Cairo University

Faculty of Engineering

SBES367 **CDSS** Spring 2025

X-Ray CDSS Report

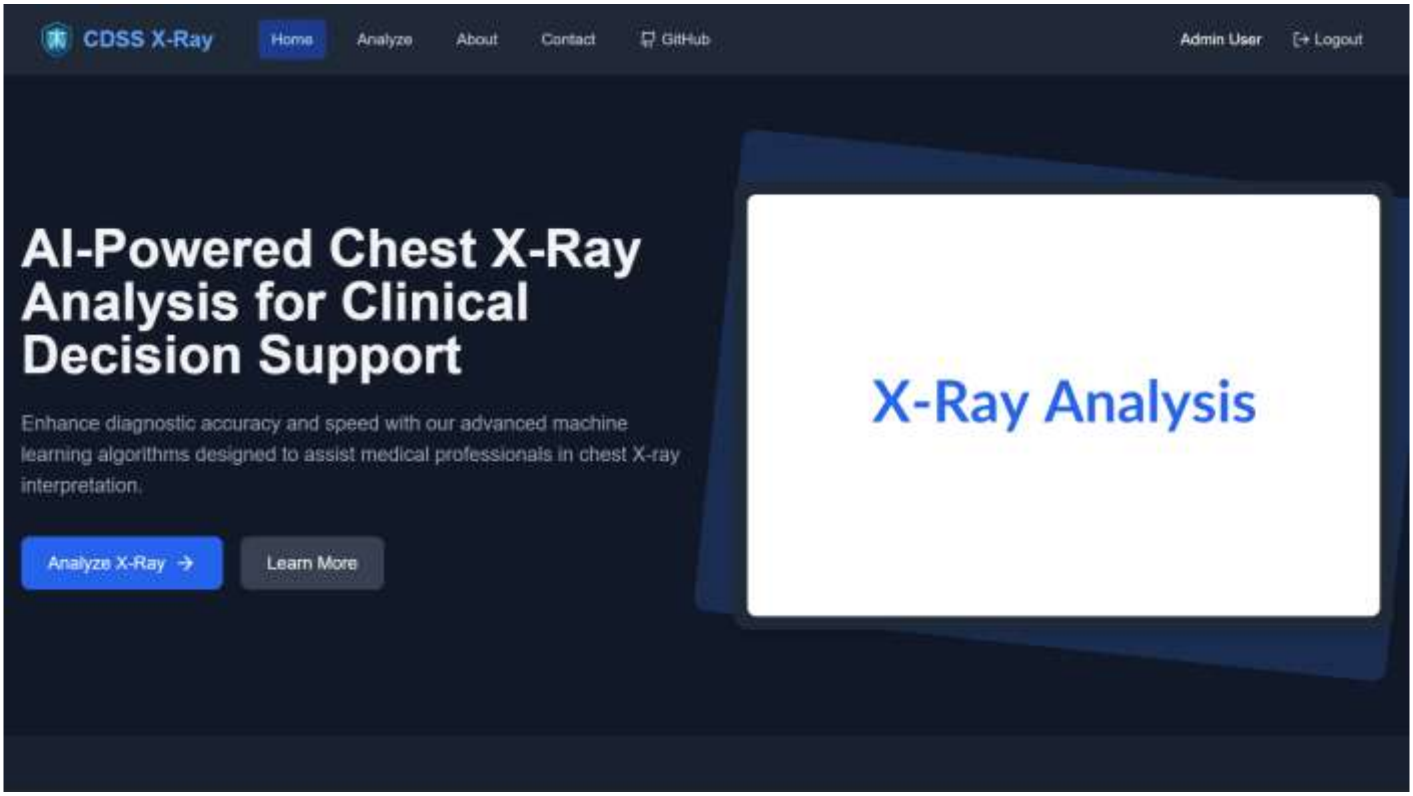
Team Members

Yussef Hassanien	2220010
Mahmoud Mohamed Abdelfattah	4220142
Zeyad Khaled	1210100
Alia Tarek	4220121

