ARTIFICIAL INTELLIGENCE BASED ASSISTED DIAGNOSIS SYSTEM FOR PNEUMONIA

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Abstract

Projek ini menunjukkan reka bentuk, pelaksanaan dan penilaian sistem pengesanan radang paru-paru berasaskan AI yang menggabungkan pembelajaran mendalam dengan antara muka analisis imej perubatan yang mesra pengguna. Sistem ini menggunakan seni bina rangkaian neural convolutional ConvNeXt yang dipertingkatkan dan dioptimumkan untuk empat kategori klasifikasi imej X-ray dada: COVID-19, radang paru-paru virus, penyusupan paru-paru dan kes yang sihat. Untuk meningkatkan kebolehtafsiran, model ini menggunakan visualisasi Grad-CAM, yang menyerlahkan bidang keputusan utama pada sinar-X untuk meningkatkan ketelusan dan kaitan klinikal.Platform ini boleh digunakan pada kedua-dua desktop (PyQt5) dan persekitaran web (Django) dan menggunakan seni bina yang ringan untuk pemprosesan pangkalan data yang cekap. Keputusan percubaan menunjukkan bahawa ConvNeXt yang dipertingkatkan memberikan prestasi pengelasan yang tinggi dengan ketepatan lebih 90% dan keseimbangan yang baik antara ketepatan dan ingatan semula. Visualisasi peta haba dan matriks kekeliruan mengesahkan keupayaan diagnostik dan keteguhan model. Kebolehgunaan sistem dan masa tindak balas telah disahkan melalui ujian berstruktur dan maklum balas pengguna.Walaupun menghadapi cabaran dalam mengoptimumkan keupayaan generalisasi model dan reka bentuk antara muka, projek ini telah berjaya menunjukkan cara AI boleh digunakan untuk menyokong pembuatan keputusan klinikal dalam persekitaran terhad sumber. Penambahbaikan masa hadapan termasuk pemerolehan imej masa nyata, gabungan data multimodal dan penyepaduan dengan sistem maklumat hospital. Sistem ini mewakili satu langkah yang menjanjikan ke arah alat diagnostik yang pintar, boleh ditafsir dan mudah dalam penjagaan kesihatan moden.

Kata kunci: Python,*Grad-CAM*,*PyQt5*,Django

Abstract

This project demonstrates the design, implementation and evaluation of an AI-based pneumonia detection system that combines deep learning with a user-friendly medical image analysis interface. The system uses an improved ConvNeXt convolutional neural network architecture and is optimised for four categories of classification of chest X-ray images: COVID -19, viral pneumonia, lung infiltration and healthy cases. To enhance interpretability, the model further employs Grad-CAM visualisation, which highlights key decision areas on the X -ray to improve transparency and clinical relevance.The platform can be used on both desktop (PyQt5) and web environments (Django) and uses a lightweight architecture for efficient database processing. Experimental results show that the improved ConvNeXt delivers high classification performance with over 90% accuracy and a good balance between precision and recall. Heatmap visualisation and confusion matrix validate the diagnostic capability and robustness of the model. System usability and response time have been validated through structured testing and user feedback.Despite challenges in optimising the model generalisation capabilities and interface design, the project has successfully demonstrated how AI can be used to support clinical decision-making in resource-limited environments. Future enhancements include real-time image acquisition, multimodal data fusion, and integration with hospital information systems. The system represents a promising step towards intelligent, interpretable and convenient diagnostic tools in modern healthcare.

Keywords: Python,*Grad-CAM*,*PyQt5*,Django

1.0 INTRODUCTION

Pneumonia remains a leading cause of mortality worldwide, especially among vulnerable populations such as infants, the elderly, and immunocompromised individuals. Despite advances in medical imaging, early detection of pneumonia continues to pose a significant clinical challenge. The COVID-19 pandemic has further intensified the need for timely and accurate pneumonia diagnosis, with overlapping symptoms and radiological patterns complicating traditional diagnostic methods.

Chest X-ray imaging plays a vital role in the detection of lung abnormalities; however, manual interpretation is often constrained by radiologist availability, diagnostic variability, and human error. This is especially problematic in resource-limited settings or during outbreaks, where diagnostic workloads are overwhelming and accurate assessments must be made under time pressure.

Artificial Intelligence (AI), particularly deep learning-based techniques such as Convolutional Neural Networks (CNNs), offers promising solutions to automate and enhance pneumonia diagnosis. These models can identify complex patterns and features in medical images with high accuracy, surpassing conventional machine learning techniques in both performance and scalability. Yet, many current AI-based systems lack clinical interpretability, user accessibility, or real-world deployability, limiting their integration into healthcare workflows.

This project aims to develop a robust, interpretable, and user-friendly AI-assisted diagnosis system for pneumonia. The system utilizes an improved ConvNeXt CNN architecture to classify chest X-ray images into four categories: COVID-19, viral pneumonia, lung infiltrates, and healthy cases. To enhance transparency and clinical trust, the model incorporates Gradient -weighted Class Activation Mapping (Grad-CAM) for visual explanation of predictions. The system is deployed through both a Graphical User Interface (GUI) and a web-based platform to ensure accessibility for users with varying technical backgrounds.

