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Bacterial Pneumonia Classification using YOLOv11-Based Image Analysis Approach

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Abstract

Bacterial pneumonia is a major health issue in all over the world. It requires precise and effective diagnostic instruments. In order to improve classification accuracy, this study combines a YOLOv11-based image processing system with other machine learning techniques to provide a unique method for pneumonia identification. The primary objectives include developing an optimized deep learning model for pneumonia detection, comparing its performance with traditional methods such as CNNs, K-Nearest Neighbors (KNN) and Decision Trees, and deploying the solution in a cloud environment for real-time inference. The proposed technique reduces overfitting by efficiently capturing spatial characteristics in chest X-ray images using YOLOv11. A comprehensive performance review demonstrated the model's ability to distinguish between cases with and without pneumonia. A cloud based online application can provide an intuitive interface for submitting photos to the medical professionals with. It will help to receive real time diagnostic predictions using Streamlit. The outcomes show that the YOLOv11-based system outperforms current techniques in terms of accuracy and efficiency while preserving computing speed and cost-effectiveness in cloud deployment. The study provides a scalable tool for pneumonia diagnosis. Future work is to focus on further optimization including feature enhancements leading to ultimately improving patient outcomes.

Keywords: Bacterial pneumonia detection, YOLOv11 model, CNN, KNN, Decision Tree, cloud environment, cloud deployment.

1. Introduction

Pneumonia is an inflammatory illness in human lung that is a deadliest disease worldwide. It is caused by bacterial, viral or fungal infection. It causes killing of most elderly people and children under five. The reports from World Health Organization depicts that pneumonia causes 15% of child fatalities that makes it a dangerous infection to diagnose [1]. Chest X-Ray radiograph imaging detects pneumonia using X-rays. However, manual interpretation and inter-observer variability can delay diagnosis. When resources are few, like qualified radiologists, this is more apparent [2]. Pneumonia has a great impact on the global healthcare systems and causes mortality particularly among children and the aged people. hence, early and accurate diagnosis has become important for effective treatment and improved patient outcomes. X-ray images of chest is the primary tool for pneumonia diagnosis. However, this traditional method heavily relies on the view of experts. This leads to potential human errors as well as delays in diagnosis. Deep learning-based medical image analysis supports the increasing demand for automated and efficient diagnostic solutions. But conventional classification methods often suffer from low accuracy, inefficiency and inconsistency in manual evaluation. These challenges further increase the difficulty in resource limited healthcare settings where timely and accurate pneumonia detection is crucial.

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With the Integration of artificial intelligence and deep learning models, it offers a promising solution for enhancing diagnostic accuracy, and accelerating the medical decision making. This research investigates the deep learning implementation in the diagnosis of bacterial pneumonia by using chest Xray images. Convolutional neural network (CNN) models are employed to develop, train and evaluate the idea. A real time detection approach was built, based on YOLOv11 algorithm to enhance the diagnostic accuracy and speed. Among all models tested, this model shows the high proficiency in classification accuracy and efficient real-time pneumonia detection. This work is made accessible by deploying in a cloud based environment that allows the professionals to analyze chest X ray images using AI with high accuracy and minimal latency. This significant advancement in medical investigation creates the path for scalable and accessible AI-driven diagnostic tools for global healthcare systems.

2. Related Work

Recent studies have emphasized the increasing utilization of cloud computing for medical image analysis. Cloud-based solutions facilitate processing extensive datasets and real-time analysis, offering a scalable option for healthcare systems [3], [4]. YOLOv5's 2020 release prompted many medical image analysis studies. Its speed and accuracy made YOLO suitable for real-time detection. This study broadly explores YOLO for rapid and accurate pneumonia detection by utilizing chest X-rays images with enhanced efficiency, especially in low resource settings. With the techniques of model optimization and attention mechanisms YOLO achieved 91% accuracy [5].

