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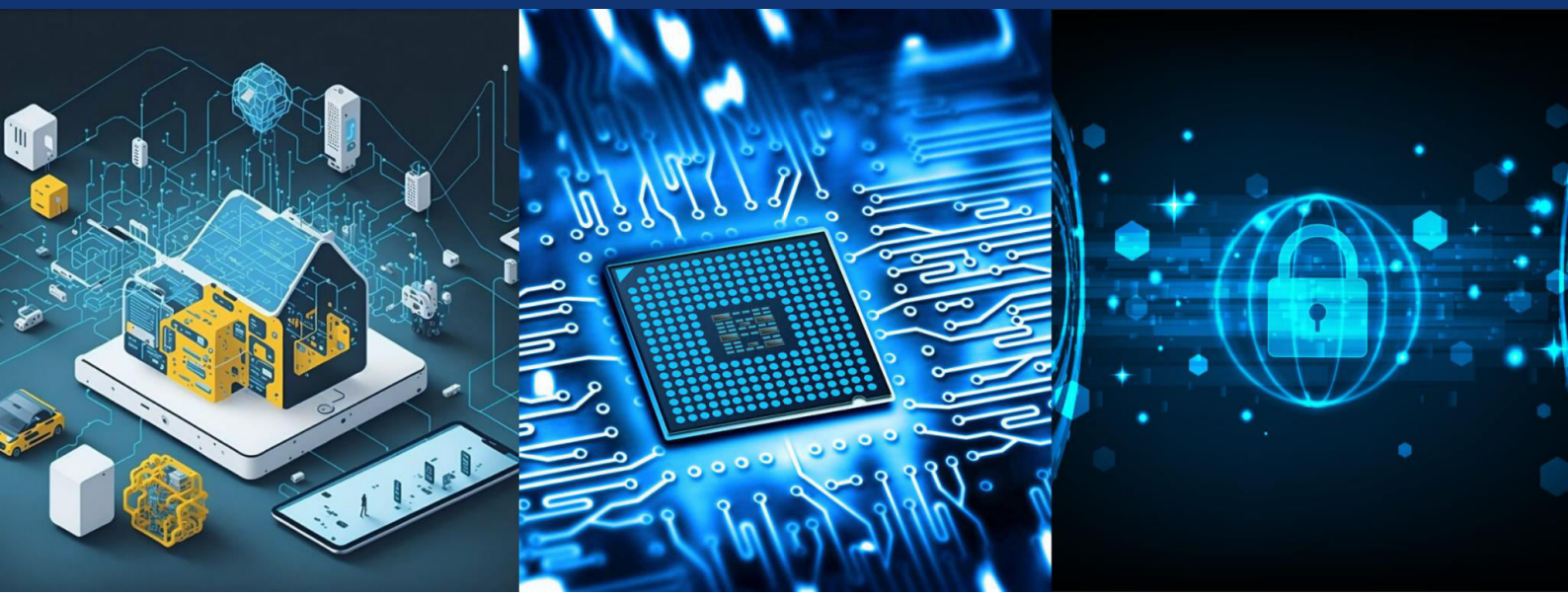