Submitted To: **Dr. Reeham**

Table of Contents

CDSS Chest X-ray Analysis Application



Key Points

- The CDSS application likely uses the Chest X-ray Pneumonia Dataset to aid doctors in diagnosing Pneumonia..
- Employs a Convolutional Neural Network (CNN) for automated image analysis.
- Provides consistent and accurate pneumonia detection to support healthcare professionals.
- Enhances diagnostic efficiency and decision-making in clinical settings.
- Uses diagnoses to aid in COVID-19 diagnosis
- Generates a detailed report for each case

Overview

The CDSS Chest X-ray Analysis Application is a web-based tool designed to assist healthcare professionals in diagnosing respiratory conditions by combining artificial intelligence with rule-based decision-making. It leverages a Convolutional Neural Network (CNN) trained on the Chest X-ray Pneumonia Dataset, which contains around 5,000 labeled images categorized as "Pneumonia" and "Normal." The CNN analyzes X-ray images to detect pneumonia with high accuracy, benefiting from extensive data augmentation techniques to enhance model robustness. Detected pneumonia is then used as a symptom in a rule-based approach for diagnosing COVID-19, creating a comprehensive diagnostic system. The application provides an intuitive interface for clinicians to upload X-ray images, receive real-time diagnostic feedback, and gain insights into the model's predictions. By integrating AI-driven image analysis with clinical rules, this system aims to enhance diagnostic accuracy, support medical decision-making, and streamline the detection of critical respiratory conditions.

Current Capabilities

The application allows doctors to upload chest X-ray images for instant AI analysis, with a CNN detecting pneumonia as a key condition. Detected pneumonia is then used in a rule-based system to assess COVID-19. In addition to image analysis, doctors can input patient vitals, such as temperature, and other symptoms, providing a more comprehensive diagnostic view. Results are displayed with clear visual indicators, and the system continuously adapts to new inputs. However, class imbalance in the training data can affect performance, potentially leading to biased predictions. Data augmentation helps mitigate this, but ongoing monitoring is essential for accuracy.

Literature review and Implementation comparison

A review of recent literature underscores the efficacy of Convolutional Neural Networks (CNNs) in detecting pneumonia from chest X-ray images. CNNs have demonstrated superior performance in image classification tasks, particularly in medical imaging, due to their ability to automatically learn hierarchical features directly from raw image data.

In a study by Jain et al. (2020), various CNN architectures, including VGG16, VGG19, ResNet50, and Inception-v3, were employed to classify chest X-ray images into pneumonia and non-pneumonia categories. The models achieved validation accuracies ranging from 70.99% to 92.31%, highlighting the potential of CNNs in medical diagnostics.

Similarly, Rahman et al. (2020) utilized pre-trained CNN models such as AlexNet, ResNet18, DenseNet201, and SqueezeNet through transfer learning to classify chest X-ray images into normal, bacterial pneumonia, and viral pneumonia categories. Their approach achieved classification accuracies of up to 98% for normal vs. pneumonia, 95% for bacterial vs. viral pneumonia, and 93.3% for normal, bacterial, and viral pneumonia classification.

Another study focused on designing a VGG-based CNN model tailored for pneumonia detection. The model was trained on a dataset comprising 4037 images, achieving high accuracy in distinguishing between normal and pneumonia cases.

These studies collectively affirm that CNNs, particularly when combined with transfer learning techniques, offer a robust framework for the automated detection of pneumonia from chest X-ray images. The ability of CNNs to learn complex patterns and features directly from images makes them well-suited for medical image analysis, where subtle differences can be critical for accurate diagnosis.

Traditional machine learning models on the other hand would require manual feature extraction first, making CNNs an ideal choice.

System Design & Architecture

The CDSS application employs a modular client-server architecture, ensuring scalability and maintainability. It is divided into four primary layers:

Frontend Layer

- **Framework**: Next.js 15.3, a React framework, supports server-side rendering and static site generation for optimal performance.
- **Technologies**: TypeScript 5.0 ensures type-safe development, while Tailwind CSS 3.0 enables rapid, consistent styling. Libraries like React Dropzone facilitate drag-and-drop uploads, and Recharts powers data visualization.
- **Features**: Includes responsive design, theme switching, and an intuitive interface for X-ray uploads and result visualization.