In 2025, YOLOv11 improved real-time image processing in multi-scale object detection scenarios. YOLOv11's architectural modifications enhance accuracy and speed, making it suitable for pneumonia diagnosis in medical imaging [6]. Kundu et al. introduced YOLOv11 as an anchor-free approach, making chest X-ray infection localization more customizable, making it excellent for pneumonia diagnosis [1]. Clinical applications for YOLOv11 real-time detection are promising. Li et al. used YOLOv11 to identify cloud chest X-rays for bacterial pneumonia in real-time with radiologists-like accuracy. This study found that YOLOv11's lightweight architecture and minimal cloud processing latency allowed it to manage large image datasets in clouds [7].

3. Research Methodology

This study introduces an advanced deep learning-based approach for accurately classifying pneumonia and normal heart conditions using chest X-ray images. The implementation methodology is divided into several phases, as illustrated in Fig. 1. Through data collection, preprocessing, feature extraction, and model training the development of a robust framework is initiated. This model is capable of accurate pneumonia diagnosis. Apart from the model optimization, a cloud based system has also been implemented. It allows the users to upload chest X-ray images for real-time classification. The diagnostic efficiency has also improved with the enhancement in the advanced accessibility. This proposed method significantly holds the potential in supporting clinical decision making. Thus, it improves the radiological assessments, and advancing AI-driven medical imaging applications.

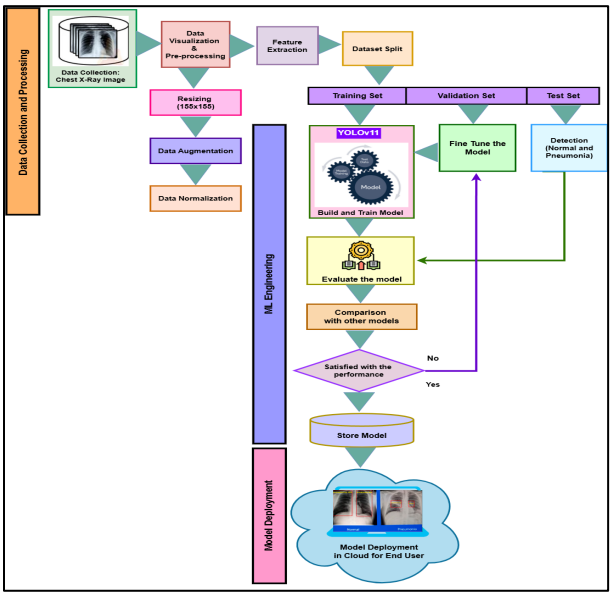


Figure 1. Research Methodology.

3.1. Data Collection and Visualization

Developing successful artificial intelligence models for chest X-ray analysis depends on the availability of large, diverse datasets with high-quality images. Despite the publica tion of numerous databases of chest X-ray images, most lack detailed pixel-level anatomical segmentation labels and only include disease diagnosis labels [8]. An extensive chest X-ray multi-centre segmentation dataset is introduced to address this gap. The dataset consists of uniform and fine-grain anatomical annotations for images from five well-known publicly available databases. The dataset was acquired by meticulously extracting chest X-ray images, guaranteeing adequate representation while preserving radiographic and labelling consistency. The chest X-ray image dataset has been acquired from the [9]. Data visualization has been presented in Figure. 2.