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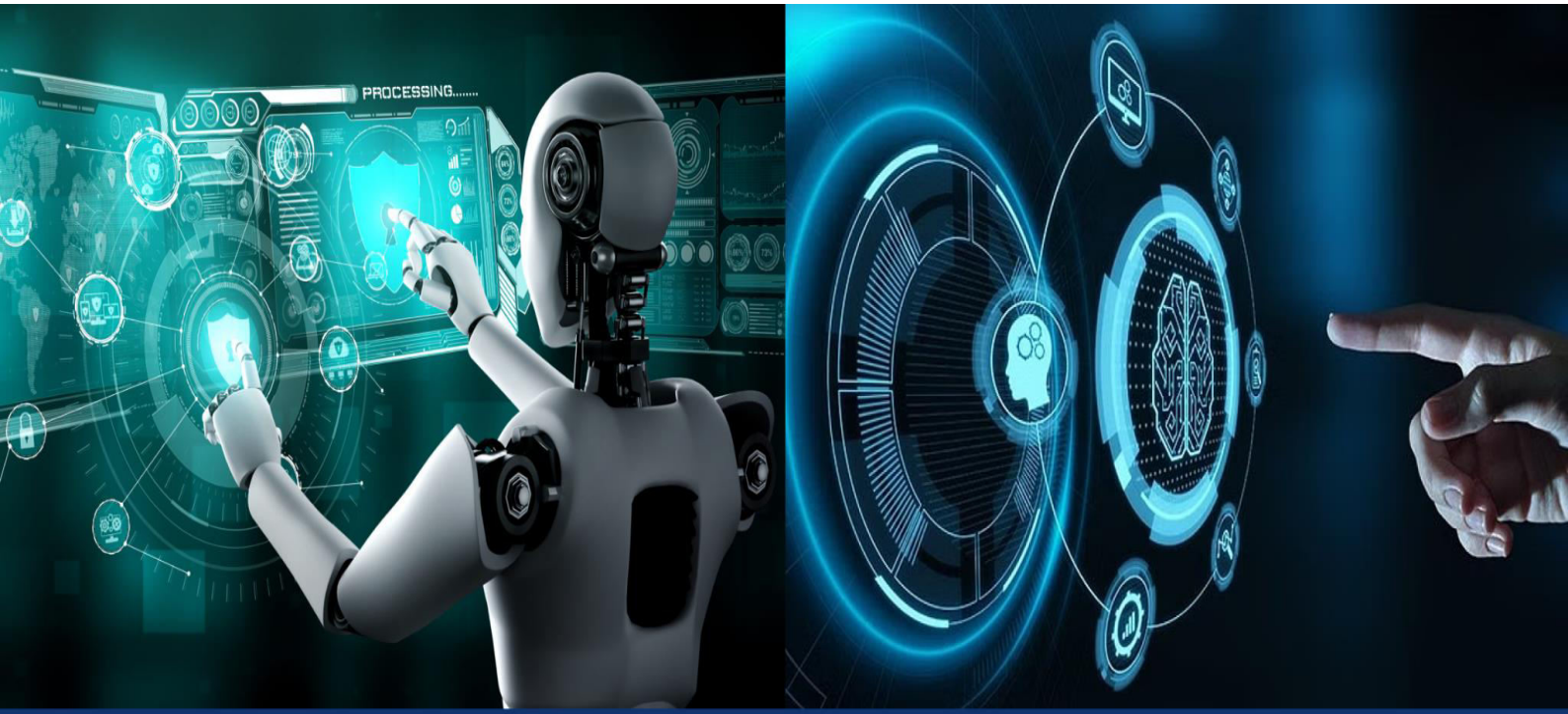

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Pneumonia Disease Detection Using Convolutional Neural Networks for Early Diagnosis

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ABSTRACT: Pneumonia is a severe respiratory infection that requires early and accurate diagnosis for effective treatment. This project presents an automated pneumonia detection system using deep learning, implemented as a web-based application. The system utilizes a Convolutional Neural Network (CNN) model trained on chest X-ray (CXR) images to classify pneumonia cases. The Flask-based application allows users to upload CXR images, which are pre processed and resized before being fed into the trained CNN model. The model normalizes image pixel values and makes predictions based on learned patterns, classifying the input as pneumonia-positive or negative. The integration of Flask enables real-time diagnosis, making the system accessible for clinical and remote use. The application efficiently processes user inputs, stores uploaded images, and displays diagnostic results through an interactive interface. The pneumonia detection model achieves reliable classification accuracy, contributing to automated medical diagnosis. The user-friendly design ensures ease of use for medical professionals and patients. The system's capability to perform rapid and accurate pneumonia detection demonstrates the potential of deep learning in healthcare applications. Future enhancements include incorporating additional preprocessing techniques, improving model performance, and expanding the system to detect other lung diseases.

KEYWORDS: Pneumonia Disease, Deep Learning, Convolutional Neural Networks, Medical Image Classification, CXR

I. INTRODUCTION

Pneumonia is a severe respiratory infection that affects millions of people worldwide, posing a significant health threat, especially to children and the elderly. Accurate and early diagnosis is crucial for effective treatment, but traditional methods rely heavily on radiologists interpreting chest X-ray (CXR) images, which can be time-consuming and prone to human error. The rise of deep learning and artificial intelligence (AI) has introduced automated approaches that enhance pneumonia detection accuracy while reducing the burden on medical professionals. Convolutional Neural Networks (CNNs) have shown promising results in medical image classification, leveraging eature extraction techniques to identify pneumonia with high precision.

