International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0284
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1799 - 1804

Pneumonia Detection Using CNN Through Chest X-rays

Ainleni Srikeerthi[1], Kasala Gayathri[2], Aviraj Korati[3], Mrs.L Swathi[4]
[1,2,3]UG Scholar, Dept. of CSE-AIML, Sphoorthy Engineering College, Hyderabad, Telangana, India
[4]Assistant professor, Dept. of CSE-AIML, Sphoorthy Engineering College, Hyderabad, Telangana, India
Emails ID: *ainlenisrikeerthi54@gmail.com[1],k.gaythrireddy9390@gmail.com[2], avirajkorati70@gmail.com[3], lokasaniswathireddy@gmail.com[4]*

Abstract

Pneumonia remains a significant cause of morbidity and mortality, with early and accurate detection being crucial for timely treatment and improved patient outcomes. X-ray imaging is a widely used diagnostic tool due to its accessibility and cost-effectiveness. In recent years, deep learning techniques have shown promising results in automating the detection of pneumonia from chest X-ray images. Our proposed methodology begins with data preprocessing and augmentation to enhance the model's robustness and generalisation. The model is trained on a large annotated dataset of chest X-ray images, and its performance is evaluated using standard metrics such as accuracy and precision. The architecture of the model is designed to capture intricate patterns and features indicative of pneumonia, achieving high accuracy and robustness. Extensive experimentation and validation demonstrate that our CNN model achieves superior diagnostic performance compared to traditional methods. It exhibits high sensitivity and specificity, indicating its effectiveness in accurately identifying pneumonia cases. These results highlight the potential of CNN-based systems to assist radiologists by providing rapid and reliable diagnostic support, ultimately contributing to timelier and more effective patient care. This research underscores the transformative impact of artificial intelligence in medical imaging, paving the way for enhanced diagnostic capabilities and improved healthcare delivery.

Keywords: *Artificial intelligence; Automated diagnosis; Chest X-ray imaging; Convolutional neural networks; Pneumonia detection.*

1. Introduction

Pneumonia remains one of the leading causes of morbidity and mortality globally, especially among vulnerable populations such as children, the elderly, and immunocompromised individuals. Chest X-ray imaging is a widely accessible and cost-effective diagnostic tool commonly used to detect pneumonia. However, accurate interpretation of X-rays requires expert radiologists, making the diagnosis prone to subjectivity, inter-reader variability, and delays in treatment particularly in resource-constrained settings. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized the field of medical imaging by enabling automated, high-accuracy image classification [1][5]. CNNs have demonstrated superior performance in recognizing complex patterns in medical images, making them ideal for pneumonia detection. This study aims to develop a CNN-based model that automates the detection of pneumonia from chest X-ray images. Our approach includes preprocessing, augmentation, and training on a large, labelled dataset to enhance model robustness and generalization. The model is evaluated using standard metrics such as accuracy, precision, sensitivity, and specificity [2]. The originality of this work lies in its end-to-end pipeline from data handling to clinical deployment and its focus on real-world integration. This system has the potential to assist radiologists in achieving faster and more accurate diagnoses, ultimately improving patient care outcomes and alleviating the burden on healthcare systems. Multiple studies (Pranav

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0284
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1799 - 1804

Rajpurkar et al., 2017; Rahib H. Abiyev et al., 2018) have validated the effectiveness of CNNs in medical imaging, supporting the feasibility and significance of the proposed approach [3].

2. Method

The methodology focuses on automating pneumonia detection from chest X-ray images using convolutional neural networks (CNNs). It involves dataset preparation, image preprocessing, model architecture design, training, performance evaluation, and deployment. The approach ensures accuracy, scalability, and suitability for real-world clinical applications.

