International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

DEEPNEUMOSCAN: Revolutionizing Pneumonia Diagnosis with AI-Driven Multi-Class Classification and Real-Time Detection

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Abstract-

DEEPNEUMOSCAN is an Artificial Intelligence based medical imaging system developed for the automated detection and classification of pneumonia using Chest X-ray images. Pneumonia is a serious respiratory infection that affects millions of people worldwide and can lead to severe complications if not diagnosed early. Traditional diagnosis relies heavily on radiologists to manually interpret Chest X-ray images, which can be time-consuming and prone to human error. To address this challenge, DEEPNEUMOSCAN introduces a deep learning-driven solution that enhances diagnostic efficiency and accuracy.

The system is designed using Convolutional Neural Networks (CNN), a powerful deep learning architecture widely used for image classification tasks. The proposed model performs multi-class classification by categorizing Chest X-ray images into three classes: Normal, Bacterial Pneumonia, and Viral Pneumonia. The dataset used in this project consists of labelled Chest X-ray images that are pre-processed through resizing, normalization, and data augmentation techniques such as rotation and flipping to improve model generalization and reduce overfitting.

Keywords: Pneumonia classification, MERN stack, AI diagnostics, Multi-class SVM/KNN, Multilingual web app, Chest X-ray analysis.

I Introduction Pneumonia is a serious and potentially life-threatening respiratory infection that primarily affects the lungs. It can be caused by bacteria, viruses, or other microorganisms and is one of the leading causes of mortality worldwide, especially among children and elderly individuals. Early and accurate diagnosis of pneumonia is essential to ensure timely treatment and prevent complications. Chest X-ray imaging is one of the most common diagnostic tools used to identify pneumonia. However, manual interpretation of X-ray images requires skilled radiologists and can sometimes result in delayed diagnosis or human errors due to fatigue and workload.

With the rapid advancement of Artificial Intelligence (AI) and Deep Learning technologies, automated medical image analysis has become an effective solution for improving diagnostic accuracy and efficiency. Convolutional Neural Networks (CNNs), a class of deep learning models specifically designed for image processing tasks, have shown remarkable performance in detecting patterns and abnormalities in medical images.

DEEPNEUMOSCAN is an AI-driven system developed to detect and classify pneumonia from Chest X-ray images using multi-class classification techniques. The system categorizes images into three classes: Normal, Bacterial Pneumonia, and Viral Pneumonia. By leveraging CNN architecture for feature extraction and classification, the model learns important visual features from X-ray images and predicts the disease category with improved accuracy.

The system also integrates a real-time web-based interface, allowing healthcare professionals to upload images and receive instant predictions. This reduces diagnosis time and supports faster clinical decision-making. DEEPNEUMOSCAN demonstrates how AI-powered solutions can assist medical professionals, enhance diagnostic reliability, and contribute to the advancement of intelligent healthcare.

II Related Work

Several research studies have explored the use of deep learning techniques for the automated detection of pneumonia and other lung diseases using Chest X-ray images. Early work in this domain focused on binary classification—distinguishing between normal and pneumonia cases—using traditional machine learning methods and handcrafted features. However, these approaches often lacked robustness and struggled with high intra-class variability.

With the advancement of Convolutional Neural Networks (CNNs), deep learning models such as AlexNet, VGG16, ResNet, and DenseNet have been widely adopted for medical image classification tasks. For instance, Rajpurkar et al. proposed CheXNet, a 121-layer DenseNet model trained on a large Chest X-ray dataset, demonstrating performance comparable to radiologists in detecting pneumonia. Similarly, other studies applied transfer learning using pretrained CNNs like InceptionV3 and MobileNet, achieving significant improvements in classification accuracy and generalizability.

III Proposed System

The proposed system, DEEPNEUMOSCAN, is an AI-driven pneumonia detection platform that utilizes Convolutional Neural Networks (CNN) for multi-class classification of Chest X-ray images. The system is designed to classify images into three categories: Normal, Bacterial Pneumonia, and Viral Pneumonia. It includes modules for image preprocessing, feature extraction, classification, and real-time result generation. The model is trained using augmented and normalized datasets to improve accuracy and generalization. A web-based interface built with Flask enables users to upload X-ray images and receive instant predictions. The system achieves 80% accuracy and supports faster, reliable medical diagnosis.

