PNEUMONIA DETECTION USING CHEST RADIOGRAPHS WITH YOLO MODELS

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Abstract_ Deep Learning–based object detection models have demonstrated significant potential for automated Pneumonia detection using chest X-ray images. This study presents a comparative analysis of advanced YOLO-based object detection algorithms for accurately identifying pneumonia-related abnormalities in radiographic images. The proposed framework evaluates four state-of-the-art models: YOLOv5 YOLOv5s6, YOLOv5x6, YOLOv8 YOLOv8, and YOLOv9.The chest X-ray dataset undergoes preprocessing and augmentation to improve model generalization and detection capability. All YOLO variants are trained and evaluated using standard object detection performance metrics including precision, recall, and mean Average Precision (mAP).Experimental results demonstrate consistently strong detection performance across all evaluated models, with each model achieving a precision score of 1.0. YOLOv5s6 achieved the highest recall value of 1.000 along with an mAP score of 0.995. YOLOv5x6 and YOLOv8 both obtained recall values of 0.997 while maintaining an mAP score of 0.995. YOLOv9 achieved a recall score of 0.996 with the same mAP value of 0.995.The comparative analysis indicates that all implemented YOLO architectures provide highly accurate, reliable, and robust performance for automated pneumonia abnormality detection in chest radiographs. Among the evaluated models, YOLOv5s6 demonstrated the best recall performance, indicating superior capability in identifying pneumonia-affected regions.Overall, the study confirms the effectiveness of modern YOLO-based object detection algorithms for intelligent pneumonia diagnosis and highlights their potential for real-time deployment in healthcare environments to support faster and more accurate clinical decision-making.

Index terms - *— Pneumonia detection, Chest X-ray, Deep learning, , YOLO, Flask framework, Medical image analysis.*

1. INTRODUCTION

Pneumonia is a serious infectious disease that causes inflammation in the air sacs of one or both lungs. It is one of the major respiratory illnesses affecting millions of people worldwide and results in a significant number of hospitalizations every year. In the United States alone, more than one million individuals are hospitalized annually due to pneumonia-related complications.The disease primarily affects the pulmonary alveoli, which are tiny balloon-shaped air sacs located at the ends of the bronchioles in the lungs. During infection, these air sacs become inflamed and may fill with fluid or pus, leading to breathing difficulties, chest pain, fever, cough, fatigue, and reduced oxygen exchange within the body.

Pneumonia can be caused by several infectious agents including bacteria, viruses, and fungi. Based on the causative organism, pneumonia is classified into multiple categories such as bacterial pneumonia, viral pneumonia, mycoplasma pneumonia, and fungal pneumonia.

Bacterial pneumonia is commonly caused by bacterial or fungal infections and may lead to severe symptoms such as weakness, fever, chest congestion,

and breathing problems. Certain groups of people are more vulnerable to bacterial pneumonia, including elderly individuals, smokers, alcohol consumers, patients recovering from surgery, asthma patients, and individuals with weakened immune systems or poor nutritional status.Viral pneumonia is caused by respiratory viruses such as influenza viruses and accounts for a significant proportion of pneumonia cases worldwide. In many situations, viral pneumonia weakens the respiratory system and increases the risk of secondary bacterial infections, making the condition more severe and difficult to manage.Early diagnosis and timely treatment are extremely important for preventing serious complications associated with pneumonia. Medical treatments commonly include antibiotics for bacterial infections, antiviral medications for viral pneumonia, and supportive respiratory care. Accurate and rapid detection plays a crucial role in reducing mortality rates and improving patient recovery outcomes.

Due to the growing number of pneumonia cases and the challenges associated with manual diagnosis, advanced technologies such as Machine Learning and Deep Learning are increasingly being explored to assist healthcare professionals in automated pneumonia detection and medical image analysis. These intelligent systems can support faster diagnosis, reduce radiologist workload, and improve overall healthcare efficiency.