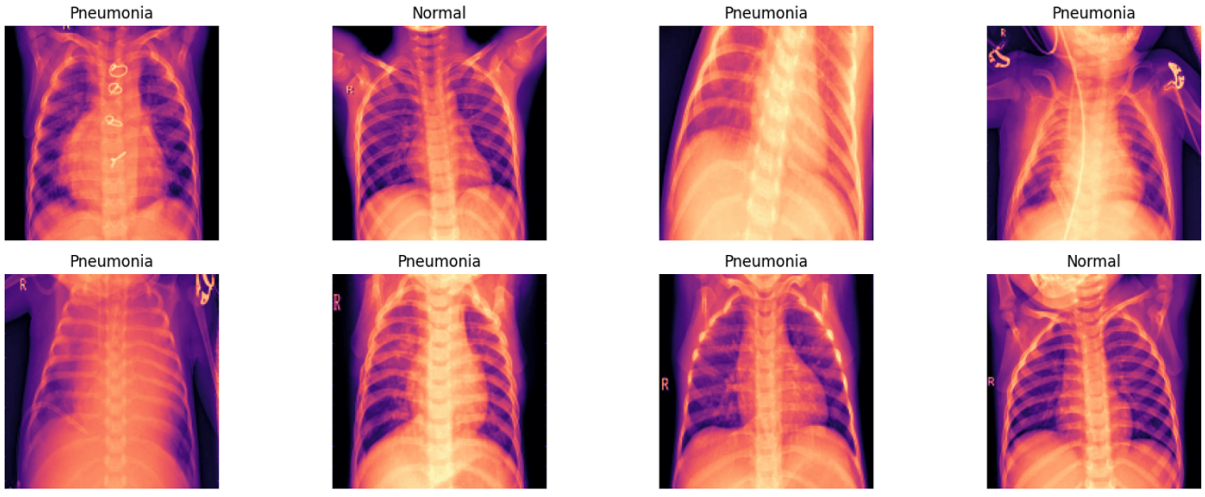


Figure 2. Sample Images.

3.2. Data Preprocessing

To enhance model performance and ensure consistency, several preprocessing steps were followed to the chest X-ray images. At first, all images of different sizes were resized to 155×155 pixels and make the dimension of the dataset standardized for input. After that, the format of the images were changed to a suitable one for deep learning models. Then, the normalization process was imposed to the datasets to scale pixel values. That helps to improve contrast and aids quickly during training. Additionally, rotation, flipping, and zoom in were applied as the form of data augmentation to balance the dataset and reduce overfitting. The following preprocessing steps, such as Data Resizing, Data Augmentation, and Data Normalization, have been followed to ensure the dataset's suitability for deep learning-based classification training and testing tasks. We identify that image-level prediction variations are not arbitrary but can be inferred accurately, even for pathologies with a negligible overall performance disparity.

This implies systematic tendencies in the models trained on various datasets. Additionally, these "predictive tendencies" are not exclusively accounted for by image statistics or attributes such as radiographic position or label; they are pathology-specific and closely associated with higher-order image characteristics. Our results underscore the necessity of a nuanced approach that prioritizes the diversity of pathology presentation, emphasizing the complexity of AI robustness and generalization [10].

3.3. Feature Extraction

To help deep learning algorithms to classify the stage of pneumonia, medical image analysis heavily relies on feature extraction classify. For doing so, in this investigation, YOLOv11 and CNN were used as techniques of feature extraction with classification strengths. YOLOv11 is a state of the art object detection model that extracted region specific characteristics by recognizing the very affected areas in chest X-ray images and finds the existence of pneumonia. Real time detection and concentration of this model on significant diseased regions potentially improve diagnosis accuracy. Feature extraction process of this model detects pneumonia related local anomalies. From X-ray pictures, the CNN model specifically extracted global spatial characteristics. Using multiple convolutional layers in the CNN architecture helps to develop hierarchical representations of input data and captures complex sign of pneumonia, like textures, forms, and patterns. By abstracting features from low level edges to high level medical problems CNNs properly distinguish normal and pneumonia affected instances. In this study, improvements of pneumonia classification accuracy is explored by using YOLOv11 for localized feature extraction. Integrating the CNN for full spatial feature representation this procedure is accelerated. This dual model method not only strengthens the diagnostic system, but also generalizes the theme of detection. A framework is created for detecting diseases by sequentially collecting data. Imposing data preprocessing, extracting features, and learning algorithms make the procedure ready to use [11].

3.4. Dataset Splitting

In this study, the dataset utilized chest X-ray images with two different classifications. The categories are-pneumonia affected tissue and normal tissue. The data is sourced from IEEE Dataport [9]. This data is preprocessed to ensure uniformity as well as facilitate effective model training. To make a standardized resolution of 155 × 155 pixel all images were resized. After that, the dataset was divided into training and testing sub sets. Here 80% of the data is reserved for training and the rest is for testing. For each subset, two directories were created. They separately store the images corresponding to pneumonia and normal cases. Thus, it maintains clear class distinctions throughout the pipeline.