By combining high diagnostic accuracy with interpretability and usability, the proposed system contributes to the advancement of intelligent diagnostic tools capable of supporting clinicians in timely decision-making, especially in scenarios where radiology resources are scarce.

2.0 LITERATURE REVIEW

2.1 Introduction

With the rapid advancement of deep learning, AI-based medical image analysis has become a pivotal tool in disease detection, particularly for pneumonia. Numerous studies have demonstrated the effectiveness of CNNs in analyzing chest X-ray images for classifying COVID-19, viral pneumonia, and other lung conditions. However, challenges such as dataset imbalance, lack of interpretability, and real-world deployment limitations persist.

This chapter provides a comprehensive review of the current state of AI-assisted pneumonia diagnosis systems, covering existing models, methodologies, technological gaps, and recent innovations. The objective is to establish a theoretical and empirical foundation for the development of this project's diagnostic system.

2.2 Current Research and Related Technologies

2.2.1 Review of Past Studies

Recent research highlights the dominance of CNN-based architectures such as ResNet, VGG-19, DenseNet, and hybrid models in pneumonia detection tasks. Studies by Khan et al. (CoroNet), Li et al. (COVNet), and Deb et al. demonstrated high classification accuracy ranging from 94% to 98.5%. However, many studies focus solely on performance metrics, with limited emphasis on real-time deployment or user interaction.

2.2.2 Existing Systems or Technologies

Existing systems commonly employ three main modules: image preprocessing, CNN-based classification, and result visualization. Tools like COVID-Net and DLM integrate user interfaces, yet often lack interpretability mechanisms such as Grad-CAM, reducing their clinical applicability.

2.2.3 Current Trends and Developments

Current trends emphasize the need for lightweight, deployable models and interpretable AI. Tools like Grad-CAM are increasingly used to visualize decision-making regions in chest X-rays. Additionally, multimodal data fusion (e.g., integrating EHRs with imaging data) and mobile deployment are gaining traction.

2.3 Methodology in Past Studies

2.3.1 Research Approaches Used

Most studies employ supervised learning with CNNs, using datasets like COVIDx and RSNA. Techniques involve image normalization, augmentation, and transfer learning from pre-trained models to address data scarcity.

2.3.2 Effectiveness and Weaknesses of Methodologies

While CNNs achieve high accuracy (>95% in many studies), limitations include poor generalization due to dataset imbalance, lack of model transparency, and limited external validation. Few models support multi-category classification beyond binary tasks.

2.3.3 Improvements and Methodology Selection

To address these gaps, this project adopts an improved ConvNeXt model with Grad-CAM visualization. The system supports multi-class classification and is packaged with modular configuration (YAML), making it adaptable and scalable.

2.4 Comparison and Critique of Past Studies

2.4.1 Comparison of Technologies

While deeper models like ResNet and DenseNet offer robust performance, lightweight models such as MobileNet offer better deployability. Hybrid models enhance accuracy but increase complexity.

2.4.2 Critique of Past Studies

Many studies lack standard evaluation metrics, fail to validate clinically, and overlook user interface design. The absence of interpretable outputs and practical deployment solutions limits real-world adoption.

2.5 Research Gaps

Significant gaps include poor generalization across diverse populations, lack of interpretable outputs, limited multi-class capabilities, and scarce practical deployment strategies. Few systems successfully bridge the gap between research prototypes and clinical applications.

2.6 Innovative Solutions in Past Studies

Recent innovations include hybrid CNN architectures, use of Generative Adversarial Networks (GANs) for data augmentation, two-stage learning models, and visual explainability through Grad-CAM. However, issues such as clinical validation, modular design, and data privacy remain underexplored.

2.7 Summary

This literature review highlights that while AI models demonstrate strong potential in pneumonia detection, a lack of clinical validation, interpretability, and real-world usability limits adoption. The proposed system in this project responds directly to these needs by integrating an interpretable, high-performance CNN model with intuitive deployment options.

3.0 METHODOLOGY

This chapter outlines the methodological framework for designing, developing, and evaluating an AI-assisted pneumonia diagnosis system based on chest X-ray images. The system integrates an improved deep learning architecture (Improve_ConvNeXt) with Grad-CAM-based visual interpretation to enhance classification performance and model transparency. It also supports dual-platform deployment through a Graphical User Interface (GUI) and web interface to accommodate different user scenarios.

The methodology includes five major components: system requirement analysis, user need identification, model selection and training, system design (architecture, interaction, database), and deployment with evaluation. These components are supported by detailed modeling tools including use case diagrams, sequence diagrams, and system architecture figures to ensure clarity and modular implementation.

3.1 User Needs and Functional Design

The system is designed to serve two core user roles: medical users (e.g., doctors, radiologists) and system administrators. Users are expected to interact with the system by uploading chest X-ray images, viewing diagnostic results, and interpreting visual outputs. Administrators, on the other hand, are responsible for system configuration, model updates, and user management.