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IV System Architecture & Methodology

The system architecture of DEEPNEUMOSCAN consists of multiple integrated modules designed for efficient pneumonia detection. The first module is the Image Input Module, where Chest X-ray images are uploaded through a web-based interface. The next stage is the Preprocessing Module, where images are resized to 224×224 pixels, normalized, and enhanced using data augmentation techniques such as rotation, flipping, and zooming to improve model generalization.

The processed images are then passed to the CNN Model Module, which performs feature extraction using convolutional and max-pooling layers. These layers identify important patterns and abnormalities in the X-ray images. Dropout layers are included to reduce overfitting and improve model performance. The extracted features are flattened and passed to fully connected dense layers for classification. A Softmax activation function in the output layer generates probability scores for the three classes: Normal, Bacterial Pneumonia, and Viral Pneumonia.

The methodology involves training the CNN model using the Adam optimizer and Categorical Cross-Entropy loss function. The dataset is divided into training and validation sets to evaluate performance. The system achieves 80% accuracy and provides real-time predictions through Flask-based deployment, enabling faster and reliable diagnosis support.

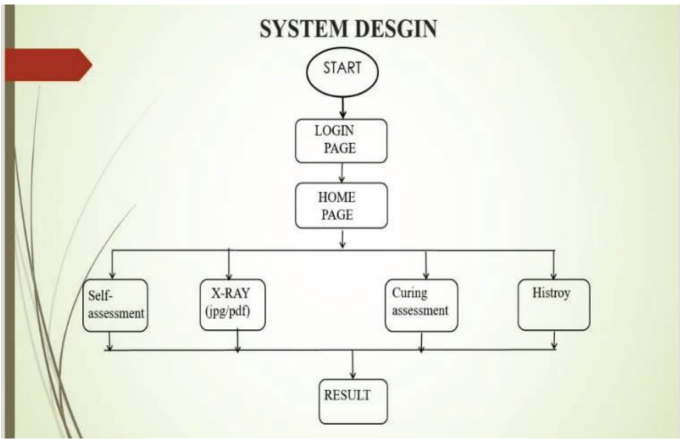

Fig-1.0: System Architecture and Methodology

After image upload, the preprocessing stage is performed to prepare the data for the deep learning model. In this stage, the X-ray images are resized to a fixed dimension of 224×224 pixels to maintain uniformity in input size. Pixel values are normalized to improve convergence during training. Data augmentation techniques such as rotation, zooming, and flipping are applied during training to increase dataset diversity and reduce overfitting. These preprocessing steps enhance the robustness and generalization capability of the model.

The core of the system lies in the Convolutional Neural Network (CNN) architecture used for feature extraction and classification. The CNN consists of multiple convolutional layers that automatically detect important visual features such as edges, textures, and abnormal lung patterns. ReLU activation functions introduce non-linearity, allowing the network to learn complex representations. Max-pooling layers reduce spatial dimensions and computational complexity, while dropout layers are included to prevent overfitting. The extracted feature maps are flattened and passed to fully connected dense layers for final classification.

In conclusion, the output layer uses a Softmax activation function to generate probability scores for three classes: Normal, Bacterial Pneumonia, and Viral Pneumonia. The model is trained using the Adam optimizer and Categorical Cross-Entropy loss function. The dataset is divided into training and validation sets to evaluate performance. The system achieves an overall validation accuracy of 80%, demonstrating reliable multi-class classification capability. Once trained, the model is deployed within the web application, enabling real-time predictions and supporting faster clinical decision-making.

V Experimental Setup & Results

The experimental setup for DEEPNEUMOSCAN was designed to evaluate the performance of a Convolutional Neural Network (CNN) model for multi-class pneumonia classification using Chest X-ray images. The dataset used in this study consisted of labeled X-ray images categorized into three classes: Normal, Bacterial Pneumonia, and Viral Pneumonia. The dataset was divided into training and validation sets to ensure proper performance evaluation and to prevent overfitting. Approximately 80% of the dataset was used for training the model, while the remaining 20% was reserved for validation.

