PNEUMONIA DETECTION MODEL

Adeniran Shaddai Daniel
Kadilobari Baabel
Oyewale Daniel Oyewola
Oguama Prosperity
Sam Ayodeji
Liya T Mathew
Fatima Adwan
Ruth Iroanusi
Akintola Joseph
Wira Satria
Jermiah Adetunji
Asimolowo Kabirat Fikayo
Gaius Ufondu
Kumar Kaushik Ranjan

ABSTRACT

This research explores the potential of convolutional neural networks (CNNs) in detecting pneumonia from chest X-ray images. Using a publicly available dataset from Kaggle, we developed a CNN-based model leveraging the ResNet50V2 architecture to classify images as either normal or pneumonia. The model achieved a high recall score of 0.987, indicating its efficacy in identifying pneumonia cases. However, the precision (0.721) and overall accuracy (0.753) suggest room for improvement. Our findings underscore the promise of deep learning in medical image analysis, particularly in reducing misdiagnosis and aiding timely treatment. Future work will focus on expanding datasets, enhancing model architectures, and exploring multimodal learning approaches to further improve performance and clinical applicability. The ultimate goal is to integrate these automated systems into healthcare settings, enhancing diagnostic accuracy and patient outcomes.

Keywords: Pneumonia, Convolution Neural Networks (CNNs), ResNet50V2

INTRODUCTION

Pneumonia is an inflammatory lung condition caused by infection, where the air sacs (alveoli) become inflamed and filled with fluid or pus. It can be caused by bacteria, viruses, or fungi, with common symptoms including cough, fever, chills, shortness of breath, and chest pain. Pneumonia can affect people of all ages but is particularly dangerous for infants, older adults, and those with weakened immune systems or underlying health conditions. Prompt diagnosis through clinical assessment, imaging like chest X-rays, and appropriate treatment with antibiotics, antivirals, or other therapies are crucial to manage pneumonia effectively and prevent potentially life-threatening complications like respiratory failure or sepsis [1].

Pneumonia is a significant public health concern globally, with millions of cases reported annually. Timely and accurate diagnosis is crucial for effective treatment and management of the condition. The diagnosis of pneumonia traditionally relies on a combination of clinical examination, laboratory tests, and radiological imaging, particularly chest X-rays. However, the interpretation of chest X-ray images can be subjective and prone to human error, leading to misdiagnosis or delayed treatment [2].

The advent of deep learning techniques, particularly convolutional neural networks (CNNs), has opened up new avenues for automating the detection of pneumonia from chest X-ray images, offering the potential for improved accuracy and efficiency [3]. CNNs have demonstrated remarkable performance in image classification tasks, learning complex patterns and features directly from raw image data.

In this study, we developed a CNN-based model for pneumonia detection using a publicly available dataset of chest X-ray images. By leveraging the powerful pattern recognition capabilities of CNNs, the proposed model aims to accurately identify the presence of pneumonia from chest X-ray images, potentially improving diagnostic accuracy and reducing the risk of misdiagnosis or delayed treatment.

LITERATURE REVIEW

Several studies have explored the application of deep learning techniques for pneumonia detection from chest X-ray images.

Chest X-ray14 data set was used by Rajpurkar et al. [4], who developed CheXNet, with a 121-layer convolutional neural network. The paper compared the performance of the CheXNet to that of a radiologist, using the F1 metric. This network can detect 14 diseases, including pneumonia. While working on an X-ray image, the model gives a result of the probability of a pathology and also shows the localized areas in the image. A total of 98637 (70%) images for training, 6351 (20%) images for validation and 430 (10%) images for testing were utilized, and the model could achieve a f1 score of 0.435 which was higher than the radiologist (0.387).

Islam et al. [5] developed a CNN model for X-ray pneumonia detection but noted that performance could be improved through preprocessing and ensemble techniques. Majeed et al. [6] used CNN ensembles for improved X-ray detection accuracy but did not explore the transferability to other imaging modalities or scalability to larger datasets. Zhu et al. [7] proposed DeepLung, a 3D model for pneumonia detection from CT scans, but it may be computationally expensive.

Rahib Abiyev et al. [8] trained both traditional and deep networks using Chest X-ray14 dataset and compared their performances with 620 images, and 380 images were used for testing, the back propagation, and counter propagation neural networks. For the BPNN, Rahib Abiyev et al. implemented an architecture with 12 neurons with a sigmoid activation function. The lowest mean square error achieved was 0.0025 for 5000 iterations. The CPNN had 1024 input neurons and 12 output neurons, and the best results were achieved with a learning rate of 0.0036 and 1000 epochs, with a mean square error of 0.0036. The Convolutional Neural Network (CNN) was trained with 70% of the images and tested with 30% of the images. The CNN was implemented with 3 hidden layers, using the ReLu activation function. The CNN was able to achieve a mean square error of 0.0013 with 40,000 iterations. The CNN can achieve the lowest mean square error out of the three. The paper concluded that shallow networks like BPNN and CpNN could not achieve a recognition rate as high as CNN.