Backend Layer

- **Framework**: Django 5.2, a Python-based web framework, supports rapid development and robust API creation via Django REST Framework.
- **Functionality**: Manages user authentication, image processing, patient data integration, and AI model inference.
- **Database**: Uses SQLite for development and PostgreSQL in production for scalability.

AI Layer

- **Frameworks**: Employs TensorFlow for deep learning model implementation.
- **Capabilities**: Models perform binary classification for pneumonia, generating diagnostic suggestions with confidence scores.
- **Libraries**: OpenCV handles image processing, while NumPy manages data.

Integration Layer

- **Role**: Coordinates communication between frontend, backend, Knowledge base, and AI components, ensuring seamless data flow from image upload to result presentation.
- **Workflow**: Preprocesses images, triggers model inference, and integrates clinical parameters with the knowledge base using Bayesian theorem to generate results

This architecture allows independent updates to components, such as retraining AI models, without disrupting the entire system.

CNN Model Implementation & Evaluation

Implementation

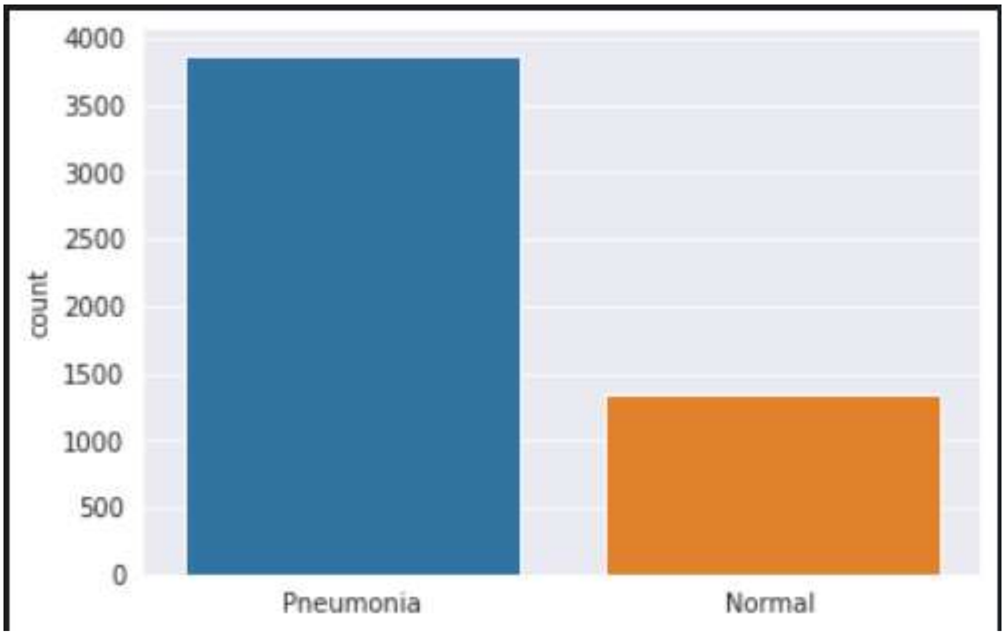
The model is a Convolutional Neural Network (CNN) with five convolutional layers for feature extraction, each followed by batch normalization, max pooling, and dropout layers to enhance training stability and prevent overfitting. Finally, a fully connected layer with 128 neurons and a sigmoid output layer is used for binary classification, making it suitable for detecting pneumonia in chest X-ray images.