2. LITERATURE SURVEY

a) A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images:

One of the leading causes of death worldwide is pneumonia. Pneumonia can be brought on by bacteria, fungus, or viruses. However, evaluating pneumonia only from chest X-rays is challenging. This study aims to make pneumonia identification easier for both professionals and beginners. Using the idea of transfer learning, we propose a novel deep learning system for pneumonia identification. This method uses several neural network models that have been pretrained on ImageNet to extract characteristics from pictures, which are then input into a classifier for prediction. We created five distinct models and evaluated how well they performed. The state-of-the-art performance in pneumonia recognition was then achieved by our ensemble model, which integrates the outputs of all pretrained models and outperforms individual models. On unseen data from the Guangzhou Women and Children's Medical Center dataset, our ensemble model achieved an accuracy of 96.4% and a recall of 99.62%.

b) Pneumonia Classification Using Deep Learning from Chest X-ray Images During COVID-19: COVID-19 outbreak in December 2019 caused worldwide disaster. On March 11, 2020, WHO labeled the illness a pandemic. As of October 10, 2020, the pandemic has spread to over 200 nations with 37 million confirmed illnesses and 1 million deaths. The conventional approach for COVID-19 detection is reverse-transcription polymerase chain reaction (RT-PCR), which has numerous drawbacks, including false positives, limited sensitivity, high cost, and expert testing. Rapid screening that is accurate, fast, and affordable is needed as the number of patients grows. Due to its speed and accessibility, chest X-ray (CXR) scan pictures might be used as an alternate or confirmatory method. The literature describes several methods for classifying CXR pictures and detecting COVID-19 infections, however most can only distinguish two groups. However, well-developed models are needed to categorize a wider variety of COVID-19 CXR pictures, including bacterial pneumonia, non-COVID-19 viral pneumonia, and normal CXR scans. A deep learning strategy based on pretrained AlexNet model is proposed to classify COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia, and normal CXR images from public datasets. The model was trained to perform two-way, three-way, and four-way classifications of COVID-19, bacterial pneumonia, non-COVID-19 viral pneumonia, and normal. The suggested model has 94.43% accuracy, 98.19% sensitivity, and 95.78% specificity for non-COVID-19 viral pneumonia and healthy CXR pictures. The model has 91.43% accuracy, 91.94% sensitivity, and 100% specificity for bacterial pneumonia and normal CXR pictures. The model has 99.16% accuracy, 97.44% sensitivity, and 100% specificity for COVID-19 pneumonia and normal CXR pictures. The model classified COVID-19 and

non-COVID-19 viral pneumonia CXR pictures with 99.62% accuracy, 90.63% sensitivity, and 99.89% specificity. The three-way classification model has 94.00% accuracy, 91.30% sensitivity, and 84.78%. Finally, the four-way classification model has 93.42% accuracy, 89.18% sensitivity, and 98.92% specificity.

c) Identification of Pneumonia Disease Applying an Intelligent Computational Framework Based on Deep Learning and Machine Learning Techniques

Pneumonia is a highly prevalent and deadly illness that must be detected in its early stages to save a patient's life and avoid further harm. Chest X-rays, CT scans, blood cultures, sputum cultures, fluid samples, bronchoscopies, and pulse oximetry are among the methods used to diagnose pneumonia. Medical image analysis is regarded as one of the most promising fields of study and is essential to the identification of several illnesses, including pneumonia, COVID-19, and MERS. An professional radiologist with knowledge and experience in the relevant field is required to effectively evaluate chest X-ray pictures. Approximately two thirds of the world's population still lack access to radiologists for illness diagnosis, according to a World Health Organization (WHO) report. In order to effectively and efficiently diagnose pneumonia, this study suggests a DL framework. To extract relevant features from the chest X-ray pictures, many Deep Convolutional Neural Network (DCNN) transfer learning approaches are used, including AlexNet, SqueezeNet, VGG16, VGG19, and Inception-V3. Several machine learning (ML) classifiers are used in this work. A dataset of CT and X-ray images of the chest was used to test and train the suggested system. Several performance metrics have been used to assess the stability and efficacy of the suggested system. The goal of the proposed method is to help physicians diagnose pneumonia effectively and correctly.

d) Deep-Pneumonia Framework Using Deep Learning Models Based on Chest X-Ray Images:

One of the leading causes of mortality for children and the elderly worldwide is pneumonia, a contagious illness that results in lung ulcers. Numerous deep learning models have been put out to identify pneumonia from chest X-ray pictures. Finding a suitable and effective model that satisfies all performance measures has proven to be one of the most difficult tasks. The primary goal of this work is to provide effective and potent deep learning models for pneumonia detection and classification. This research develops four models by varying the deep learning technique: a Long Short-Term Memory (LSTM), a Convolutional Neural Network (CNN), and two pre-trained models, ResNet152V2 and MobileNetV2. Python is used to develop and assess the suggested models, and they are contrasted with recent studies of a similar nature. The findings show that our suggested deep learning framework increases recall, accuracy, precision, F1-score, and Area Under the Curve (AUC) by 99.22%, 99.43%, 99.44%, 99.44%, and 99.77%, respectively. The findings clearly show that the ResNet152V2 model performs better than other previously suggested studies. Additionally, the other suggested models—MobileNetV2, CNN, and LSTM-CNN—outperformed the previously published models in the literature, achieving outcomes with more than 91% in accuracy, recall, F1-score, precision, and AUC.