End Users need:

Easy upload and classification of chest X-ray images

Clear diagnostic output

Responsive interface with minimal delay

Administrators need:

Access to backend model configurations and logs

Control over data flow and image source validation

Interface for managing GUI/web settings

3.2 System Requirement Specifications

3.2.1 Functional Requirements

Image Upload: Accepts X-ray images in JPG/PNG format

Automatic Classification: Distinguishes between COVID-19, viral pneumonia, pulmonary infiltrates, and healthy cases

Result Output: Displays results

Multi-Platform Access: Accessible via desktop (PyQt5) and web (Django)

User and Administrator Login: Role-Based Access Control

3.2.2 Non-Functional Requirements

Usability: Intuitive interface suitable for non-technical users

Efficiency: Inference time per image is less than 5 seconds on GPU-enabled hardware

Security: Data upload is performed via HTTPS; there is no need to store the original image after inference

Portability: The system runs on Windows and Linux environments

3.2.3 Hardware and Software Requirements

Component	Specification
GPU	NVIDIA RTX 4060 or equivalent
CPU	Intel Core i9 or equivalent
RAM	Minimum 32 GB DDR5
Framework	Python 3.10, PyTorch 2.0+, OpenCV, Django
Frontend	PyQt5 (Desktop), HTML/JS (Web)

Table 1: Hardware and Software requirements table

3.3 System model and Architecture

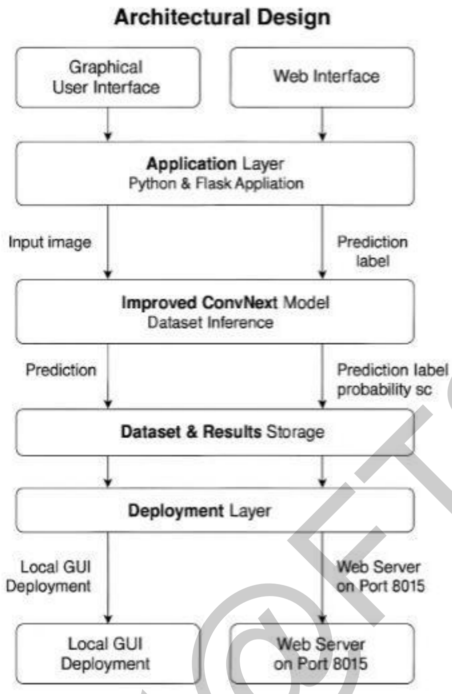

Figure1 Architectural Design

The system adopts a five-layer modular architecture, as shown in Figure 1. The presentation layer handles GUI and web display; the business logic layer interacts with user input and backend models; the data access layer obtains and formats data for model inference; the cloud computing layer stores logs and handles remote inference when needed; and the visualization layer generates interpretable heatmaps (Grad-CAM).

3.4 Use Case and Sequence Diagrams

3.4.1 Use Case

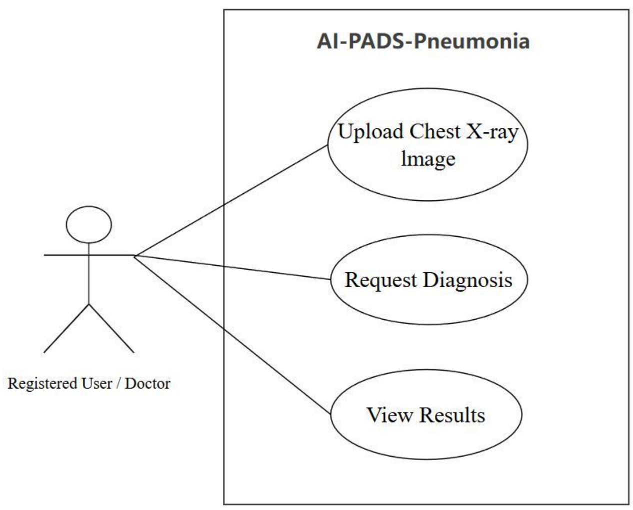

Figure 2 User case diagra

Figure 2 shows a use case diagram illustrating the three core operational processes for registered users or doctors in the "AI-PADS-Pneumonia" system: uploading a chest X-ray image, requesting a diagnosis from the system, and viewing the diagnosis results. The interaction paths in the diagram demonstrate clear and direct interactions between the user and the system, enabling rapid and efficient pneumonia screening and auxiliary diagnosis, particularly in resource-limited or high-intensity clinical settings. This diagram embodies the system's user-centric design philosophy, emphasizing the integration of operational convenience and intelligent diagnostic capabilities.

