

Prediction-of-Pediatric-Pneumonia-in-Chest-X-Rays-using-Deep-Learning

Project Report



Submitted to
Dr. Faryal Nosheen

Submitted by

Noor-ul-Huda Gillani

{01-136212-038}

Noor-ul-Huda

{01-136212-037}

Farhan Ahmed

{01-136221-052}

Department of Computer Science,
Bahria University, Islamabad.

[19-december-2024]

Table of Contents

1. Introduction.....	2
2. Problem Statement:	2
3. Problem Description:.....	3
4. Literature Review	3
5. Objective:.....	3
6. Methodology	4
7. Basic System Architecture:	5
8. Flow chart:.....	5
9. Project Scope:.....	6
10. Tools/Technology	6
11. Conclusion:	6
12. References.....	7

1. Introduction

Pneumonia is a severe respiratory infection that inflames the air sacs in one or both lungs, leading to symptoms such as cough, fever, and difficulty breathing. It is a leading cause of morbidity and mortality among children worldwide, particularly in developing countries. Early and accurate diagnosis is crucial for effective treatment and improved patient outcomes. Chest X-ray imaging is a standard diagnostic tool for pneumonia; however, interpreting these images requires significant expertise and is subject to human error. Advancements in deep learning, particularly convolutional neural networks (CNNs), have shown promise in automating and enhancing the accuracy of medical image analysis, including the detection of pneumonia from chest X-rays.

2. Problem Statement:

The objective of this project is to develop an automated system that utilizes deep learning techniques to accurately classify pediatric chest X-ray images as either pneumonia-positive or normal, thereby assisting healthcare professionals in the early and reliable diagnosis of pneumonia.

3. Problem Description:

Manual interpretation of chest X-rays for pneumonia diagnosis is time-consuming and prone to inter-observer variability, which can lead to misdiagnosis or delayed treatment. An automated system based on deep learning can provide a consistent and efficient alternative, reducing the burden on radiologists and improving diagnostic accuracy. By training a CNN on a large dataset of labeled pediatric chest X-ray images, the model can learn to identify patterns indicative of pneumonia, facilitating prompt and accurate detection.

4. Literature Review

- **CheXNet:** Developed by Stanford University researchers, CheXNet is a 121-layer CNN trained on a large dataset of chest X-rays to detect pneumonia. It achieved performance comparable to expert radiologists, demonstrating the potential of deep learning in medical image analysis.
- **Vision Transformers:** Recent research has examined the use of Vision Transformers (ViTs) for pneumonia detection, achieving high accuracy by capturing global dependencies in chest X-ray images. This approach offers an alternative to traditional CNN architectures.
- **Transfer Learning Approaches:** Studies have utilized pre-trained CNNs, such as DenseNet121 and ResNet50, applying transfer learning to adapt these models for pneumonia detection in pediatric chest X-rays. These approaches have shown promising results in improving diagnostic accuracy.

5. Objective:

The primary objective of this project is to develop a deep learning-based model that can accurately classify pediatric chest X-ray images as either pneumonia-positive or normal. The system aims to assist healthcare professionals by providing a reliable tool for early pneumonia detection, ultimately improving patient care and outcomes.

6. Methodology

- **Data Collection:** The dataset used in this project comprises labeled pediatric chest X-ray images, including both pneumonia-positive and normal cases. The data is sourced from publicly available repositories, ensuring a diverse and representative sample.
- **Data Preprocessing:** Preprocessing steps include resizing images to a uniform dimension, normalizing pixel values to standardize the input, and applying data augmentation techniques such as rotation, flipping, and zooming to enhance model robustness and prevent overfitting.
- **Model Selection:** The project explores various CNN architectures, including DenseNet169, MobileNetV2, and Vision Transformer models. Transfer learning is employed by initializing models with weights pre-trained on large image datasets, allowing the network to leverage learned features and adapt them to the specific task of pneumonia detection.
- **Training and Validation:** The dataset is split into training, validation, and test sets. The model is trained on the training set, with hyperparameters optimized using the validation set. Techniques such as early stopping and learning rate scheduling are implemented to enhance training efficiency and prevent overfitting.
- **Evaluation:** Model performance is assessed on the test set using metrics including accuracy, sensitivity (recall), specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). These metrics provide a comprehensive evaluation of the model's diagnostic capabilities.