e) Standardized interpretation of paediatric chest radiographs for the diagnosis of pneumonia in epidemiological studies:

Background: The interpretation of chest radiographs varies greatly, despite the fact that radiological pneumonia is utilized as an end measure in epidemiological research. Comparing the outcomes of vaccination trials and epidemiological studies of pneumonia would be made easier with a consistent technique for diagnosing radiological pneumonia.

Methods: Definitions for radiological pneumonia were created by a WHO working committee. By comparing the readings from 20 radiologists and physicians with a reference reading, inter-observer variability in classifying a set of 222 chest radiography pictures was assessed. By comparing the initial readings of a randomly selected subset of 100 radiographs with repeat readings taken 8–30 days later, intra-observer variability was quantified.

Results: 208 of the 222 pictures were deemed interpretable. 43% of these pictures were classified by the reference reading as exhibiting alveolar consolidation or pleural effusion (primary end-point pneumonia); the percentage that each of the 20 readers classified in this way varied from 8% to 61%. 13 out of 20 readers had a kappa index of > 0.6 when compared to the reference reading, and 14 out of 20 readers had sensitivity and specificity of > 0.70 when diagnosing main end-point pneumonia using the reference reading as the gold standard. Nineteen out of twenty readers had a kappa index greater than 0.6 for the 92 radiographs that were judged interpretable out of the 100 pictures evaluated for intra-observer variability.

Conclusion: It is feasible to reach consensus in the identification of radiological pneumonia by the use of uniform criteria and training, which makes it easier to compare the findings of epidemiological studies that employ radiological pneumonia as an endpoint.

3. METHODOLOGY

i) Proposed Work:

The suggested method uses powerful YOLO object detection algorithms to reliably recognize and pinpoint pneumonia-affected regions in chest X-ray images. The framework automatically detects aberrant lung regions and highlights sick areas in radiographic images to help healthcare providers.Several preprocessing steps improve image quality and model generalization in the chest X-ray dataset. Preprocessing includes image resizing, normalization, and augmentation methods like rotation, flipping, scaling, and transformation. Data augmentation diversifies datasets and makes deep learning models more resistant to image orientation, intensity, and location.The framework uses cutting-edge YOLO-based object detection designs like YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n. These methods generate bounding boxes around infected lung areas in chest radiographs to automatically identify pneumonia-related anomalies.

YOLO-based designs use deep convolutional neural network topologies and real-time object identification to quickly and accurately locate pneumonia-affected areas. The single-stage detection method provides simultaneous feature extraction, classification, and localization, resulting in fast prediction for clinical use.The selected YOLO versions are compared for detection accuracy, computational efficiency, and real-time performance to establish the best design. Classic object detection metrics like precision, recall, and mean Average Precision are used to evaluate the models.

This approach increases automated pneumonia diagnosis interpretability by visually identifying diseased regions using bounding box localization, helping radiologists and healthcare professionals make faster, more reliable, and more informed clinical judgments. The framework offers an effective computer-aided pneumonia detection approach employing chest X-ray imaging.

ii) System Architecture:

The above figure illustrates the workflow of an object detection system using YOLO models. Initially, the image dataset is collected and provided as input to the image processing stage, where preprocessing operations such as image resizing, normalization, and enhancement are performed to improve image quality and prepare the data for model training. The processed images are then used to train multiple object detection models, including YOLOv5x6, YOLOv5s6, YOLOv8n, and YOLOv9n. After training, the models perform object detection by identifying and locating target objects within the images. The performance of the trained models is evaluated using standard evaluation metrics such as Precision, Recall, and F1-Score. These metrics help measure the accuracy, reliability, and overall effectiveness of the detection models. Based on the evaluation results, the best-performing model can be selected for accurate and efficient object detection in real-world applicationspneumonia detection from chest X-ray images.