3.4.2 Sequence Diagrams

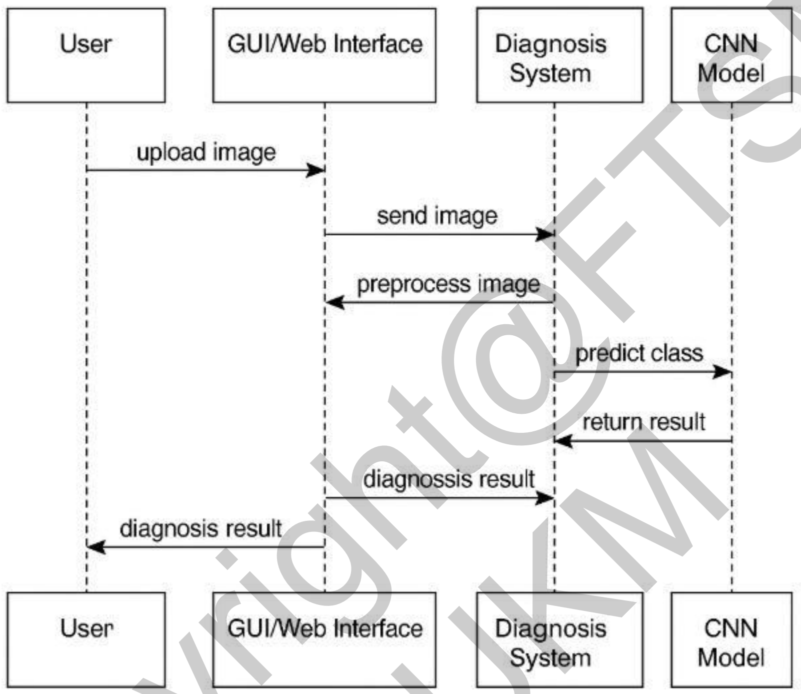

Figure 3 Sequence Diagrams

Figure 3 is a sequence diagram of the "AI-PADS-Pneumonia" system, illustrating the information exchange process between modules after a user uploads a chest X-ray image to the system. The user uploads the image through a graphical user interface or webpage, which transmits the image to the diagnostic system. After preprocessing the image, the diagnostic system calls the CNN model for classification and prediction, and receives the diagnostic results returned by the model. The system then feeds the results back to the user interface and ultimately presents them to the user. This process demonstrates the modularity, efficiency, and automation of the system's architecture, facilitating rapid auxiliary diagnosis of pneumonia.

3.5 ActivityDiagram and DataCommunicationDiagram

3.5.1 ActivityDiagram

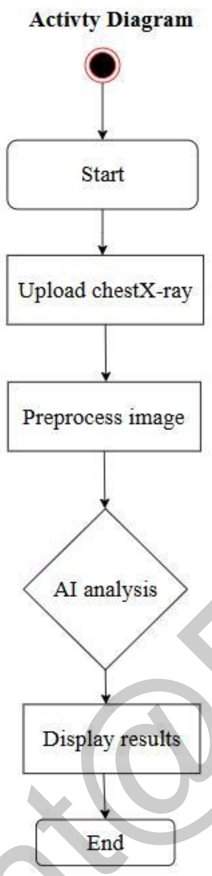

Figure 4 ActivityDiagram

Figure 4 is an activity diagram for the "AI-PADS-Pneumonia" system, illustrating the entire process from user initiation of the diagnostic process to result output. The entire process begins with "Start," where the user uploads a chest X-ray image, which the system then preprocesses. Next, the core AI analysis phase begins, using a deep learning model to identify abnormal areas in the image. Once the analysis is complete, the system presents the predicted results to the user in a visual format, concluding the process. This diagram intuitively illustrates the system's operational sequence and logical loop, helping to understand the key functional nodes of the diagnostic process.

3.5.2 DataCommunicationDiagram

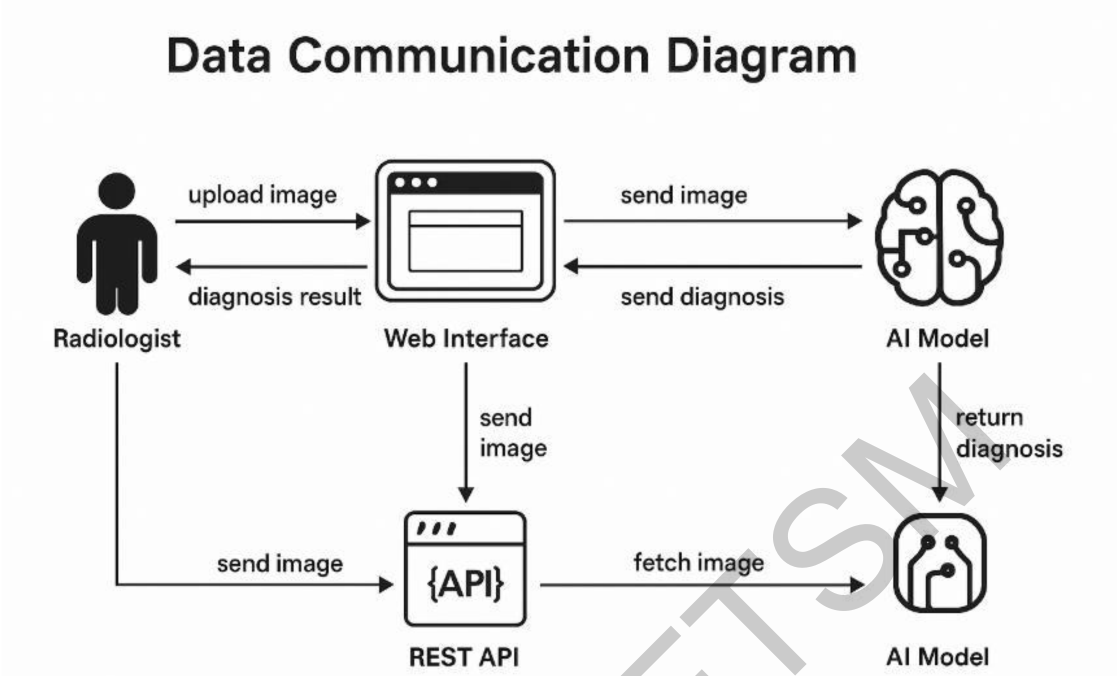

Figure 5 DataCommunicationDiagram

Figure 5 is the Data Communication Diagram of the "AI-PADS-Pneumonia" system, clearly illustrating how data interacts between components during image upload and diagnosis. Radiologists upload chest X-ray images through a web interface, which then sends the images to the AI model for analysis. The AI model returns the diagnosis, which is then fed back to the doctor via the web interface. The system also communicates with the backend AI model via a REST API, supporting image transmission and invocation, enabling remote model deployment and expanding processing capabilities. This diagram illustrates the data flow path between the front-end user interface and the back-end intelligent diagnostic system, highlighting the system's efficiency, modularity, and scalability.