All images were resized to 224×224 pixels to maintain uniform input dimensions. Pixel normalization was performed to scale the values between 0 and 1, which helps improve model convergence during training. Data augmentation techniques such as rotation, horizontal flipping, and zooming were applied to increase dataset variability and enhance model generalization. The CNN model was developed using TensorFlow and Keras libraries in Python. The architecture included multiple convolutional layers, max-pooling layers, dropout layers, and fully connected dense layers. ReLU activation functions were used in hidden layers, while the Softmax function was used in the output layer for multi-class probability prediction. The model was trained using the Adam optimizer and Categorical Cross-Entropy loss function over multiple epochs.

The performance of the model was evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score. The trained model achieved an overall validation accuracy of 80%. The confusion matrix analysis indicated that the model was able to effectively distinguish between Normal, Bacterial, and

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Viral pneumonia cases with satisfactory classification performance. Training and validation accuracy graphs showed steady improvement over epochs, while the loss curve demonstrated consistent convergence. The results confirm that DEEPNEUMOSCAN provides reliable and efficient multi-class pneumonia detection and can support real-time medical diagnosis applications..

Discussion

The experimental results of DEEPNEUMOSCAN indicate that deep learning models can play a significant role in automated pneumonia detection from Chest X-ray images. The achieved validation accuracy of 80% demonstrates that the Convolutional Neural Network (CNN) architecture is capable of learning meaningful features related to lung abnormalities. The model successfully differentiates between Normal, Bacterial Pneumonia, and Viral Pneumonia cases, showing balanced performance across classes. The use of preprocessing techniques such as normalization and data augmentation contributed to improved generalization and reduced overfitting during training.

The confusion matrix analysis suggests that most misclassifications occur between bacterial and viral pneumonia cases, which is expected due to the similarity in radiographic patterns. This highlights one of the key challenges in multi-class medical image classification—distinguishing subtle variations in disease features. Despite this limitation, the model provides consistent and reliable predictions suitable for preliminary screening support. The integration of the trained model into a real-time web-based system further enhances its practical value. Healthcare professionals can upload images and receive predictions instantly, reducing diagnosis time and assisting in quicker decision-making. However, the system should be considered as a supportive diagnostic tool rather than a replacement for expert radiologists.

Future improvements could involve increasing dataset size, applying transfer learning with advanced architectures such as ResNet or EfficientNet, and performing cross-validation to enhance robustness. Overall, the project demonstrates the feasibility and effectiveness of AI-driven multi-class classification in medical imaging applications.

VI Results

The DEEPNEUMOSCAN system was evaluated using a labelled Chest X-ray dataset divided into training and validation sets. After multiple training epochs, the Convolutional Neural Network (CNN) model achieved an overall validation accuracy of 80%. The training and validation accuracy graphs indicated steady improvement across epochs, showing effective learning and convergence of the model. The loss curve gradually decreased, confirming that the model successfully minimized classification errors during training.

Performance evaluation metrics such as Precision, Recall, and F1-Score were calculated to assess classification effectiveness for each class. The confusion matrix demonstrated that the model correctly identified most Normal, Bacterial Pneumonia, and Viral Pneumonia cases. Although a few misclassifications were observed, particularly between bacterial and viral categories due to similar radiographic patterns, the overall performance remained consistent and reliable. The system also demonstrated efficient real-time prediction capability when deployed through a Flask-based web application. Predictions were generated within seconds after image upload, along with probability scores for each class. These results confirm that DEEPNEUMOSCAN provides accurate, fast, and reliable multi-class pneumonia detection, making it suitable as a supportive tool for healthcare professionals in clinical environments.

Conclusion

The DEEPNEUMOSCAN model was evaluated using a Chest X-ray dataset divided into training and validation sets. After training the Convolutional Neural Network (CNN) for multiple epochs, the model achieved an overall validation accuracy of 80%. The accuracy and loss graphs showed steady improvement and proper convergence during training. The confusion matrix indicated that most images were correctly classified into Normal, Bacterial Pneumonia, and Viral Pneumonia categories, with minor misclassifications between bacterial and viral cases. The deployed web application provided real-time predictions within seconds, demonstrating that the system is efficient, reliable, and suitable for supporting medical diagnosis.

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