3.5. Model Selection and Description

In this study employed multiple deep learning models are imposed to classify chest X-ray images into pneumonia and normal cases. These models are YOLOv11, CNN, k-nearest neighbors (KNN) and Decision Tree. To derive spatial features through convolutional layers, CNN, a widely used architecture for medical image classification, was implemented. Subse quently the generation of final predictions is done by pooling and fully connected layers. Utilizing all perfectly augmented images, the CNN model was trained. This helps to enhance generalization and robustness of the model. On the other hand, YOLOv11 is used as an advanced object detection model. It was specifically adapted for the classification task that utilized real time detection capability. Apart from conventional CNN models, YOLOv11 finds image classification as a different task. It consider this as a detection problem. By segmenting and analyzing the X ray images it used a single forward pass. The strength of this model lies in capturing local and global features, It also enables accurate classification with minimal computational overhead. The above two models were trained in the same dataset separately. All the images were resized to 155 × 155 pixels and divided into an 80:20 for train-test split. The performance of each model was assessed using the F1-score, recall, precision, and accuracy.

3.5.1. YoloV-11

YOLOv11 (You Only Look Once, version 11) is an advanced real-time object detection algorithm for high accuracy and efficient image classification. YOLOv11 is the most recent version of Ultralytics's YOLO series. It substantially updates previous versions based different characteristics. It enhanced backbone and neck architecture of the model that results in superior feature extraction that specifically enables it to achieve higher detection accuracy. At the same time, it also maintains computational efficiency utilizing fewer parameters [12]. The model is highly adaptable. It can handle to various tasks, including pose estimation, segmentation, classification, as well as object detection too. YOLOv11 is particularly optimized for deployment on cloud platforms. In the peripheral devices, it can balance adaptability, accuracy, and speed.

The YOLOv11 model maintains the core YOLO architecture. it consists of three main components 3:

I) Backbone (Feature Extraction): Extracts multi-scale features from input images using modules like:

- Conv Layer for low-level feature extraction.
- C3k2 Module for efficient local feature extraction with bypass connections.
- SPPF Module for multi-scale feature representation

• C2PSAModulefor enhancing critical features in complex scenes.

II) Neck (Feature Fusion): Merges multi-scale features to improve the detection of objects of various sizes. It includes:

• Upsample to enhance small object detection.

• Concat for fusing multi-resolution feature maps.

• C3k2 Module for enriching feature representations.

III) Head (Detection Output): Converts processed feature maps into precise object detections. The detection module enables multi-scale object recognition, ensuring accurate identification across diverse environments.

The aim of this study is to employ YOLOv11 for classi fication of chest X-ray images into pneumonia and normal categories. It leverages transformer based feature extraction. As a backbone the model architecture utilizes of a deep convolutional network with a transformer-based detection. This model also enables a better contextual understanding of medical imaging. Though, images were preprocessed through resizing, normalization, and augmentation techniques, the training process utilized a custom dataset. Further integration of transfer learning ensured fine tuning of the model on different pre trained weights to improve convergence. The YOLOv11 framework provided efficient classification results. It demonstrated robustness in identifying pneumonia from dataset of chest X-rays. As a compact solution for real world diagnostic applications, the model inference speed and accuracy [13]. It also reduces the required time for perfect assessment by radiologist and also maintain high diagnostic reliability [14].