Model architecture:

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 150, 150, 32)	320
batch_normalization_5 (BatchNormalization)	(None, 150, 150, 32)	128
max_pooling2d_5 (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_6 (Conv2D)	(None, 75, 75, 64)	18,496
dropout_4 (Dropout)	(None, 75, 75, 64)	0
batch_normalization_6 (BatchNormalization)	(None, 75, 75, 64)	256
max_pooling2d_6 (MaxPooling2D)	(None, 38, 38, 64)	0
conv2d_7 (Conv2D)	(None, 38, 38, 64)	36,928
batch_normalization_7 (BatchNormalization)	(None, 38, 38, 64)	256
max_pooling2d_7 (MaxPooling2D)	(None, 19, 19, 64)	0
conv2d_8 (Conv2D)	(None, 19, 19, 128)	73,856
dropout_5 (Dropout)	(None, 19, 19, 128)	0
batch_normalization_8 (BatchNormalization)	(None, 19, 19, 128)	512
max_pooling2d_8 (MaxPooling2D)	(None, 10, 10, 128)	0
conv2d_9 (Conv2D)	(None, 10, 10, 256)	295,168
dropout_6 (Dropout)	(None, 10, 10, 256)	0
batch_normalization_9 (BatchNormalization)	(None, 10, 10, 256)	1,024
max_pooling2d_9 (MaxPooling2D)	(None, 5, 5, 256)	0
flatten_1 (Flatten)	(None, 6400)	0
dense_2 (Dense)	(None, 128)	819,328
dropout_7 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 1)	129

Evaluation Metrics

- **Accuracy**: Overall prediction correctness.
- **Precision**: True positives among positive predictions, critical to avoid unnecessary tests.
- **Recall (Sensitivity)**: True positives among actual positives, essential for detecting severe conditions.
- **F1-Score**: Balances precision and recall. Used in this case as accuracy is not a reliable metric in the presence of imbalance.



- **AUC-ROC**: Measures class discrimination ability.

Performance

The model achieved an accuracy of 89.9% as well as balanced f1 scores.

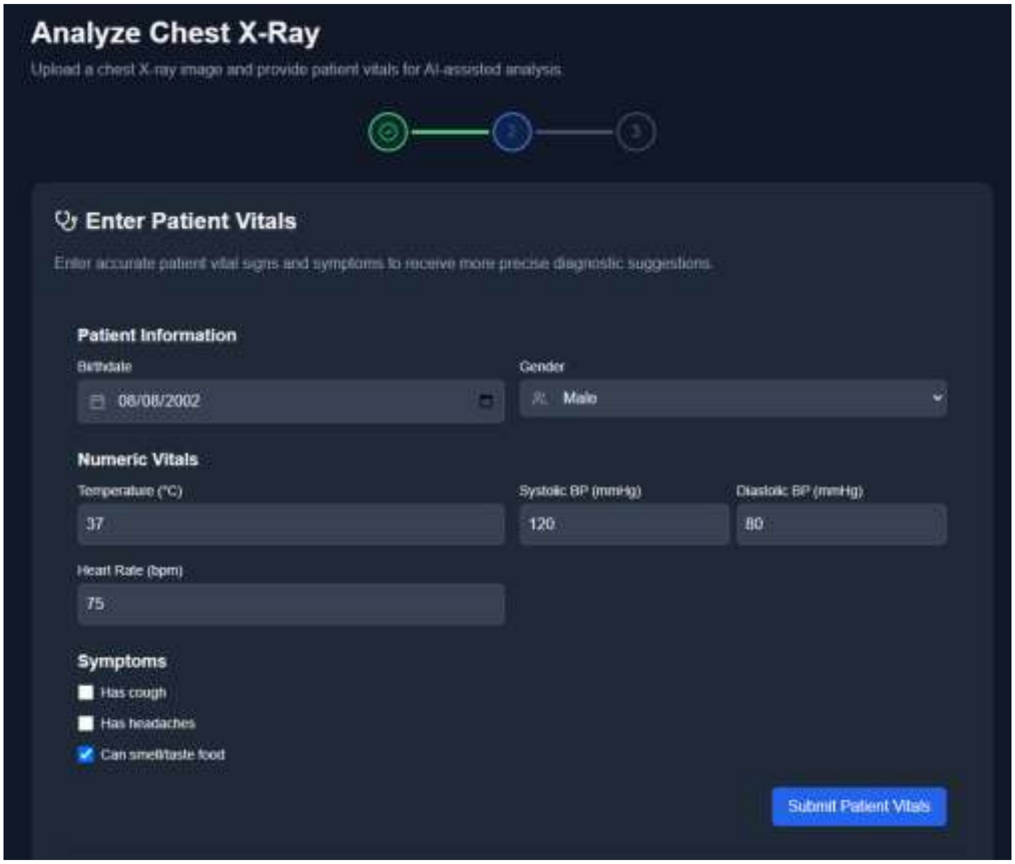
	precision	recall	f1-score	support
Pneumonia (Class 0)	0.85	0.88	0.87	234
Normal (Class 1)	0.93	0.91	0.92	390
accuracy			0.90	624
macro avg	0.89	0.90	0.89	624
weighted avg	0.90	0.90	0.90	624