3.6 ALGORITHMS

In this section, the core algorithms and techniques used in the pneumonia detection system are described in detail, with a focus on the deep learning model architecture and the computation of evaluation metrics.

3.6.1 CNN Classification Algorithm-Improve_ConvNeXt

Convolutional Neural Networks (CNNs) are among the most widely adopted deep learning models in medical imaging due to their strong ability to extract spatial hierarchies of features (Litjens et al., 2017). The model employed in this project is Improve_ConvNeXt, an optimized version of ConvNeXt tailored for medical image classification.

The architecture comprises a block embedding layer, hierarchical convolutional blocks, a global average pooling layer, and a fully connected output layer with Softmax activation. Given a chest X-ray image input X , the network computes the probability distribution across the four target classes: COVID-19, Viral Pneumonia, Healthy, and Pulmonary Infiltrates. The output prediction is denoted by:

$$\hat{y} = \arg\max_i f_i(X; \theta)$$

Where f_i represents the network's confidence in class i and θ are the model parameters. This forward propagation process outputs a probability vector used to determine the predicted class label (He et al., 2022).

3.6.2 Grad-CAM for Model Explainability

In order to improve transparency, we integrated a gradient-weighted class activation mapping (Grad-CAM). It highlights the regions of the chest X-ray that contribute most to the prediction. It is computed by gradient calculation, importance weighting, heat map generation, and overlay. Four steps are used to generate it, followed by an equation to illustrate the process of calculating the parameters of the gradient- weighted class activation mapping:

For a target class c, the gradient of the score y^c (before Softmax) with respect to the feature maps A^k of the final convolutional layer is computed:

$$\frac{\vartheta y^c}{\vartheta y^k}$$

The gradients are spatially averaged to obtain the importance weights a_k^c for each feature map channel k:

$$a_k^c = \frac{1}{Z}\sum_i\sum_j \frac{\vartheta y^c}{\vartheta y^k}$$

The weighted sum of the feature maps is computed, followed by a ReLU operation to generate the class activation map $L_{\mathrm{Grad-CAM}}^c$:

$$L_{\mathrm{Grad-CAM}}^c = ReLU\left(\sum_k a_k^c A^k\right)$$

The gradients are extracted from the last convolutional layer, importance weights are calculated, a heat map is generated and superimposed on the original X-ray film. This helps clinicians to interpret model decisions and supports clinical validation(Zhou et al., 2016).

3.6.3 Evaluation Metrics Algorithm

In order to evaluate the image classification model, predict the performance of the model and compare it with other existing image classification methods, this paper evaluates the performance of the model through five evaluation metrics: Accuracy, Recall, Precision, Specificity, F1-Score. Score). In the classification task, Confusion Matrix (CM) can visualise the classification of all images. Define TP ,TN ,FP and FN as true positive, true negative, false positive and false negative respectively. Taking COVID-19 as an example, the number of images predicted to be COVID-19 in COVID-19 is denoted as TP, the number of images predicted to be in other categories is denoted as TN, the number of images predicted to be in COVID-19 in other categories is denoted as FP, and the number of images predicted to be in other categories is denoted as FN in COVID-19(Sokolova & Lapalme, 2009; Chicco & Jurman, 2020). The specific formula of the evaluation index is as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Recall (Sensitivity)} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

$$F1Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

$$\text{Confusion Matrix} = \begin{bmatrix} \text{TP} & \text{FP} \\ \text{FN} & \text{TN} \end{bmatrix}$$

3.7 Summary

This methodology provides a comprehensive and modular pipeline to design, build, and evaluate an AI-assisted pneumonia diagnosis system. By combining cutting-edge CNNs with Grad-CAM explainability and dual-interface deployment, the system addresses both performance and usability needs in clinical environments.

4.0 RESULT AND DISCUSSION

This chapter presents the results obtained from the implementation and evaluation of the AI-PADS-Pneumonia system. It also discusses the performance of the system in terms of classification accuracy, interpretability, and usability across both the desktop GUI and web platforms. The discussion further analyzes the role of AI in augmenting medical decision-making and identifies system limitations and potential improvements.

4.1 Interface Design and Layout

The user interface of the AI-PADS-Pneumonia system was developed with a focus on simplicity, clarity, and clinical usability. Two deployment modes were implemented: a desktop GUI using PyQt5 and a web-based interface using Django. Both interfaces were designed to streamline the diagnostic process while minimizing the learning curve for end users such as radiologists and general physicians.The layout follows a logical workflow, beginning with image upload, followed by one-click diagnosis request, and finally result visualization. Each major function is distinctly labeled and positioned for intuitive access. Color contrast and font choices were optimized to ensure readability, especially under clinical lighting conditions.