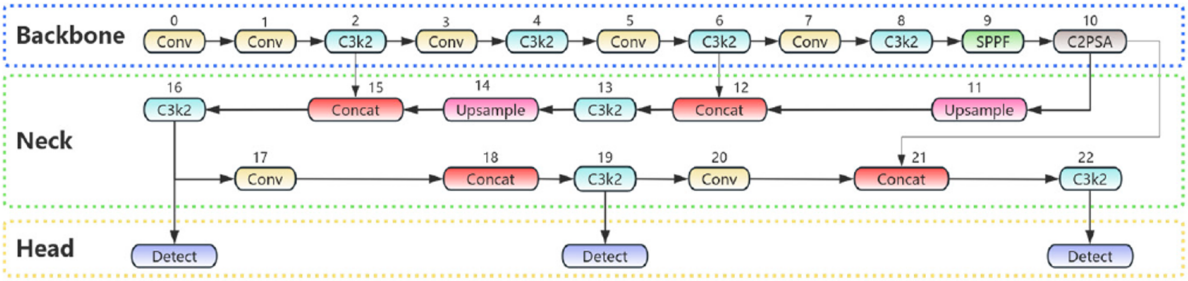


Figure 3. YOLOv11 network structure diagram [12].

3.5.2. CNN

CNNs are Deep Learning algorithms that work with processing the input images, assign learnable weights and biases to certain visual features, and identify them [15]. CNNs typically include four layers: convolutional, non-linearity, pooling, and fully-connected. Convolutional and fully connected layers have parameters. However, pooling and non-linearity layers do not. CNNs excel at image data applications. CNNs are used to assess spatial and temporal information in video frames. Abstract properties are essential for CNN when input propagates to deeper layers. Image categorization may recognize edges in the first layers, simpler shapes in the second levels, and faces in the third layers [16], [17].

3.5.3. KNN

The Nearest Neighbor Classifier is a fundamental machine learning algorithm. It potentially classifies requests by matching them with their closest neighbors. With the utilization of available processing capacity, the bad runtime performance doesn't remain a barrier. It makes this categorization approach important [18], [19]. This article discusses all the Nearest Neighbor classification methods. The result includes distance assessment, computational problems, and data reduction.

3.5.4. Decision Tree

Decision trees (DTs) represent interpretable machine learning (ML) models. An informal reason is that DT pathways are sometimes substantially smaller than feature counts. Decision support systems enable physicians and significantly contribute to medical decision-making [20]. They are founded on many models, with the most effective offering explanations with accurate, dependable, and prompt responses. Experimental results on a wide range of publicly available datasets with well-known DT-learning methods show that most DTs have routes that are appropriate supersets of detection algorithm explanations.

4. Result & Analysis

4.1. Performance Metrics

The detection algorithms for class-wise performance are based on several evaluation metrics used to test data for these ML models.

$$Recall = \frac{True\ Positive}{True\ Positive + True\ Negative} \quad (1)$$

$$F1\ Score = \frac{2\times Precision \times Recall}{Precision + Recall} \quad (2)$$

The performance evaluation of the CNN and YOLOv11 models for classifying pneumonia and normal chest X-ray images yielded valuable insights. A balanced evaluation was guaranteed by dividing the dataset into training and assessment sets in an 80:20 ratio. YOLOv11 achieved an impressive 99% accuracy, significantly outperforming CNN, which reached 92% accuracy. The confusion matrices for both models are presented in Figures 1 and 2, illustrating the correct and incorrect classifications across both categories.

4.2. Comparison Study

4.2.1 CNN

In the CNN model, an overall accuracy of 92.31% in depicted that effectively distinguished between pneumonia and normal cases. However, it exhibited some misclassifications. Such happened due to overlapping patterns of X-ray images in the dataset. Moreover, the model achieved a precision of 92% for normal X-rays and 92% for pneumonia X rays. This data indicates a strong ability to classify both cases correctly. Another parameter, called recall values, suggests that the CNN model successfully identified 96% of pneumonia cases though it had a lower recall of 87% for normal cases. In some normal image justification cases, the images were misclassified as pneumonia. On the other hand, F1 scores for pneumonia and normal cases were 94% and 89%, respectively. It reflected a balanced trade-off between precision and recall.