7. Basic System Architecture:

The system architecture consists of the following components:

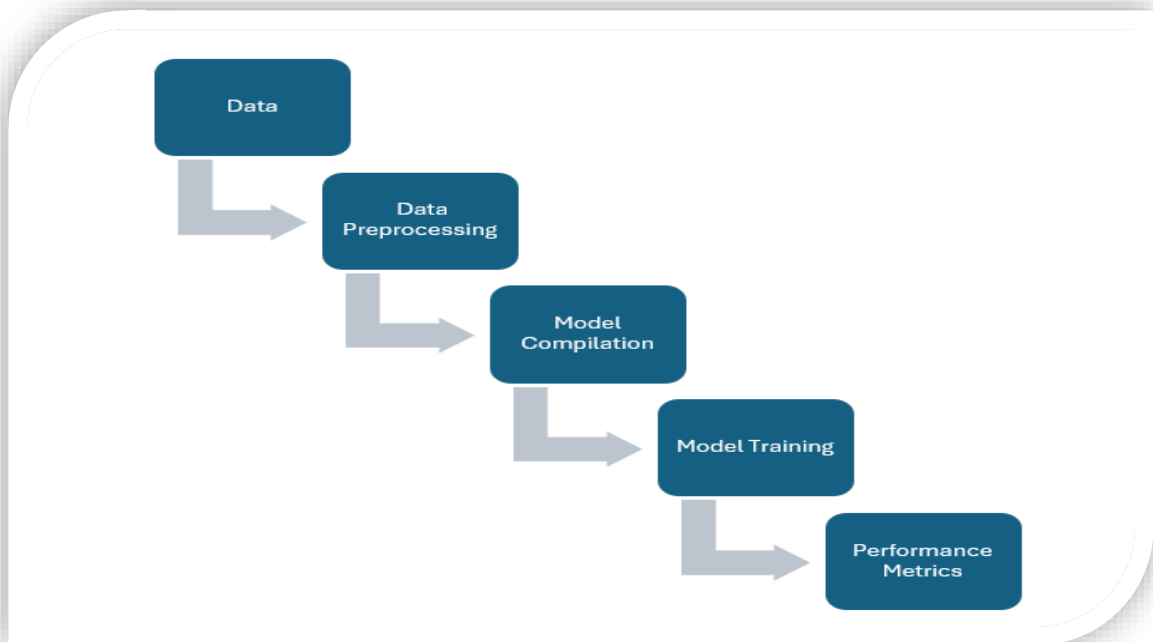
Input Layer: Accepts preprocessed chest X-ray images as input.

Feature Extraction Layers: Utilize convolutional and pooling layers to extract hierarchical features from the input images.

Classification Layers: Fully connected (dense) layers that process extracted features to perform binary classification (pneumonia-positive or normal).

Output Layer: Applies a sigmoid activation function to produce a probability score indicating the likelihood of pneumonia presence.

8. Flow chart:



9. Project Scope:

This project focuses on developing and evaluating a deep learning model for the classification of pediatric chest X-ray images into pneumonia-positive and normal categories. The scope includes data preprocessing, model development using various CNN architectures, training, validation, and performance evaluation. Integration of the model into clinical workflows, real-time deployment, and considerations of model interpretability are acknowledged as important aspects but are beyond the current scope of this project.

10. Tools/Technology

- Programming Language: Python
- Deep Learning Frameworks: TensorFlow, Keras
- Libraries: NumPy, OpenCV, scikit-learn
- Development Environment: Jupyter Notebook

11. Conclusion:

The development of a deep learning-based system for the detection of pediatric pneumonia from chest X-ray images has the potential to significantly enhance diagnostic accuracy and efficiency. By automating the classification process, the system can assist healthcare professionals in making timely and reliable diagnoses, ultimately improving patient outcomes. Future work may involve integrating the model into clinical settings, addressing challenges related to model interpretability, and expanding the system to detect a broader range of pulmonary conditions.

12. References

- Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Ng, A. Y. (2017). CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. arXiv preprint arXiv:1711.05225.
- Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2020). An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. arXiv preprint arXiv:2010.11929.
- Kermany, D. S., Zhang, K., & Goldbaum, M. (2018). Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification. Mendeley Data, v2.
- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 770-778).
- Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv preprint arXiv:1409.1556.
- Tan, M., & Le, Q. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. arXiv preprint arXiv:1905.11946.
- Chollet, F. (2017). Xception: Deep Learning with Depthwise Separable Convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 1251-1258).
- Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv preprint arXiv:1704.04861.
- Sandler, M., Howard, A., Zhu