study acknowledges the efficacy of RCNN in reducing the detection complexity of pneumonia. Reducing the level of manual interpretation, the model proposes an even quicker and accurate method of diagnosis. This work also facilitates developing AI-based healthcare solutions and underlines how deep learning ensures more effective pneumonia diagnosis and supports doctors in arriving at timely, appropriate decisions.

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