4.2.2 YoloV11

The YOLOv11 model demonstrated superior performance compared to all other models. It is achieving an impressive overall accuracy of 94%. Besides it is confirming its effectiveness for real-time pneumonia

detection using chest X-ray images. The model's architecture is particularly adept at capturing localized spatial features and enabling it to accurately identify pneumonia-affected regions with high precision and speed key attributes for practical deployment in clinical environments. TABLE I The grouping report based on, the model recommended an accuracy of 97% for normal X-rays and 91% for pneumonia cases. It is signifying near-perfect type. This is indicating that the model efficiently identifies true pneumonia cases. while supporting a low rate of false positives and false negatives. The recall values were 88% for normal cases and 98% for pneumonia cases, put forward minimal false negatives. The confusion matrix on test data from the YOLOv11 model has been presented in Fig. 4.

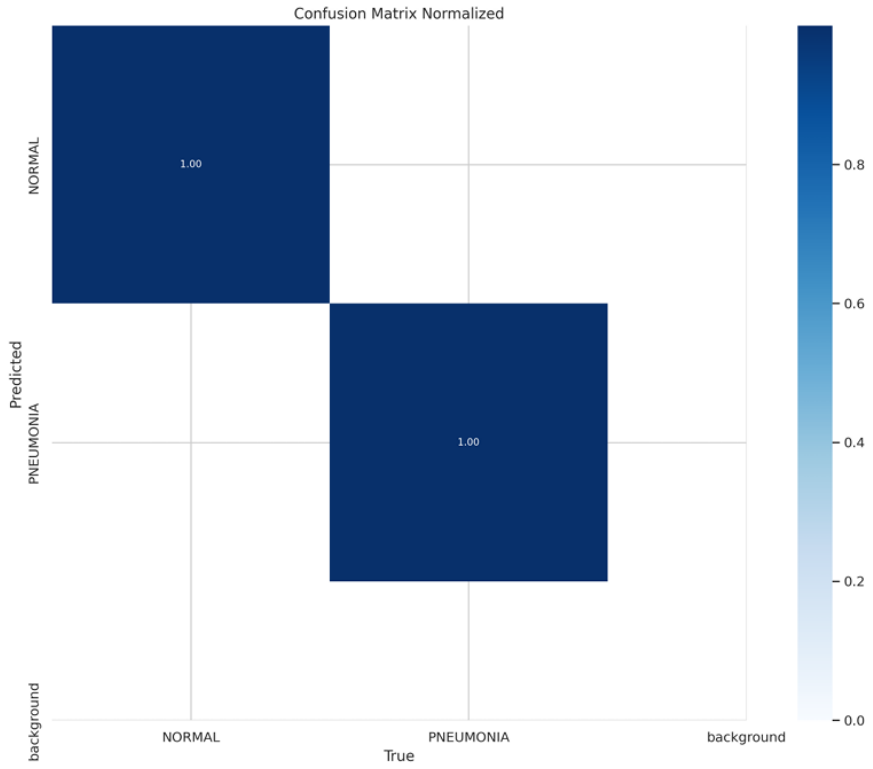


Figure 4. Confusion Matrix.

Table 1. Classification report for different models

Models	Class	Precision	Recall	F1 Score
Caption	Pneumonia	0.95	0.93	0.94
	Normal	0.96	0.97	0.96
Contents	Pneumonia	0.92	0.96	0.94
	Normal	0.92	0.87	0.89

4.2.3 Decision Tree

The Decision Tree model performed the weakest among all evaluated models. It achieved overall 76% accuracy with precision of 72% for normal X-rays and 88% for pneumonia X-rays. However, its recall for normal cases was significantly lower at 40% for pneumonia cases, indicating a high misclassification rate for normal cases. The F1-score for pneumonia cases was 54% for normal cases, it was 82% for pneumonia, making the Decision Tree model less reliable compared to CNN and YOLOv11.