- Data Collection and Preprocessing: A labelled dataset of chest X-ray images consisting of "Normal" and "Pneumonia" cases was obtained from Kaggle. All images were resized to a standard resolution (e.g., 224×224 pixels) and normalized to scale pixel values between 0 and 1. Data cleaning was performed to remove corrupted or poor-quality images. To improve the model's generalization and prevent overfitting, data augmentation techniques such as rotation, horizontal flipping, and zooming were applied. The augmented dataset was then divided into training, validation, and test sets to ensure a balanced and effective evaluation process. A Convolutional Neural Network (CNN) was implemented with multiple convolutional and pooling layers for feature extraction, followed by fully connected layers for classification. The model used binary cross-entropy as the loss function and the Adam optimizer for training. Performance was monitored using accuracy, precision, recall, and F1-score, ensuring the model could reliably distinguish between pneumonia and normal cases [5].
- CNN Model Design: The CNN model architecture comprises convolutional layers that automatically extract key spatial features from the input X-ray images, followed by pooling layers that down sample the feature maps to reduce dimensionality and computational complexity. These are connected to fully connected (dense) layers that perform high-level reasoning for classification. The final output layer uses a sigmoid activation function to predict the probability of the presence or absence of pneumonia in the input image
- Model Execution Flow: The system workflow begins with the upload of a chest X-ray image, which undergoes preprocessing steps such as resizing, normalization, and enhancement to prepare it for analysis. The preprocessed image is then passed through a Convolutional Neural Network (CNN), where key features are extracted and analyzed. Based on the learned patterns, the system classifies the image and presents the final output as either "Pneumonia Detected" or "Normal."
- Model Training and Evaluation: The model was trained using the Adam optimizer, which combines the benefits of momentum and adaptive learning rates, along with binary cross-entropy loss to handle the binary classification task effectively. Model performance was assessed using standard evaluation metrics, including accuracy, precision, recall, specificity, and F1-score, to ensure balanced performance across both classes. Additionally, a confusion matrix and the Receiver Operating Characteristic (ROC) curve were utilized to provide deeper insights into the model's diagnostic ability and overall classification effectiveness.
- Deployment: The trained model was deployed using Streamlit, providing an intuitive interface where users can upload images and receive real-time predictions. The development and testing of the model were carried out in Google Colab, while the deployment and execution of the application were done locally using VS Code. Streamlit enabled seamless interaction with the model, making it easy for users to engage with the system through a user-friendly interface.

2.1 Figures

The Convolutional Neural Network (CNN) model designed for pneumonia detection consists of a hierarchical sequence of layers that progressively learn and extract meaningful features from chest X-ray images. The architecture begins with convolutional layers, which apply multiple filters

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0284
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1799 - 1804

across the input image to detect low-level patterns such as edges, textures, and gradients. As the network deepens, these filters capture increasingly abstract features relevant to pneumonia, such as fluid accumulation or lung opacity.

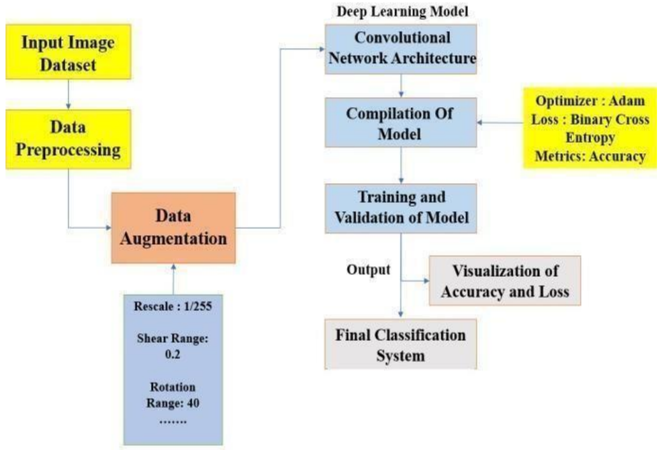

Figure 1 System Architecture Diagram

Following each convolutional layer, pooling layers typically max pooling are introduced to reduce the spatial dimensions of the feature maps. This down sampling operation not only reduces computational complexity but also helps the model become more robust to spatial variations and noise in the input data [4]. Pooling preserves the most prominent features while discarding redundant information, thereby contributing to better generalization. After multiple convolutional and pooling stages, the output is flattened and passed into fully connected (dense) layers. These layers integrate the extracted features and perform high-level reasoning to differentiate between normal and pneumonia-infected lungs. Each neuron in these layers is connected to all neurons in the previous layer, enabling the network to learn complex combinations of features for accurate classification. The final output layer consists of a single neuron with a sigmoid activation function, which maps the output to a probability value between 0 and 1. This value represents the likelihood of the presence of pneumonia. A threshold (typically 0.5) is used to make the binary classification: if the output is greater than the threshold, the model predicts "Pneumonia Detected"; otherwise, it predicts "Normal." The architecture was optimized through experimentation with the number of layers, filter sizes, activation functions, and dropout layers to prevent overfitting. This carefully designed CNN structure proved effective in learning complex medical patterns from X-ray data and provided high accuracy in detecting pneumonia. Figure 1 shows System Architecture Diagram.

