Preprocessing-Enhanced Diagnosis for Pneumonia Detection

Allada Sankara Rao[1], Karri lavanya[2], Bhargavi Durga[3], Manikanta Sirasapalli[4], Kudupudi Jyothi Sindhura[5], Manoj Kumar Nigam[6]

Dadi Institute of Engineering and Technology (A), Anakapalli, India

asankararao@diet.edu.in[1], pindilavanya94173@gmail.com[2], Bhargavidurga0905@gmail.com[3], manikantasirasapalli24@gamil.com[4], kudupudisindhu555@gmail.com[5], mamoj.nigam@kalingauniversity.ac.in[6]

Abstract.
This study explores deep learning to improve pneumonia diagnosis using chest X-rays. Traditional methods are slow and less accurate, so we developed an ensemble model combining pre-trained CNNs for better results. By applying preprocessing techniques and leveraging *ResNet-50* for classification and *MobileNetV2* for feature extraction, our approach ensures faster, more accurate detection, leading to improved patient care.

Keywords. Chest X-rays, Pre-trained convolutional neural networks (CNNs), Image preprocessing, Normalization, Median filtering application, Binarizing, Resnet50, MobileNetV2, Feature extraction.

1. INTRODUCTION

Pneumonia is a lung infection caused by bacteria, viruses, or fungi, leading to breathing difficulties. It primarily affects children and the elderly, causing 2.5 million deaths annually. The infection fills alveoli with fluid, reducing oxygen levels. Traditional X-rays lack accuracy, but deep learning models using CNNs improve detection. Ensemble learning enhances accuracy by combining multiple algorithms, making diagnosis faster and more reliable. AI-driven imaging ensures early detection, leading to better treatment and improved patient outcomes..Classification models are:

1. Pretrained CNN models
2. ResNet-50 (classification)
3. MobileNetV2 (feature extraction)

2. LITERATURE REVIEW

An ensemble-based CAD system has shown high accuracy in detecting pneumonia from chest X- rays, though some mispredictions and inefficiencies remain. Deep learning, especially CNNs, outperforms traditional methods, while transfer learning improves accuracy with less computation. Enhanced textural features aid early detection, and ML models like KNN, SVM, and RF achieve 4–8% better F-scores.

3. METHODOLOGY

This model uses deep learning to analyze chest X-rays for pneumonia diagnosis. Data preprocessing ensures consistency, while augmentation adds variability. Pre-trained models like ResNet-50 classify images, and MobileNetV2 extracts features. CNNs capture spatial details, and ensemble classifiers improve accuracy. Performance is evaluated using accuracy, precision, recall, and F1-score.

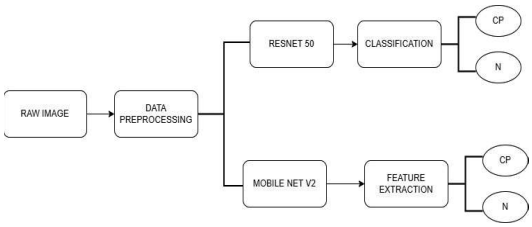


Figure 3.1-Block diagram of proposed model

3.1. Preprocessing

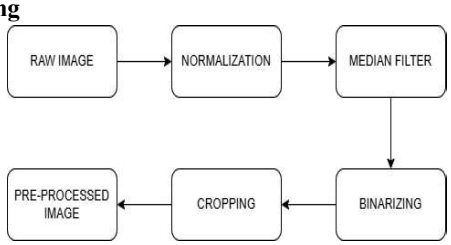


Figure 3.2-Block diagram of pre-processing

- **Image enhancement.**

Study images came from various sources in different formats. Negin Radiology's 16-bit TIFF files appeared black on standard screens, while Harvard and SRMC's DICOM images required enhancement. Normalization adjusted pixel values, converting images to 32-bit float format. Final images were saved as 8-bit TIFF files for compatibility and easier handling.

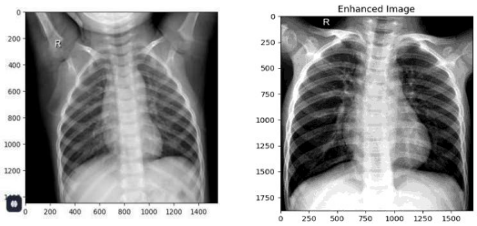


Figure 3.3- Normalization of Raw Images

- **Selection**

We focused on lungs in each image, essentially zooming in on a specific area (rows 241-340, columns 121-370). Then, we cleaned up the images by removing anything too bright (pixel intensity above 200). This made the data clearer and sped things up.

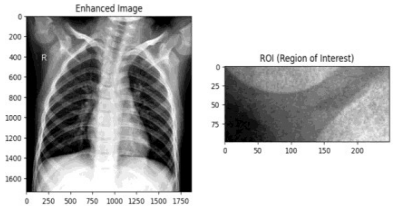


Figure 3.4-Selection of Normalized Images

- **Median Filtering and Binarizing**

Median filtering removes noise while preserving crucial details in chest X-rays, enhancing clarity for pneumonia detection. Proper kernel size ensures balance—too much blurs details, too little retains noise. Binarization sharpens key areas, highlighting abnormalities for faster, more accurate diagnoses. This refined image aids doctors in making reliable medical decisions efficiently.