Clinical Workflow & Integration

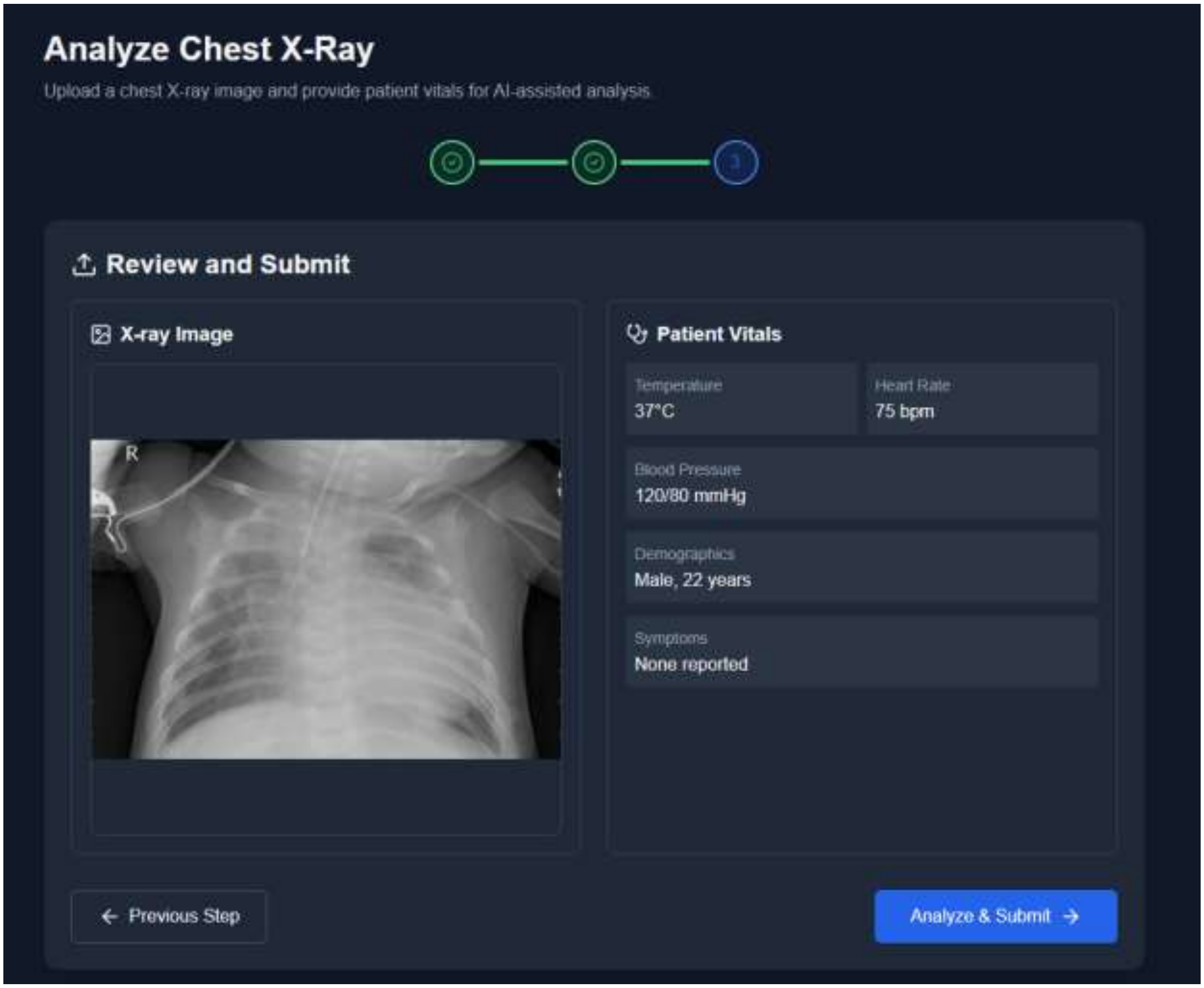
The application integrates into clinical workflows as follows:

1. **Image Acquisition**: Clinicians upload X-rays via a drag-and-drop interface.

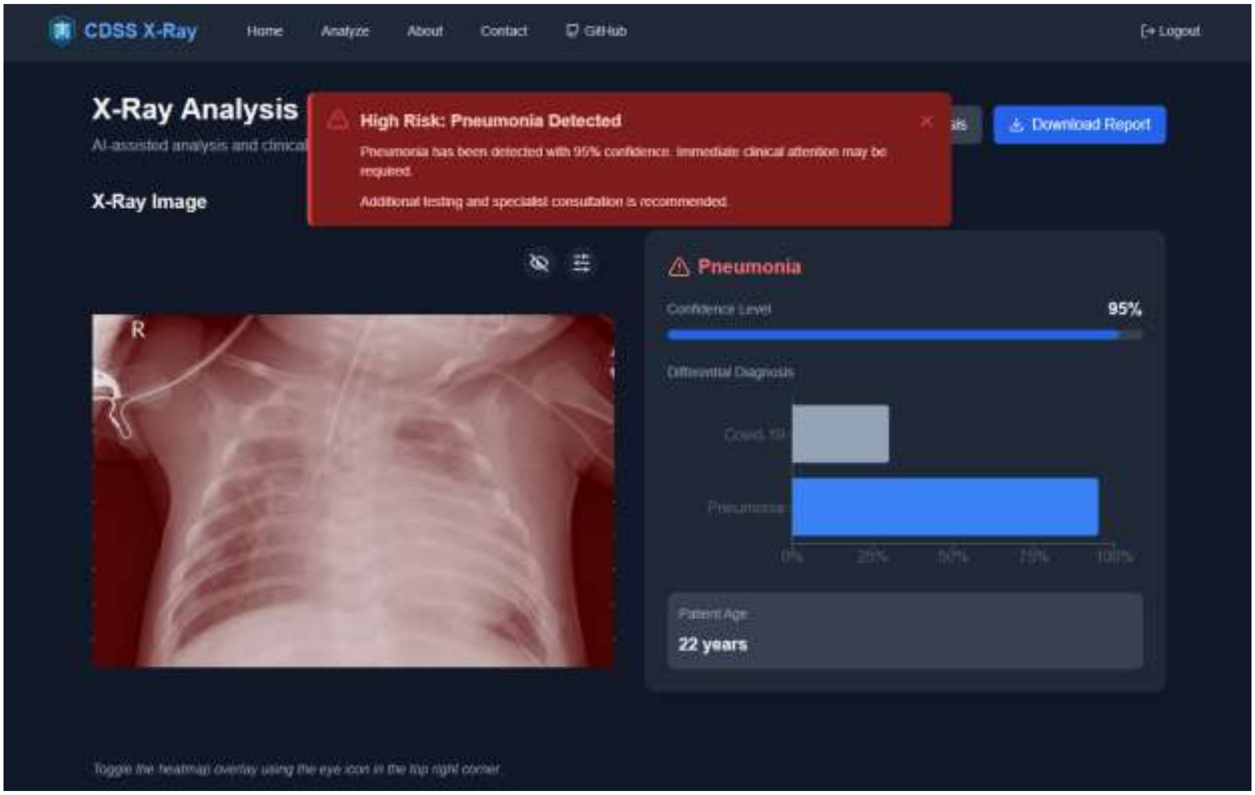
2. **Clinical Parameters**: Clinicians input vitals (temperature, blood pressure, heart rate) and symptoms (cough, headaches, loss of smell/taste).