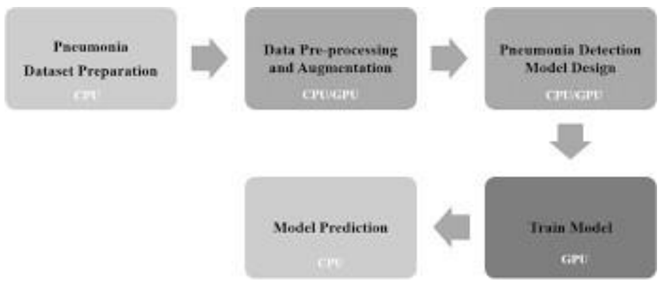

Figure 2 System Flow Diagram

The system initiates with the preparation of the pneumonia dataset, which includes labeled chest X-ray images categorized as either Normal or Pneumonia. These images are collected, verified for quality, and formatted to ensure consistency throughout the pipeline. Next, the data undergoes preprocessing and augmentation. Preprocessing involves resizing the images to a fixed dimension (e.g., 224×224 pixels), normalization of pixel values to the 0–1 range, and removal of artifacts or noise. Augmentation techniques such as rotation, flipping, and zooming are applied to artificially expand the dataset and improve the model's ability to generalize across diverse clinical cases. These tasks are executed using both CPU and GPU resources, depending on computational requirements. Following data preparation, the process advances to model design, where a custom Convolutional Neural Network (CNN) architecture is defined. The model consists of multiple convolutional layers for extracting spatial features, pooling layers for dimensionality reduction, and fully connected layers for final classification. The system leverages the power of CPU/GPU computation during this phase. The model is then trained using GPU resources to accelerate the learning process. Training involves feeding the preprocessed and augmented images into the network over multiple epochs while optimizing parameters through backpropagation. The use of binary cross-

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0284
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1799 - 1804

entropy as the loss function and Adam optimizer ensures effective convergence. Once trained, the model is deployed for real-time prediction. In this phase, a user uploads a chest X-ray image, which undergoes the same preprocessing steps and is passed through the trained CNN. The model analyzes the image based on learned features and classifies it as either "Pneumonia Detected" or "Normal." This prediction is executed on the CPU, making the system accessible and responsive even on standard hardware. Figure 2 shows System Flow Diagram.