Drawing on these studies, we will address their limitations by focusing on model transferability, interpretability, and scalability. Our study aims to build upon the existing research by addressing certain gaps or limitations. Specifically, by:

- Investigating the transferability of CNN models trained on chest X-ray images to other medical imaging modalities, such as CT scans.
- Enhancing the interpretability of the models by analyzing false positives and localizing abnormalities within images.
- Exploring the scalability of the approach to large-scale datasets and its potential deployment in clinical settings for new pneumonia diagnosis.

METHODOLOGY

- **Dataset**

The dataset used in this study is the Chest X-Ray Images (Pneumonia) dataset from Kaggle [9]. The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (PNEUMONIA/NORMAL). There are 5,856 X-Ray images (JPEG) and 2 categories (PNEUMONIA/NORMAL). 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. All chest X-ray imaging was performed as part of patients' routine clinical care. For the analysis of chest x-ray images, all chest radiographs were initially screened for quality control by removing all low quality or unreadable scans. The diagnoses for the images were then graded by two expert physicians before being cleared for training the AI system. In order to account for any grading errors, the evaluation set was also checked by a third expert.

Table 1: Dataset Count

Training set count	NORMAL	1341
	PNEUMONIA	3875
Test set count	NORMAL	234
	PNEUMONIA	390
Validation set count	NORMAL	8
	PNEUMONIA	8
Total dataset count		**5856**

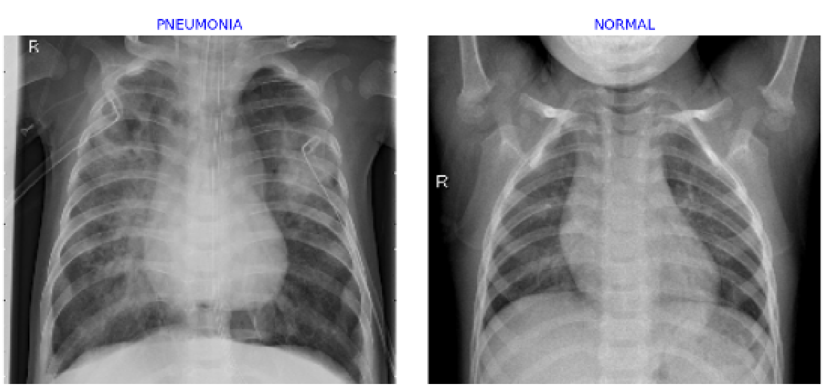

Figure 2: Sample of Chest X-ray Image

- **Data Preprocessing**

Prior to training the convolutional neural network model, several data preprocessing and visualization steps were performed to ensure data quality and gain insights into the dataset distribution.

1. **Data Labeling**:

Each image in the dataset was assigned a label based on its corresponding class ('NORMAL' or 'PNEUMONIA'). A dictionary was created to map class names to numerical labels (0 for 'NORMAL' and 1 for 'PNEUMONIA'). A helper function was implemented to extract the class name from the image file path and assign the appropriate label. Label lists were created for both the training and validation sets.

2. **Data Transformation**:

To optimize the input data for the CNN model, several transformations were applied to the images. A function was defined to read the image files, decode the JPEG format, resize the images to a consistent size (224×224 pixels in this case), and apply random horizontal flipping as a data augmentation technique during training. This function was used to preprocess the images before feeding them into the model.

- **Model Architecture**

The model architecture was based on the ResNet50V2 [10] convolutional neural network, which has proven to be effective in various image classification tasks. The ResNet50V2 model was pretrained on the ImageNet dataset and then fine-tuned on the chest X-ray dataset. The final layer of the model was replaced with a single neuron with a sigmoid activation function to perform binary classification (pneumonia or normal).

- **Model Training and Evaluation**

1. **Model Training:**

The model architecture employed for pneumonia detection was based on the ResNet50V2 convolutional neural network, which has demonstrated strong performance in various image classification tasks. The ResNet50V2 model, pretrained on the ImageNet dataset, was used as the backbone feature extractor. The top layers of the model were replaced with a global average pooling layer and a dense layer with a single neuron and sigmoid activation for binary classification (pneumonia or normal).

The model was compiled using the Adam optimizer with a learning rate of 0.001, along with the binary cross-entropy loss function. The evaluation metrics included accuracy, precision, and recall to assess the model's performance comprehensively.