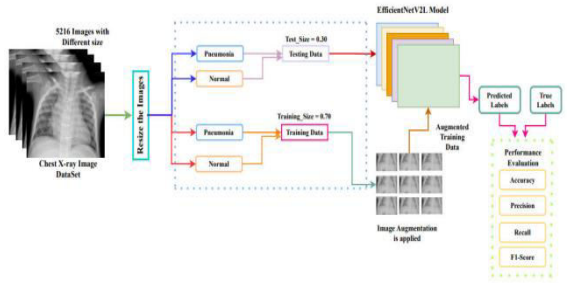

Fig1 proposed architecture

iii) Modules:

1. Data Collection and Preprocessing

The first stage of the proposed pneumonia detection framework involves collecting chest X-ray images containing both normal and Pneumonia-infected cases. These radiographic images serve as the primary dataset for training and evaluating the deep learning models.

To improve image quality and enhance model generalization, several preprocessing techniques are applied. The chest X-ray images are resized into a uniform dimension suitable for deep learning architectures. Normalization is performed to standardize pixel intensity values and improve numerical stability during training. In addition, data augmentation techniques such as image rotation, flipping, scaling, and transformation are used to increase dataset diversity and reduce overfitting. These preprocessing operations help the models learn robust visual representations from varied imaging conditions.

2. Model Development

In this phase, multiple advanced object detection architectures from the YOLO family are implemented for automated pneumonia detection and localization. The developed models include YOLOv5s6, YOLOv5x6, YOLOv8, and YOLOv9.

These deep learning architectures utilize convolutional neural networks for feature extraction and real-time object detection to identify pneumonia-related abnormalities within chest X-ray images. Suitable hyperparameters such as learning rate, batch size, epochs, and optimizer configurations are selected to improve training performance. The Adam optimizer is employed to enhance convergence speed and optimize weight updates during model training.

3. Model Training and Validation

All implemented YOLO models are trained using the prepared chest X-ray dataset. During training, the models learn to identify and localize pneumonia-affected regions by generating bounding boxes around abnormal lung areas.

To improve reliability and reduce overfitting, k-fold cross-validation is applied during the evaluation process. This validation strategy divides the dataset into multiple subsets, ensuring that each portion of the dataset is used for both training and validation at different stages. Cross-validation helps produce more generalized and stable performance estimates for the developed models.

4. Performance Evaluation

The trained models are evaluated and compared using standard deep learning and object detection performance metrics. These metrics include accuracy, precision, recall, F1-score, and confusion matrix analysis.

Additionally, object detection performance is measured using mean Average Precision (mAP), which evaluates the accuracy of predicted bounding boxes and localization quality. Comparative analysis among YOLOv5s6, YOLOv5x6, YOLOv8, and YOLOv9 helps identify the most

5. Extension Module

As an extension to the core framework, advanced YOLO-based object detection models are integrated for enhanced abnormality localization within chest X-ray images. These models visually highlight infected lung regions by generating precise bounding boxes around pneumonia-affected areas.

This localization capability improves the interpretability of the diagnosis process and assists healthcare professionals in identifying disease severity and affected lung regions more effectively.

6. Frontend and Deployment

To provide user accessibility and practical usability, a web-based application is developed using Flask. The frontend interface enables healthcare professionals and authorized users to interact with the system efficiently.

The application includes secure user authentication and access control mechanisms to protect medical data and restrict unauthorized usage. Users can upload chest X-ray images through the interface and receive real-time pneumonia detection and localization results generated by the trained YOLO models.

This deployment framework supports intelligent computer-aided diagnosis and facilitates faster, more reliable clinical decision-making in healthcare environments.

iv) Algorithms:

I. YOLOV5x6

YOLOv5 YOLOV5x6 is a high-performance real-time object detection model recognized for its strong balance between detection speed and accuracy. The architecture utilizes deep convolutional layers and advanced feature extraction mechanisms to identify objects efficiently within images.

In the proposed pneumonia detection framework, YOLOV5x6 is employed to detect and localize pneumonia-related abnormalities in chest X-ray images. The model generates bounding boxes around infected lung regions, enabling rapid identification of suspicious areas. Its real-time processing capability supports faster diagnosis and improves clinical efficiency for healthcare professionals.

II. YOLOV5s6

YOLOV5s6 is a lightweight variant of the YOLOv5 architecture optimized to achieve an effective balance between computational speed and detection accuracy. Due to its smaller architecture and reduced computational complexity, it is highly suitable for real-time medical image analysis applications.