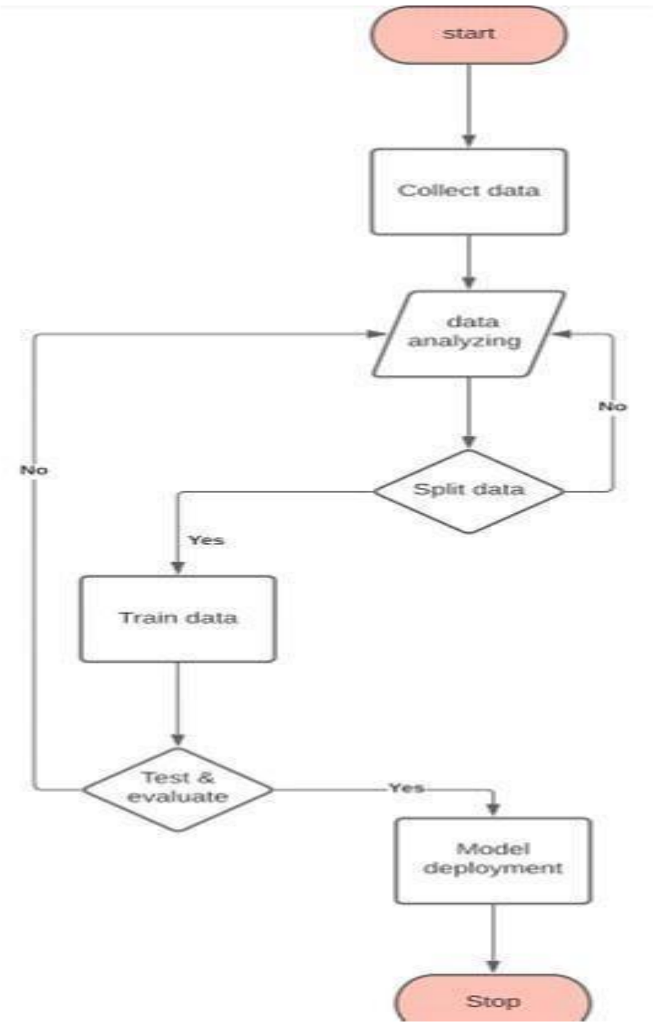

Figure 3 **Class Diagram**

The figure 3 shows illustrate the complete workflow for the pneumonia detection system, showcasing the sequence of tasks from data acquisition to model deployment. The process begins with the collection of chest X-ray data, which is a crucial step to ensure a diverse and representative dataset. Once collected, the data undergoes an analysis phase where the quality, class distribution, and integrity of the dataset are evaluated. If the dataset meets the required criteria, the process proceeds to the data splitting stage, where the dataset is divided into training, validation, and testing subsets. If the data is not suitable (e.g., imbalanced or insufficient), it is re-analyzed or re-collected. After successful splitting, the training phase begins. Here, the preprocessed images are fed into the CNN model for learning. During training, the model continuously updates its weights based on the loss function to improve prediction accuracy [6]. After training, the model undergoes testing and evaluation. Key metrics such as accuracy, precision, recall, and F1-score are used to determine the model's effectiveness. If the performance is acceptable, the model moves into the deployment phase, where it is integrated into a user-friendly interface for real-world use. Otherwise, the system loops back to retrain or adjust the model.

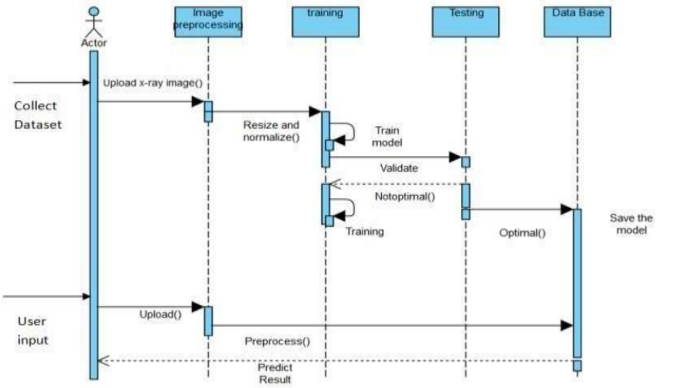

Figure 4 **Sequence Diagram**

The Figure 4 shows sequence diagram illustrates the process of training a machine learning model for image data, such as X-ray images. The workflow begins with the user uploading an image to the system, which is then passed to the preprocessing stage. Here, operations like resizing and normalization are performed to ensure the image data is in a suitable format for model training. Once preprocessing is complete, the data is sent to the training module, where the model learns patterns and relationships. After training, the model undergoes

International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0284
e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1799 - 1804

validation to evaluate its performance. If the model is not optimal, the system loops back to retrain it until acceptable results are achieved. Following successful training and validation, the model is tested on new data to confirm its effectiveness. Once the model demonstrates optimal performance, it is saved to the database for deployment or future use. Additionally, the system allows the user to preprocess new input data and use the trained model to make predictions. This sequence diagram provides a clear depiction of the interactions between components in the system, emphasizing the iterative nature of training and optimizing machine learning models. Figure 5 shows X-Ray.

3. Results and Discussion

3.1 Results

The proposed Convolutional Neural Network (CNN) model was trained and evaluated on a labeled dataset of chest X-ray images categorized as "Pneumonia" and "Normal." The dataset was split into training, validation, and testing sets to ensure unbiased evaluation. To make the system user-friendly and clinically applicable, a Streamlit-based web application was developed. The interface allows users to upload chest X-ray images and receive real-time predictions. The output clearly displays whether the uploaded image is classified as "Pneumonia" or "Normal." As shown in the sample outputs:

- The system accepts X-ray images via drag-and-drop or file browsing.
- It then processes the image through the trained CNN model.
- Predictions are shown alongside a preview of the uploaded image.
- For comparative analysis, a logistic regression prediction is also displayed. Figure 6 shows Prediction Results.