To facilitate real-time diagnosis, this study implements a web-based pneumonia detection system using Flask, allowing users to upload CXR images for automated analysis. The backend utilizes a pre-trained CNN model for image classification, which processes input images through normalization and resizing before making predictions. The Flask framework handles image storage, user interaction, and result visualization, providing a seamless experience for both medical professionals and patients. The system efficiently classifies pneumonia cases with a high accuracy rate, demonstrating the effectiveness of deep learning in medical imaging. By integrating a user-friendly interface with advanced machine learning techniques, this study contributes to the growing field of AI-driven healthcare solutions. Future improvements will focus on refining the model's accuracy, incorporating additional lung disease classifications, and deploying the system for real-world clinical applications.

II. LITERATURE SURVEY

Numerous studies have explored deep learning-based methods for pneumonia detection using chest X-ray (CXR) images, demonstrating the effectiveness of CNNs in medical image classification. Jain et al. evaluated various CNN architectures, including VGG16, ResNet50, and InceptionV3, achieving a validation accuracy of 92.31% and a recall of 98% for

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pneumonia detection. Chouhan et al. proposed an ensemble learning approach that combined multiple pre-trained models—AlexNet, DenseNet121, InceptionV3, ResNet18, and GoogLeNet—resulting in a test accuracy of 96.4% and a recall of 99.62%. Similarly, Rahman et al. explored transfer learning models such as AlexNet, ResNet18, DenseNet201, and SqueezeNet, with DenseNet201 achieving the highest classification accuracy of 98%. These studies highlight the potential of deep learning models in medical image analysis but also emphasize challenges such as high computational cost, data augmentation requirements, and the risk of overfitting due to limited training data.

In an effort to improve pneumonia classification performance, researchers have investigated hybrid approaches that combine CNN feature extraction with other machine learning techniques. Wu et al. developed an ACNN-RF model, integrating an adaptive CNN with a Random Forest classifier, achieving 97% accuracy. Mittal et al. introduced capsule networks for pneumonia detection, obtaining an accuracy of 96.36% on the Mendeley CXR dataset. Sarker et al. applied Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance image contrast and used deep residual learning to achieve 98.82% accuracy. Liang and Zheng incorporated residual connections with dilated convolution to improve feature extraction, achieving an F1-score of 92.7%. While these models improve classification accuracy, they often involve extensive computational resources and prolonged training times.

To address these limitations, recent research has explored extreme learning machines (ELM) as an alternative to traditional deep learning classifiers. ELMs eliminate iterative tuning parameters, significantly reducing training time while maintaining competitive accuracy. Ibrahim et al. proposed an ELM-based pneumonia classification model that achieved high accuracy with minimal computational requirements. Lahoura et al. developed a cloud-based ELM framework for breast cancer detection, demonstrating the effectiveness of ELM in medical diagnostics. Khan et al. introduced a deep extreme learning machine (DELM) for COVID-19 detection, achieving 97.59% accuracy. Inspired by these advancements, our study integrates a hybrid CNN-PCA feature extraction technique with an ELM classifier, optimizing performance while minimizing computational complexity. By incorporating CLAHE for contrast enhancement and deploying the system as a Flask-based web application, our approach ensures accurate, efficient, and accessible pneumonia detection

III. PROBLEM STATEMENT

Pneumonia is a serious respiratory infection that affects millions of people worldwide, requiring timely and accurate diagnosis for effective treatment. Traditional diagnostic methods rely on chest X-ray (CXR) analysis by radiologists, which can be time-consuming, prone to human error, and inaccessible in remote or resource-limited areas. With the advancements in artificial intelligence and deep learning, automated pneumonia detection systems have emerged as a potential solution. However, many existing models require high computational resources and struggle with issues such as image noise, low contrast, and class imbalance, affecting their reliability. Therefore, there is a need for an efficient, accurate, and accessible pneumonia detection application that can process CXR images in real-time, providing quick and reliable diagnostic results. This application should integrate deep learning techniques to improve accuracy while minimizing computational costs, making pneumonia diagnosis more efficient and widely available.