Within this project, YOLOV5s6 is applied to identify pneumonia indications in chest radiographs. Its efficient processing speed allows rapid analysis of X-ray images, making it especially useful in emergency healthcare environments where quick diagnostic support is essential.

III. YOLOV8n

YOLOv8 YOLOV8n is a next-generation object detection architecture designed to improve feature extraction, localization accuracy, and real-time performance. The model incorporates advanced optimization techniques and enhanced neural network structures to improve detection reliability across complex image datasets.

In the proposed system, YOLOV8n is utilized to accurately detect pneumonia-related anomalies within chest X-ray images. Its improved architecture enables better recognition of infected lung regions and enhances diagnostic performance through precise localization and efficient real-time processing.

IV. YOLOV9n

YOLOV9n represents an advanced evolution within the YOLO family, focusing on further improvements in detection accuracy, computational efficiency, and inference speed. The architecture is designed to handle complex object detection tasks while maintaining lightweight and scalable performance.

In this project, YOLOV9n is implemented for pneumonia abnormality detection in chest radiographs. The model assists healthcare professionals by providing accurate and timely localization of pneumonia-affected areas, supporting improved patient diagnosis, treatment planning, and clinical decision-making processes.

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4. EXPERIMENTAL RESULTS

Performance evaluation was carried out using standard metrics such as Accuracy, Precision, Recall, and F1-Score, confirming that the proposed system provides reliable and accurate results. These findings highlight that the system can effectively assist in early pneumonia diagnosis and support clinical decision-making.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

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

mAP: Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).

$$\boldsymbol{mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k}$$

$$\boldsymbol{AP_k = \text{the AP of class } k}$$

$$\boldsymbol{n = \text{the number of classes}}$$

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

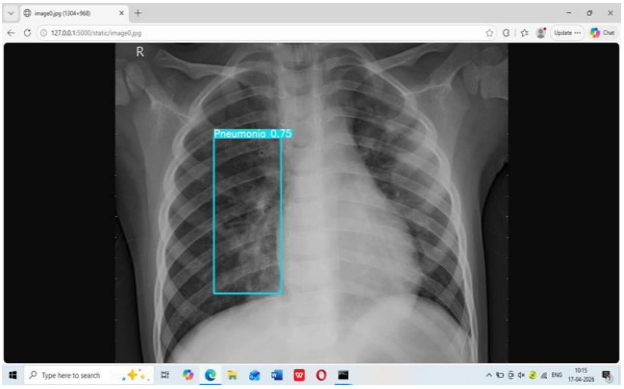

Fig 2:In above screen system successfully detected pneumonia image. The YOLO models identified infection in lung using bounding boxes with confidence scores.

Fig 3 In above screen system successfully detected non pneumonia image. The YOLO models identified infection in lung using bounding boxes with confidence scores.

5. CONCLUSION

Finally, the proposed approach shows that improved YOLO-based object detection models can accurately detect and localize pneumonia in chest X-ray pictures. The system quickly, reliably, and intelligently identifies pneumonia-affected lung areas

in radiographic images using recent deep learning algorithms.Image scaling, normalization, and augmentation methods like rotation and flipping improve dataset quality and model learning. These improvements improve generalization and detection across varied chest X-ray samples.The implementation of numerous YOLO variants—YOLOv5 YOLOv5x6, YOLOv5s6, YOLOv8 YOLOv8n, and YOLOv9n—enables a full computing efficiency and detection accuracy comparison. Each model generates bounding boxes around infected lung regions to detect pneumonia-related anomalies, enhancing diagnostic interpretability above previous image classification methods.Precision, recall, and mean Average Precision (mAP) demonstrate the framework's robustness, reliability, and efficacy. Faster inference speed and real-time medical applications are possible with lightweight designs like YOLOv8n and YOLOv9n, whereas larger architectures like YOLOv5x6 improve localization accuracy through deeper feature extraction.The suggested technology helps healthcare workers make faster, more accurate, and more informed clinical judgments by graphically indicating diseased chest radiographs. Healthcare efficiency, manual diagnostic effort, and human error are reduced with automated pneumonia diagnosis.YOLO-based models' real-time processing makes them ideal for deployment in hospitals, healthcare facilities, and diagnostic centers, improving patient care and intelligent computer-aided medical diagnosis.

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