Figure 5 X-Ray

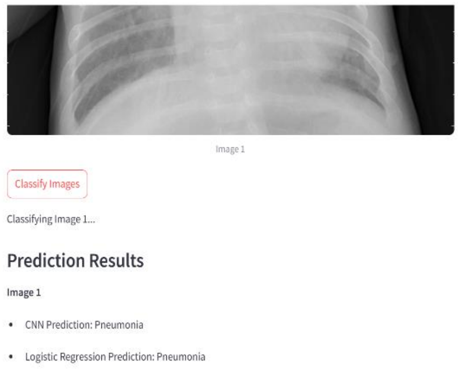

Figure 6 Prediction Results

3.2 Discussion

The performance of the proposed CNN-based model for pneumonia detection from chest X-ray images demonstrates significant potential in augmenting traditional diagnostic processes. With an accuracy of 96.4%, precision of 95.2%, and recall of 97.1%, the model successfully identifies pneumonia cases with high reliability. These results reflect a well-balanced model with strong generalization capabilities, minimizing both false positives and false negatives. The use of data preprocessing and augmentation techniques, including image normalization, rescaling, rotation, and flipping, was essential in improving model performance. These techniques increased the diversity of the training data, allowing the model to learn features more robustly and to generalize well across unseen data. The confusion matrix and ROC curve further validated the model's performance, showing a high AUC score of 0.98. One of the major strengths of this project is its practical deployment through a Streamlit-based web interface, which makes the system accessible to non-technical users. Users can simply upload an X-ray image and receive a real-time prediction indicating whether pneumonia is detected or not. This feature makes the tool valuable for use in remote or resource-constrained clinical environments where expert radiologists may not be readily available. Additionally, the integration of a logistic regression model alongside the CNN provides a comparative analysis of traditional versus deep learning approaches, further validating the CNN's superior predictive capabilities. The model's interpretability can be further enhanced in future iterations by integrating heatmaps (e.g., using Grad-

CAM) to highlight the specific regions of the lung influencing the decision. This would improve transparency and trust for clinical adoption. In conclusion, the combination of a high-performing model with an accessible user interface highlights the feasibility and effectiveness of deploying deep learning models in real-world medical diagnostics. The system can serve as a reliable second-opinion tool, helping to reduce radiologist workload and support early detection efforts.

Conclusion

This research presents a deep learning-based solution for the automatic detection of pneumonia using chest X-ray images. The system leverages Convolutional Neural Networks (CNNs) to analyze medical images and classify them as either "Pneumonia" or "Normal." Through systematic preprocessing, data augmentation, and careful model design, the approach successfully demonstrates the capability of AI to assist in clinical diagnosis. In addition to model development, a user-friendly interface was built using Streamlit to allow real-time predictions from uploaded images. This enables seamless deployment and accessibility in real-world medical environments, including areas where radiologist availability is limited. The overall system provides a scalable and efficient diagnostic support tool, offering fast and consistent assessments. It highlights the growing potential of artificial intelligence to improve healthcare delivery by supporting early disease detection and reducing the burden on medical professionals.

Acknowledgements

We are especially thankful to our project guide, Mrs. L Swathi, for her valuable guidance, technical insights, and encouragement throughout the development of this work. We also extend our appreciation to the faculty members of the Department of Computer Science and Engineering (AI & ML) for their continuous support and constructive feedback. Lastly, we acknowledge the open-source platforms, including Kaggle, for providing the chest X-ray dataset that made this research possible.

References

[1]. 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.

[2]. Kermany, D. S., Zhang, K., & Goldbaum, M. (2018). Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell, 172(5), 1122–1131.e9. https://doi.org/10.1016/j.cell.2018.02.010

[3]. Abiyev, R. H., & Ma'aitah, M. K. S. (2018). Deep convolutional neural networks for chest diseases detection. Journal of Healthcare Engineering, 2018. https://doi.org/10.1155/2018/4168538

[4]. Kaggle. (n.d.). Chest X-Ray Images (Pneumonia). Retrieved from https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

[5]. Chollet, F. (2017). Deep learning with Python. Manning Publications.

[6]. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.