IV. OBJECTIVES

A. Early Detection

Develop a comprehensive tool capable of detecting of the major disease Pneumonia at an early stage to improve patient outcomes and reduce mortality rates.

B. High Accuracy

Utilize advanced deep learning models, including CNN to achieve high accuracy in disease detection, ensuring reliable diagnostic results for each condition.

C. User – Friendly Interface

Design and implement an intuitive and accessible user interface that allows healthcare professionals and non-experts alike to use the application effectively for disease detection and diagnosis

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D. Non -Invasive Diagnostic Tool

Provide a non-invasive diagnostic solution that reduces the need for costly and uncomfortable procedures, making healthcare more accessible and less burdensome for patients.

V. PROPOSED SYSTEMS

The proposed system is a web-based pneumonia detection application that automates the diagnosis of pneumonia using deep learning. The system is built using Flask as the backend framework and integrates a Convolutional Neural Network (CNN) model for classifying chest X-ray (CXR) images. The goal is to provide a fast, accurate, and accessible pneumonia detection tool that can assist healthcare professionals and individuals in identifying pneumonia cases without requiring specialized radiological expertise. By leveraging deep learning, the system enhances diagnostic accuracy while reducing manual effort and human error.

The system architecture consists of three main components: a user-friendly web interface (frontend), a Flask-based backend, and a deep learning model for classification. The frontend allows users to upload CXR images through a simple web form, while the backend processes the images, makes predictions, and returns the results to be displayed on the interface. The CNN model, trained on a pneumonia dataset, is responsible for analyzing the images and determining whether pneumonia is present. The entire system operates in real-time, ensuring a seamless and efficient diagnostic process.

The workflow of the system begins with the user uploading a CXR image in PNG, JPG, or JPEG format. The image is then stored in the system's uploads directory, where it undergoes preprocessing. OpenCV (cv2) is used to read and resize the image to a fixed 150×150 pixels dimension, ensuring consistency with the trained model. The image is then normalized by scaling pixel values between 0 and 1, improving the model's performance. After preprocessing, the CNN model analyses the image and produces a prediction. The output is a probability score, which is converted into a binary classification—either "Pneumonia Detected" or "No Pneumonia."

Once the prediction is generated, the Flask application updates the result page dynamically, displaying the user's name, age, gender, uploaded image, and diagnostic result. If pneumonia is detected, the system alerts the user with a positive classification, otherwise, it confirms a negative classification. The system ensures secure file handling and follows best practices for handling medical images efficiently.

By integrating Flask for backend processing, CNN for deep learning-based classification, and OpenCV for image preprocessing, this pneumonia detection system provides an efficient, scalable, and accessible solution for real-time medical diagnostics. Future enhancements will include improving model accuracy with larger datasets, implementing additional preprocessing techniques, and expanding the application to detect other lung diseases.

VI. METHODOLOGY

6.1. Data Pre Processing

The pneumonia detection system utilizes chest X-ray (CXR) images to classify cases as either pneumonia-positive or normal. Since raw images may have variations in size, contrast, and noise, preprocessing is performed to ensure consistency and enhance model performance. The preprocessing steps include resizing images to 150×150 pixels, normalizing pixel values to the range [0,1], and reshaping them to fit the CNN input format. OpenCV (cv2) is used for image reading and resizing, while NumPy is used for normalization. These steps help improve model accuracy and generalization while ensuring uniform input across different samples.

6.2. Model Development and Training

A Convolutional Neural Network (CNN) model is used for pneumonia classification. The model consists of convolutional layers for feature extraction, max-pooling layers for dimensionality reduction, and fully connected layers for classification. A sigmoid activation function is applied in the final layer to produce a binary classification output. The model is compiled using the Adam optimizer and trained with binary cross-entropy loss. During training, image augmentation techniques such as rotation, flipping, and zooming are used to improve generalization. The model is trained over multiple epochs with early stopping to prevent overfitting and optimize performance.

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6.3. Performance Evaluation

The trained model is evaluated on a separate test dataset using key performance metrics, including accuracy, precision, recall, F1-score, and AUC (Area Under the Curve). A confusion matrix is generated to analyse the classification accuracy and error rates for pneumonia and normal cases. The evaluation ensures that the model can reliably differentiate between pneumonia-positive and normal images while maintaining computational efficiency.