4.2.4 KNN

The KNN model exhibited performance as shown in Figure 4.3. It adds up to an overall accuracy of 78%, effec tively distinguishing between pneumonia and normal cases. It pulls off an precision of 52% for normal cases and 62% for pneumonia cases, throw back a high misclassification rate. The recall values were 53% for normal X-rays and 65% for pneumonia X-rays, indicating its limited capability in correctly identifying cases. The F1 scores were 54% for normal X rays and 57% for pneumonia cases, indicating the model's inefficiency in distinguishing between normal and pneumonia cases convincingly.

The superior performance of YOLOv11 is demonstrated by the experimental results, which achieved the highest accuracy (96%) and the best balance between precision, recall, and F1-score. CNN also performed well, gaining a substantial accuracy of 92% but struggling slightly in pneumonia detection due to overlapping features in certain images. The Decision Tree and KNN models, however, showed limitations in classification performance, particularly for normal cases, where they had low recall scores.

4.3 Practical Implementation: Cloud Deployment

After extensive training session, the model is designed carefully. It has become ready to incorporate smoothly into cloud infrastructure. Thus, it makes enables the real time inference capabilities. To choose a cloud service provider, there is an important task, such as, taking a comprehensive approach as well as considering key factors like computation speed, cost-effectiveness, and integration capabilities (Jia, 2025). This selection process with careful integration guarantees that the selected provider is in perfect sync with the project's goals. This results in increased efficiency and reduced operational costs. For proper enhancement of both accessibility and us ability, here we have developed a cloud-based web application. for developing the web access, we used Streamlit and it is depicted in Figure. 5. This UI is truly interactive and provides an intuitive interface to the users, e.g. experts or patients. One can upload chest X-ray images and receive real time pneumonia detection results. It belongs a lightweight nature of Streamlit. So that seamless integration with deep learning models can be enabled for a smooth and efficient deployment process. Thus, it ensures a user-friendly environment without compromising performance.

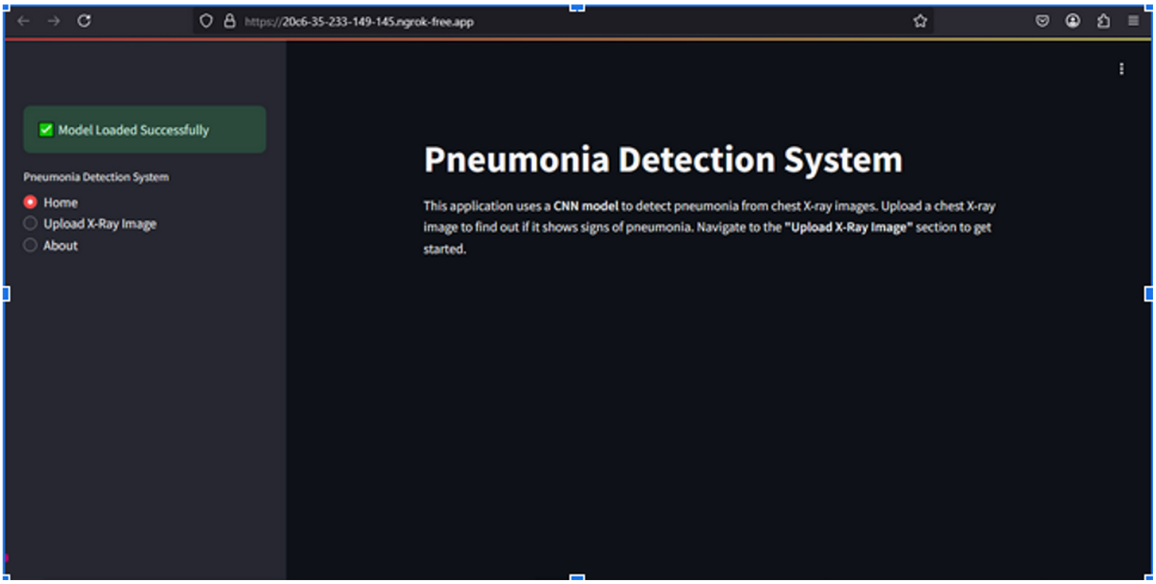


Figure 5. User Interface for Chest X-Ray Pneumonia Detection

The results of the prediction from YOLOv11 model are shown in Figure. 6. This result is essential for clinicians to correctly interpret results.