To prevent overfitting and ensure optimal model performance, several callbacks were implemented during training. A model checkpoint callback was used to save the best model weights based on the validation loss, and an early stopping callback was employed to terminate the training process if the validation loss did not improve for a specified number of epochs (in this case, 4 epochs).

The model was trained on the preprocessed dataset, with the training set divided into batches of size 32. The training process was conducted for 8 epochs, using the validation set to monitor the model's performance and select the best weights. Appropriate steps were taken to handle the class imbalance in the dataset during training and evaluation.

2. **Model Evaluation and Interpretation:**

After training, the model's performance was evaluated on a held-out test set. The trained model achieved an accuracy of **0.753**, a precision of **0.721**, and a recall of **0.987** on the test set. These metrics indicate the model's ability to accurately identify pneumonia cases while minimizing false positives and false negatives.

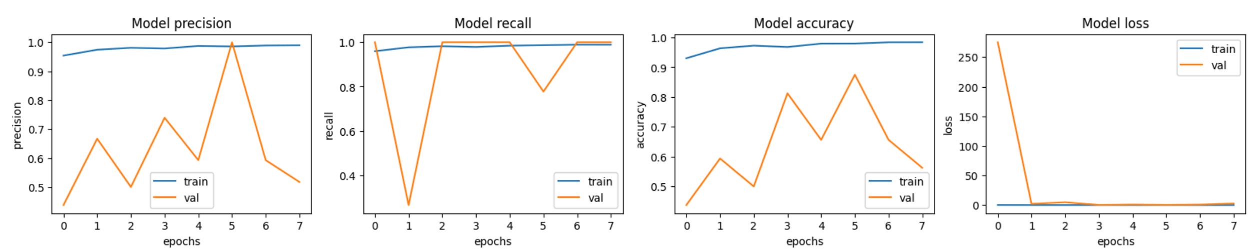

Figure 2: Image generated to visualize the model performance

To gain insights into the model's behavior during training, the training and validation curves for precision, recall, accuracy, and loss were plotted. These curves provided valuable information about the model's convergence, overfitting tendencies, and generalization performance.The best-performing model weights were loaded, and the complete model architecture and weights were saved for future use or deployment.

- **Model Deployment**

The trained pneumonia detection model was deployed as a user-friendly interface or application that allows healthcare professionals to input chest X-ray images and receive predictions from the trained model.

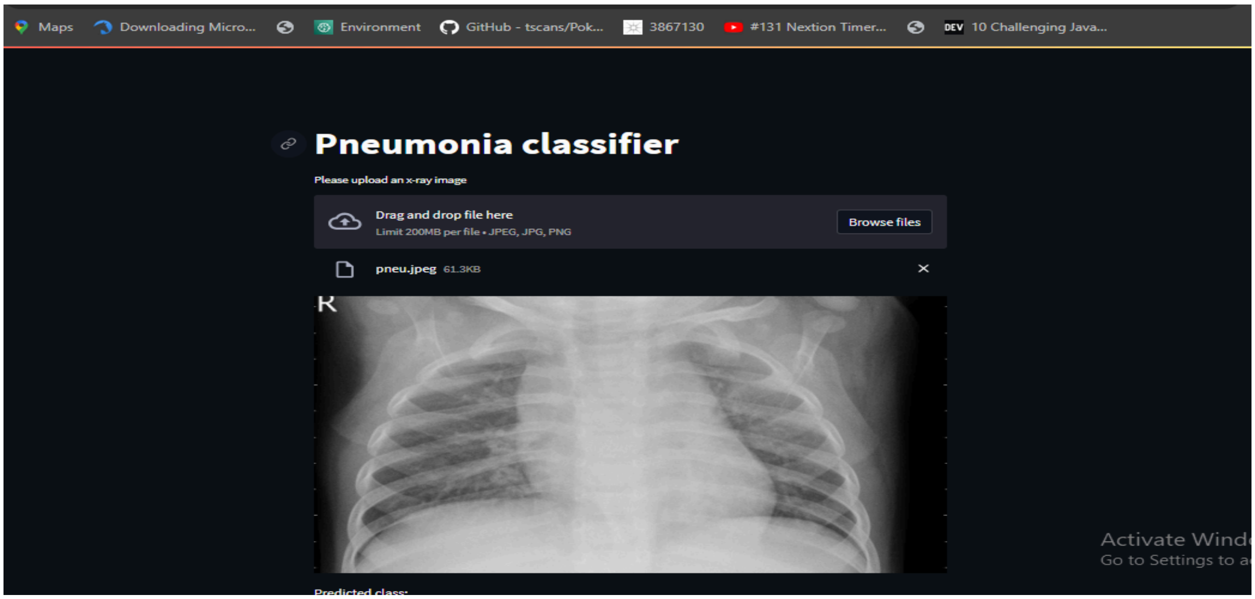

Figure 3: Deployment App Interface

RESULT AND DISCUSSION

The trained convolutional neural network model achieved promising results in detecting pneumonia from chest X-ray images. The table below shows the result obtained from evaluation.