6.4. Web Based Deployment

To provide real-time pneumonia detection, the trained model is integrated into a Flask-based web application. Users can upload chest X-ray images via the web interface, and the backend processes them using the trained CNN model. The results are displayed instantly, indicating whether pneumonia is detected. The frontend, developed with HTML, CSS, and JavaScript, provides an intuitive and responsive user experience. Flask handles image uploads, model inference, and result rendering dynamically. This deployment enables remote medical diagnosis, making pneumonia detection more accessible to healthcare professionals and individuals without requiring in-person visits.

VII. USE CASE DIAGRAM

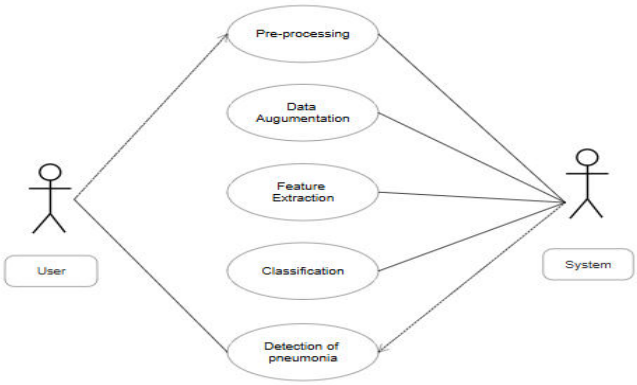

FIGURE 1. Use case diagram

VIII. SYSTEM ARCHITECTURE

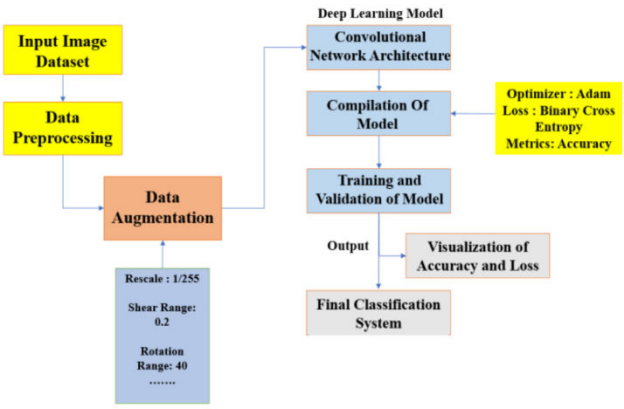

FIGURE 2. System architecture for proposed pneumonia detection model .

IX. RESULTS AND DISCUSSION

The Pneumonia detection system achieves accuracy of 91% using the CNN approach.
This application has the front-end website where the user can enter their details and get the results.

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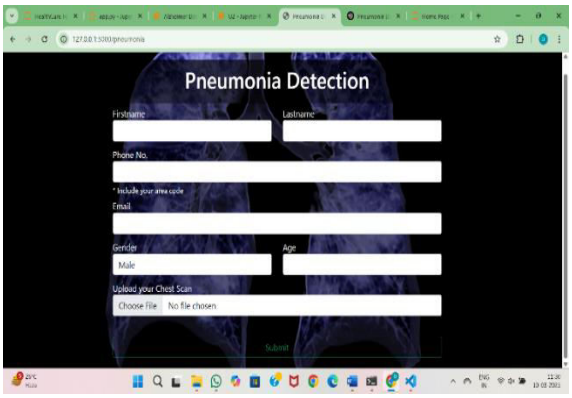

FIGURE 3. Home Page

The user gives the details asked in the form then the model takes those input from the user and predicts whether the person has the pneumonia or not. Let's see an example for Negative.