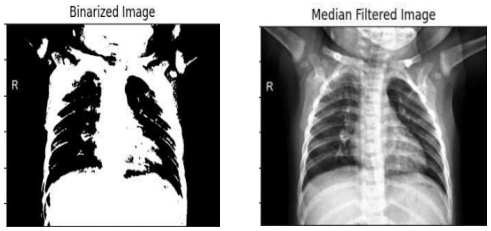


Figure 3.5- Binarization of Median Filtered Images

- **Automated cropping**

Our technique refines chest X-rays like cleaning a window for clarity. Noise is removed while preserving crucial details, enhancing essential features. Highlighting the lung area ensures abnormalities stand out for easier detection. This sharper image enables faster, more accurate diagnoses, ultimately leading to improved patient care and timely medical intervention.

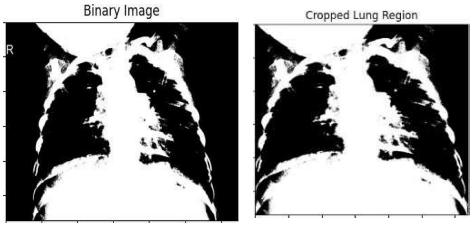


Figure 3.6- Cropping of Binarized Images

3.2. Leveraging pre-trained models

- RESNET-50

A pre-trained model for image recognition on adapting pneumonia from chest X-ray images, by transferring much of its pre-existing knowledge with most of its layers initially frozen to adapt for an even bigger dataset 14,049 images while subsequently being fine-tuned in an even more limited yet specially oriented dataset with 6,826 images.

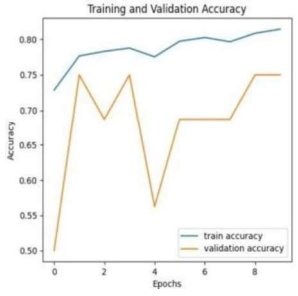
- MOBILENETV2

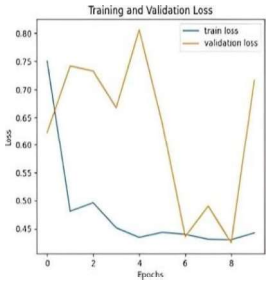
MobileNetV2, a pre-trained image-recognition engine, aids a gradient boosting classifier in learning efficiently. Modifying its final layers optimizes accuracy while saving time and preventing confusion.

4. RESULTS AND DISCUSSIONS

TRAINING AND VALIDATION ACCURACY :This pattern shows strong training performance but struggles with unseen validation data. Fluctuations in validation accuracy, especially a final drop, indicate overfitting. Regularization, data augmentation, and early stopping improvegeneralization. Tuning learning rate and batch size enhances stability. Mid-epoch stability suggests convergence, but a steep validation drop confirms overfitting. Adjusting hyperparameters helps balance model speed and data processing, reducing overfitting for better generalization and making pneumonia detection more reliable.

TRAINING AND VALIDATION LOSS: The training loss steadily decreases, showing effective learning, but fluctuating validation loss suggests poor generalization and possible overfitting. The model may memorize patterns instead of learning general features. Regularization, dropout, and data augmentation can improve generalization. Adjusting learning rate and training duration may stabilize validation performance. A steep validation loss increase in final epochs confirms overfitting. Applying dropout, early stopping, or data augmentation helps the model handle unseen data more effectively.





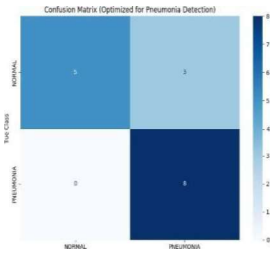


Figure 4.1-Training and validation accuracy Figure 4.2- Training and validation loss

Figure 4.3- Confusion matrix

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Biographies

Mr. Sankara Rao Allada, a VLSI System Design postgraduate, is pursuing a Ph.D. in Wireless Sensor Networks. He is an Assistant Professor at Dadi Institute of Engineering and Technology with 13 years of teaching experience in electronics, communication, and microprocessors. His interests include digital image processing, IoT, and VLSI coding.

Mrs.Karri Lavanya, post graduate in Computer Science and Engineering.Currently she is working as Assistant Professor in the department of CSE(AIML&DS) at Dadi Institute of Engineering and Technology.She has over 4 years of teaching experience.Her areas of interest include Data base systems, Computer Networks, Cloud Computing.

Dr. Manoj Kumar Nigam, Professor of Electrical Engineering at Kalinga University, Raipur, has 22 years of teaching experience. He holds a Ph.D. in Power Systems and has published 85 research papers. With 12 granted patents, he has authored multiple books. His research focuses on multilevel inverters, power grid stability, renewable energy, and microgrids.

Bhargavi Durga, Manikanta Sirasapalli, and Kudupudi Jyothi Sindhura are final year Bachelor's students in Electronics and Communication Engineering at Dadi Institute of Engineering and Technology. Bhargavi is an ambitious learner focused on innovation and excellence. Manikanta is dedicated to applying his technical skills to real-world challenges. Jyothi Sindhura is eager to grow and contribute to the field through continuous learning. Together, they strive to enhance their knowledge and make a meaningful impact in the engineering domain.