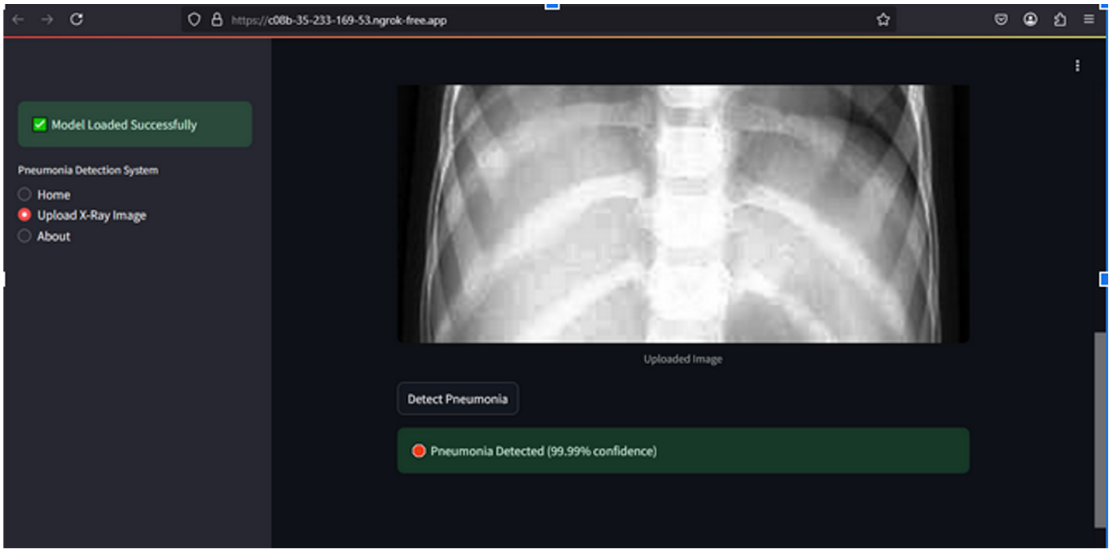


Figure 6. Result Based on Detection.

5. Limitations & Future Works

This study has some minor limitations, relying on the dataset including frontal chest X rays may h9ighly hinder generalization across different imaging conditions. Additionally, despite its accuracy the YOLOv11 model is computationally memory demanding. Further, future work will

focus on optimizing the model for real time applications. It is important to expand the dataset to improve robustness, exploring model compression techniques, and integrating radiologists' expertise to enhance decision-making and classification performance. Future work will focus on optimizing YOLOv11 in real time adaptation in limited lab setting by more accurate prediction.

This part presents results or findings. Figures or graphs can also be presented here to support your findings, and there should be no duplication of data in graphs or figures. We suggest that you mention supporting instrument(s), in forms of illustration, figures, photographs, tables, and graphs. Each instrument must be orderly numbered and given a title, followed by source from which you make the citation. Should the instrument be the result from the author's analysis, please write: 'source: author's analysis.' Meanwhile, figures are presented center, as shown below in the manuscript.

6. Conclusion

The study introduces a novel pneumonia detection system using the YOLO11 architecture to automate the analysis of chest X-ray images. Resizing images and normalizing pixel values were necessary preprocessing steps. Data augmen tation techniques like rotation and brightness adjustments were also used to avoid overfitting. Confusing matrix demon strated the model's ability to differentiate between normal and pneumonia-affected images across all datasets. Furthermore, a user-friendly web interface enables medical professionals to upload images and get confidence-level predictions in real time. The results demonstrate the potential of the YOLO11 based system as a valuable diagnostic tool in clinical set tings and the efficacy of deep learning in medical imaging for diagnosing pneumonia. Further optimization and feature improvements could further enhance its usefulness in sup porting medical professionals in making timely diagnosis and treatment decisions.

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