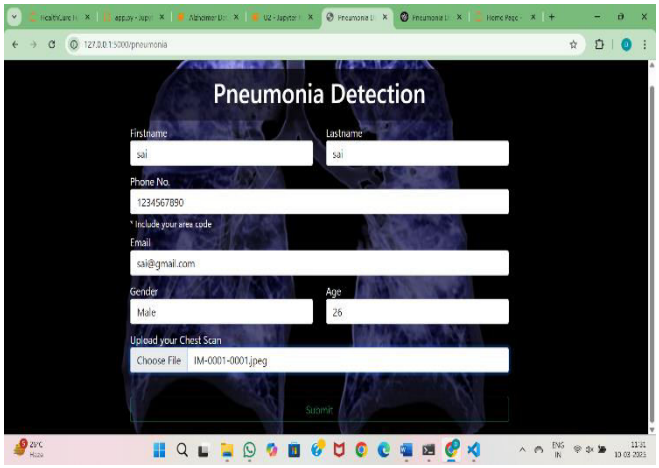

FIGURE 4. Image input

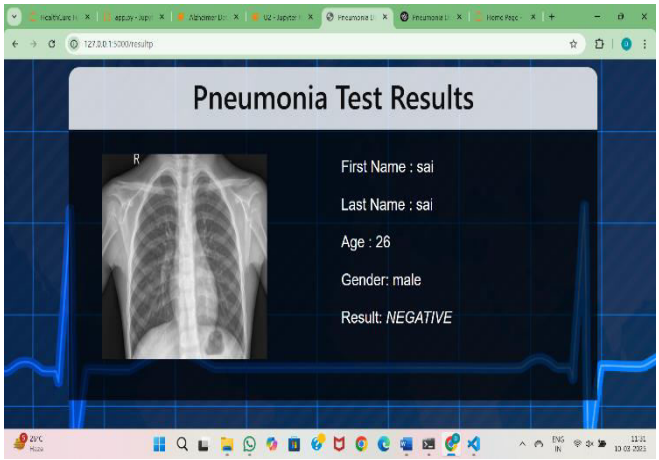

FIGURE 5. Test Results

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Let's see an example for Positive.

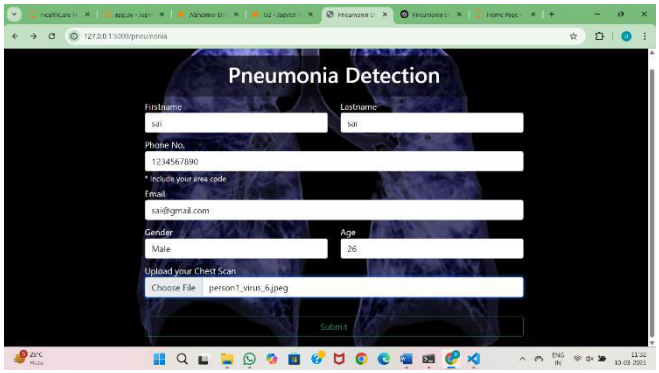

FIGURE 6. Image input

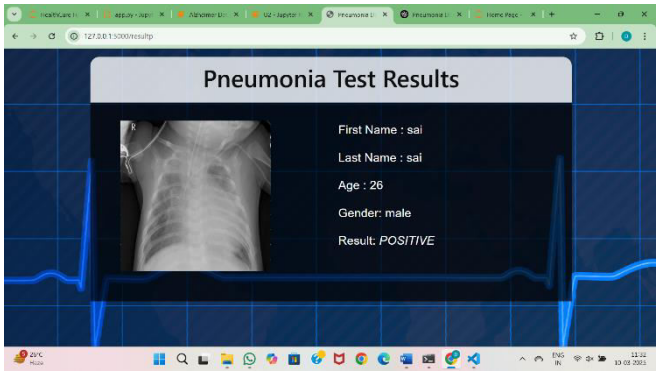

FIGURE 7. Test Results

TABLE 1. RESULTS

Name	Age	Gender	Result
Ramu	31	Male	Positive
Shiva	47	Male	Positive
Sai	53	Male	Negative
Laxmi	35	Female	Positive
Pooja	39	Female	Negative
Geetha	25	Female	Positive

X. CONCLUSION

The pneumonia detection system developed in this study effectively utilizes deep learning techniques to classify chest X-ray images into pneumonia-positive and pneumonia-negative cases. The preprocessing steps, including rescaling, resizing, and data augmentation, ensure that the model is trained on a diverse and standardized dataset, improving its robustness. The convolutional neural network (CNN) implemented in the code extracts relevant features from X-ray images and performs classification with high accuracy. Additionally, the model is deployed through a Flask-based web application, enabling real-time image upload and diagnosis. This system provides a reliable and accessible solution for automated pneumonia detection, assisting healthcare professionals in early diagnosis and treatment planning. Future enhancements could include integrating more advanced deep learning architectures and expanding the dataset to further improve model performance.

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