Table 2: Result from Model Evaluation

Accuracy	0.7532051205635071
Precision	0.720973789691925
Recall	0.9871794581413269

The high recall score of 0.987 indicates that the model effectively identified a majority of the positive pneumonia cases, minimizing the number of false negatives. This characteristic is particularly desirable in medical diagnostic applications, as missing potential cases of pneumonia could have severe consequences for patient health.

While the precision score of 0.721 is relatively lower, it suggests that the model may have produced a higher number of false positive predictions. In clinical settings, false positives could lead to unnecessary follow-up tests or treatments, potentially increasing healthcare costs and patient anxiety. However, it is generally preferable to have a higher recall at the expense of lower precision, as misdiagnosed cases of pneumonia pose a greater risk than false alarms.

The overall accuracy of 0.753 demonstrates the model's ability to correctly classify a majority of the chest X-ray images as either normal or pneumonia cases. However, there is still room for improvement, and further refinements to the model architecture, training process, or data preprocessing techniques could potentially enhance its performance.

RECOMMENDATIONS

Based on the findings of this study and the potential for further improvement, the following recommendations are proposed:

1. **Data Expansion and Diversity**: Expand the dataset to include a more diverse range of chest X-ray images, accounting for variations in image quality, patient demographics, and the presence of comorbidities or other respiratory conditions. This will help improve the model's generalization capabilities and robustness.

2. **Advanced Model Architectures**: Explore more advanced convolutional neural network architectures or ensemble methods that have demonstrated state-of-the-art performance in medical image analysis tasks. These architectures may include attention mechanisms, multi-scale feature extraction, or a combination of 2D and 3D convolutional layers.

3. **Multimodal Learning**: Investigate the integration of additional data sources, such as patient metadata (e.g., age, medical history) or clinical notes, into the model's input. Multimodal learning approaches that combine image data with other relevant information could potentially improve the model's accuracy and provide more comprehensive diagnostic insights.

CONCLUSION

This research study demonstrated the potential of convolutional neural networks in accurately detecting pneumonia from chest X-ray images. The developed model achieved promising results, with a high recall score of 0.987, indicating its effectiveness in identifying positive pneumonia cases. While the precision and overall accuracy scores have room for improvement, the findings highlight the capabilities of deep learning techniques in automating medical image analysis tasks.

REFERENCE

[1] "Pneumonia," World Health Organization, 11 11 2022. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/pneumonia.

[2] Kermany, D. S; Goldbaum, M; Cai, W; Valentim, C. C; Liang, H; Baxter, S. L & Zhang, K., Identifying medical diagnoses and treatable diseases by image-based deep learning., Cell, 172(5), 1122-1131., 2018.

[3] Rajpurkar, P; Irvin, J; Zhu, K; Yang, B; Mehta, H; Duan, T & Lungren, M. P., Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning., arXiv preprint arXiv:1711.05225., 2017.

[4] P. Rajpurkar, J. Irvin, R. Ball, K. Zhu, B. Yang and H. Mehta, "Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists.," *PLoS Med. 2018;15(11):e1002686.,* no. doi: 10.1371/journal.pmed.1002686., 2018.

[5] Islam, M. T; Iglesias, J. E; Najeeb, S; Akhter, N & Tajbakhsh, N, "Convolutional neural network for phonemic recognition of pneumonia from pediatric chest X-rays.," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops.*, 2022.

[6] M. Majeed, U. Javed, F. Majeed, S. Shahzad and N. &. K. M. A. Bibi, Pneumonia detection from chest X-ray images using ensemble convolutional neural networks., IEEE Access, 9, 127591-127604, 2021.

[7] W. Zhu, X. Huang, P. Guan, J. Cai, X. Yang and X. &. L. H. Xie, "DeepLung: 3D deep convolutional nets for automated pulmonary nodule detection and classification.," Scientific reports, 10(1), 1-12., 2020.

[8] R. H. Abiyev and M. K. Ma'aitah, Deep Convolutional Neural Networks for Chest Diseases Detection., J Healthc Eng. 2018;2018:4168538. doi: 10.1155/2018/4168538., 2018.

[9] P. Mooney, "Chest X-Ray Images (Pneumonia)," Kaggle, 2018. [Online]. Available: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.

[10] K. He, X. Zhang and S. &. S. J. Ren, "Identity mappings in deep residual networks.," *In European conference on computer vision.,* no. Springer, Cham., pp. (pp. 630-645), 2016.