3. **Review** inserted vitals, symptoms and x-ray scan



4. **AI Analysis**: Models generate diagnostic suggestions, confidence scores, and heatmaps.
5. **Enhanced Diagnosis**: Combines imaging and clinical data for refined assessments and severity classification (Low, Moderate, High).



6. **Decision Support**: Presents results intuitively, supporting clinician judgment with downloadable reports.

X-Ray Analysis Report

Generated: 5/8/2025, 10:36:28 AM

Diagnosis Results

Pneumonia: 95%

Covid-19: 30%

Clinical Recommendations

Bacterial pneumonia suspected. Consider antibiotic therapy based on local guidelines. Evaluate respiratory status and consider sputum culture if available.

This workflow enhances diagnostic accuracy by integrating AI insights with clinical expertise.

Identified Challenges

Development faced challenges such as securing high-quality, diverse datasets and ensuring real-time performance for clinical use. The dataset is small, and its class imbalances could bias the model toward the pneumonia class. Integrating Next.js, Django, and AI components was challenging. Additionally, gaining doctors' trust in AI suggestions is another hurdle, as clinicians may hesitate to rely on unvalidated systems.

Recommended Enhancements

To improve the application, developers could verify and expand dataset labels through expert collaboration or community contributions. Adding more bounding box annotations for disease localization would enhance diagnostic precision. Addressing class imbalances with techniques like data augmentation or class weighting could improve performance on rare conditions. Conducting clinical trials to validate the system against human diagnoses would build trust and ensure practical utility. These steps could make the application more accurate and widely adopted in healthcare settings.

Conclusion

In conclusion, the CDSS Chest X-ray Analysis Application is a powerful diagnostic tool that combines AI-driven image analysis with rule-based decision-making. By detecting pneumonia using a Convolutional Neural Network (CNN) and leveraging a knowledge-based approach to assess COVID-19, the system offers a comprehensive diagnostic solution. It allows doctors to upload X-ray images, view AI-generated diagnoses, and input patient vitals, ensuring a holistic evaluation. This hybrid approach enhances diagnostic accuracy, supports clinical decision-making, and demonstrates the potential of AI in healthcare.

Workload

Mahmoud Mohamed Abdelfatah	Frontend and Backend Integration
Zeyad Khaled	Backend Design Architecture and Authentication Service (Login, Signup, Logout)
Youssef Hassanien	Knowledge Base, Image Upload Service and AI model integration with backend
Alia Tarek	AI Model (Deep Learning model using CNN)

References

- A Review of Recent Advances in Deep Learning Models for Chest Disease Detection Using Radiography
- Does imbalance in chest X-ray datasets produce biased deep learning approaches for COVID-19 screening
- Lightweight convolutional neural network for chest X-ray images classification
- Pneumonia Detection using CNN
- AI-based radiodiagnosis using chest X-rays: A review
- Classification of COVID-19 chest X-rays with deep learning: new models or fine tuning?
- Evaluating diagnostic content of AI-generated chest radiography: A multi-center visual Turing test
- AI-CenterNet CXR: An artificial intelligence enabled system for localization and classification of chest X-ray disease
- Artificial Intelligence-Based Classification of Chest X-Ray Images into COVID-19 and Other Infectious Diseases
- Next.js Official Documentation
- Django Official Website
- TypeScript Official Website
- React Official Website
- Tailwind CSS Official Website
- React Dropzone Documentation
- Recharts Official Website
- Django REST Framework Documentation
- PyTorch Official Website
- TensorFlow Official Website
- OpenCV Official Website
- NumPy Official Website
- Jain, R., Gupta, M., & Taneja, S. (2020). Deep Learning based Detection and Analysis of Pneumonia in Chest X-ray Images. Measurement, 165, 108046.
- Rahman, T., Chowdhury, M. E. H., Khandakar, A., Islam, K. R., Islam, K. F., Mahbub, Z. B., & Mazhar, R. (2020). Transfer Learning with Pre-trained Deep Convolutional Neural Networks for Pneumonia Detection using Chest X-ray Images. arXiv preprint arXiv:2004.06578.