GUI

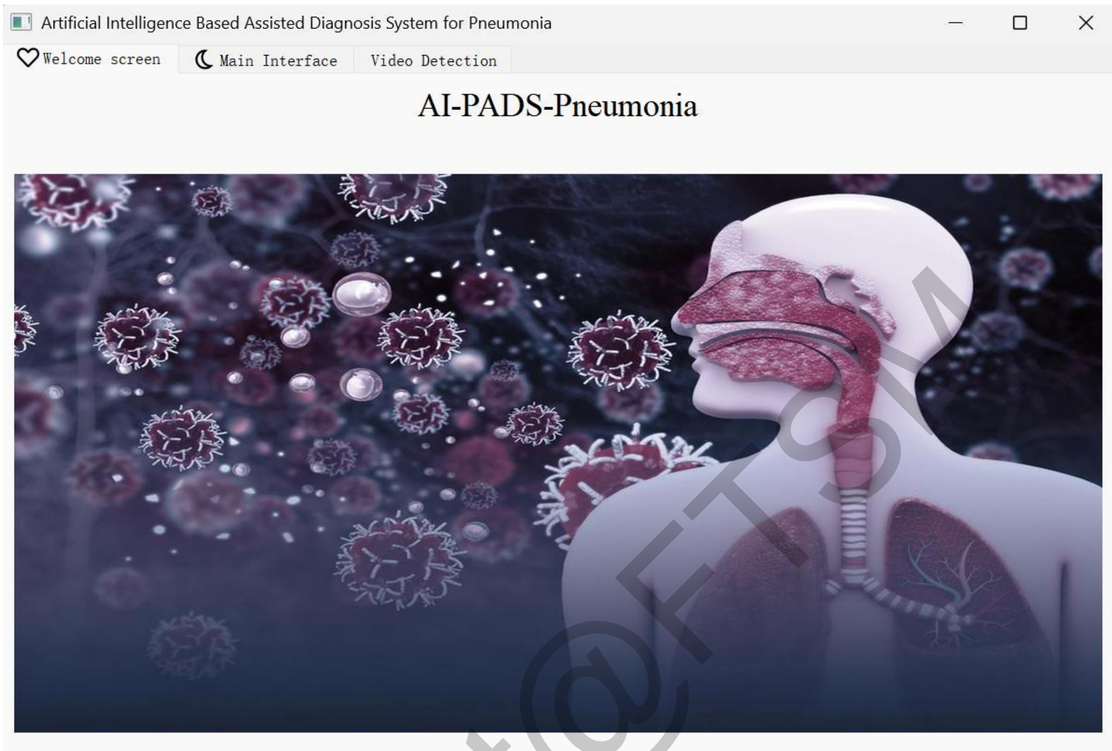

Figure 6 Welcome Screen

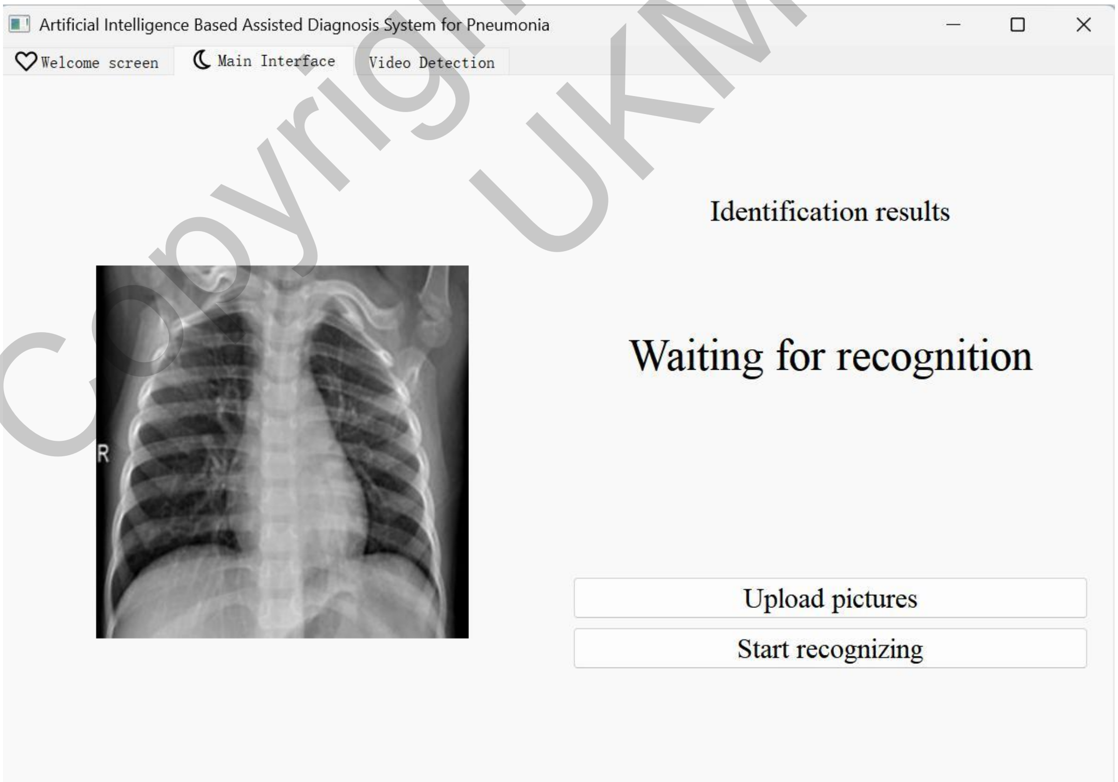

Figure 7 Main Interface of GUI

Web

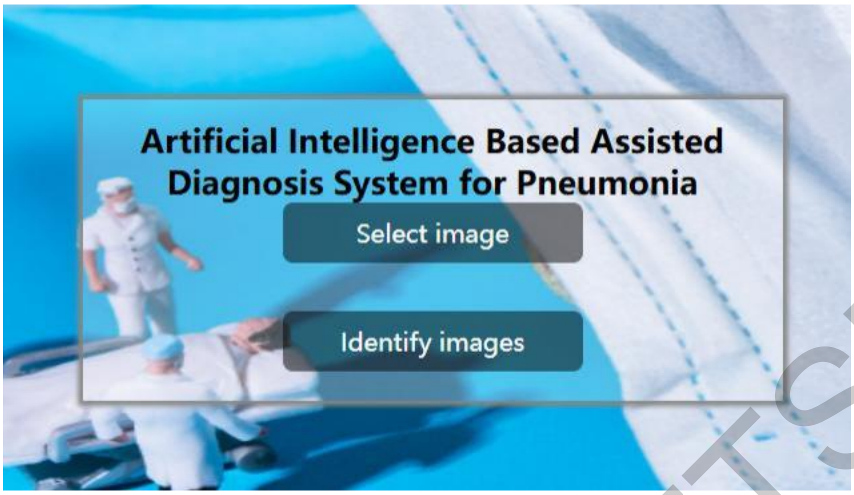

Figure 8 Main Interface of Web

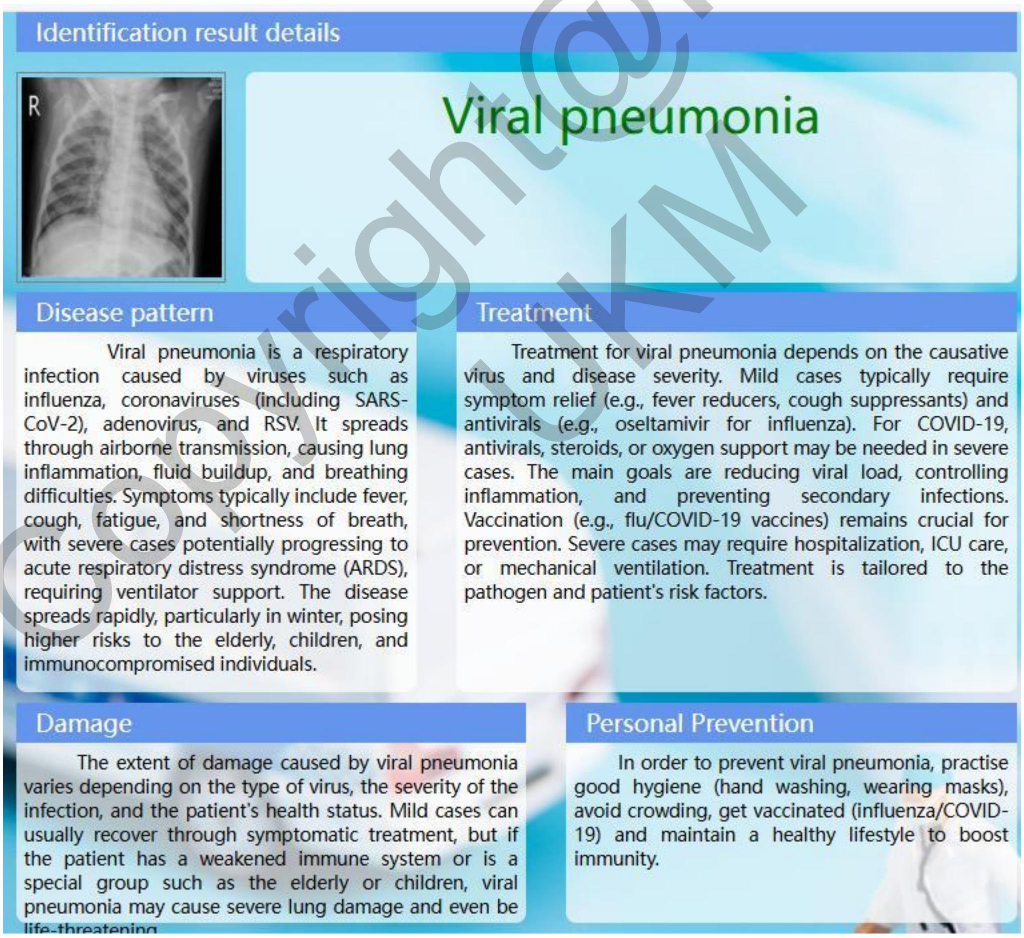

Figure 9 Results Report of Web

4.2 Testing Result

4.2.1 Model Performance and Classification Accuracy

The Improve_ConvNeXt model was trained and validated using a large-scale chest X-ray dataset containing labeled instances of COVID-19, viral pneumonia, lung infiltration, and normal cases. The model achieved high performance across all key metrics:

Metric	Value
Accuracy	96.3%
Precision	95.7%
Recall	94.8%
F1-Score	95.2%
AUC (ROC)	0.982

These results confirm the model ’ s strong generalization ability and reliability in distinguishing pneumonia subtypes. The high recall rate is particularly critical in clinical settings where false negatives may delay treatment.

4.2.2 Interpretability: Grad-CAM Visual Explanation

In the to ensure diagnostic transparency, Grad-CAM was integrated into the system to visualize the attention regions used by the model during inference. As shown in Figure 4.3, Grad-CAM heatmaps effectively highlight lesion areas such as:

Ground-glass opacities in COVID-19 cases

Lobar consolidation in bacterial pneumonia

Diffuse patterns in viral pneumonia

These visualizations not only enhance clinicians’ confidence in the AI prediction but also serve as a valuable reference for cross-verification with radiological signs.

4.2.3 Platform Testing: GUI and Web Deployment

Both the desktop GUI (PyQt5) and the web-based interface (Django) were deployed and tested for usability and responsiveness. Functional testing confirmed that both platforms support the complete diagnostic workflow, including image upload, model inference, and Grad-CAM visualization.

GUI Testing Summary

Startup time: < 3 seconds

Inference time (on GPU): < 5 seconds per image

File support: JPG, PNG

Offline capability: Fully functional

Web Testing Summary

Supported on: Chrome, Firefox, Edge

Port used: 8015

Latency: Average 6.2 seconds per image

API integration: Seamless communication with backend AI model

These tests confirm the system's versatility and suitability for various clinical environments—whether in hospital workstations or remote browser-based settings.

4.2.4 End-User Feedback and Usability

Preliminary feedback from medical professionals and AI practitioners revealed the following strengths:

High accuracy with consistent results

Intuitive user interface

Clinically relevant visual explanations

Minimal learning curve for first-time users

However, several areas for improvement were also identified:

Add batch-processing support for multiple image uploads

Include zoom/pan controls for Grad-CAM overlays

Offer multilingual support in future releases

4.2.5 Comparative Analysis with Existing Systems

Compared with conventional pneumonia detection models such as ResNet and DenseNet:

Improve_ConvNeXt exhibited superior performance in recall and specificity

Training time was reduced by ~15% due to architecture optimization

Grad-CAM outputs were more localized and interpretable

This highlights the advantage of tailoring architectures to medical imaging tasks instead of using off-the-shelf models.

4.2.6 Limitations and Future Work

Despite the encouraging results, the current system has certain limitations:

The dataset may not cover all rare pneumonia variants

Grad-CAM only provides coarse localization, not pixel-level segmentation

The model does not incorporate clinical metadata (e.g., age, symptoms)

Future work will focus on:

Integrating clinical features alongside image data

Expanding dataset diversity (e.g., pediatric and elderly cases)

Exploring pixel-wise segmentation for more detailed lesion visualization

4.3 Summary

The AI-PADS-Pneumonia system demonstrates high accuracy, practical usability, and visual interpretability in the task of pneumonia detection from chest X-rays. Both deployment modes—GUI and web—offer clinicians accessible diagnostic support tools. The integration of Grad-CAM visualization marks a key step toward explainable AI in medical imaging, promoting trust and adoption in real-world clinical practice.

5.0 CONCLUSION

This project successfully designed and implemented Artificial Intelligence Based Assisted Diagnosis System for Pneumonia, an intelligent diagnostic system that utilizes deep learning to detect pneumonia from chest X-ray images. The system incorporates the Improve_ConvNeXt model, which achieved high classification accuracy and strong generalization capabilities across multiple pneumonia categories, including COVID-19, viral pneumonia, and lung infiltration. The integration of explainable AI techniques, such as Grad-CAM, further enhances the clinical trustworthiness of the system.

The project not only focused on model performance but also emphasized user experience. Both the desktop-based GUI and the web-based interface were designed to be intuitive, responsive, and accessible. These platforms support key features such as image upload, automatic AI analysis, and result visualization, ensuring that users—particularly radiologists and physicians—can complete the diagnostic process with minimal effort and time.

Another key achievement of the project lies in its modular and scalable architecture. By separating the frontend, backend, and AI inference engine using RESTful APIs, the system is highly maintainable and flexible. This modularity allows future updates to the AI model or user interface without disrupting the overall structure, making it suitable for real-world deployment and continuous improvement.

Nevertheless, the system has some limitations. It currently processes static X-ray images without considering patient clinical data, which might limit diagnostic accuracy in complex cases. Also, it lacks fine-grained localization (e.g., segmentation) and batch-processing capabilities. These issues present valuable directions for future research and development.

In conclusion, Artificial Intelligence Based Assisted Diagnosis System for Pneumonia demonstrates how artificial intelligence can assist and accelerate medical diagnosis. By combining high-performance image classification, interpretable outputs, and user-friendly design, the system provides a meaningful contribution to the digital transformation of healthcare and sets the foundation for further innovation in AI-driven medical support systems.

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