Explainable Deep Learning Model for Pneumonia Diagnosis

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Abstract Pneumonia diagnosis poses a critical challenge, particularly in resource-constrained settings where access to skilled radiologists is limited. This research addresses the problem using two deep learning models: a Convolutional Neural Network (CNN) integrated with Local Interpretable Model-Agnostic Explanations (LIME) and transfer-learning-based InceptionV3 model coupled with Gradient-weighted Class Activation Mapping (Grad-CAM). The CNN model achieves an accuracy of 93.44%, offering reliable classification with localized interpretability through LIME, which highlights the specific image regions influencing predictions. Meanwhile, the InceptionV3 model outperforms with a 95% accuracy, a precision, recall, and F1-score of 97%, demonstrating its robustness for pneumonia detection. Grad-CAM enhances the interpretability of InceptionV3 by providing heatmaps that visually identify pneumonia-affected regions in chest X-rays. By combining high diagnostic accuracy with interpretable AI techniques, this study establishes that both models are highly effective for pneumonia diagnosis, with InceptionV3 and Grad-CAM being particularly wellsuited for clinical adoption. This approach ensures transparency, reliability, and scalability, making it a promising solution for healthcare applications and hence enhancing the quality of life in the society.

Keywords: Pneumonia diagnosis, Deep learning, Explainable AI, Chest X-ray analysis, CNN, InceptionV3, LIME, Grad-CAM

1 Introduction

Pneumonia is a severe lung disease caused by various pathogens, including bacteria, viruses, and fungi. It leads to inflammation of the lung's alveoli, often resulting in fluid or pus accumulation. Symptoms such as persistent cough with mucus, fever, chills, and difficulty breathing can range from mild to life-threatening. Vulnerable populations, including young children, the elderly, and individuals with weakened immune systems or underlying health conditions, face a significantly higher risk of severe complications. Despite advancements in medical care, pneumonia remains one of the leading causes of death worldwide, particularly in low-resource settings where early diagnosis and timely treatment remain challenging. The burden of pneumonia is especially pronounced in under-resourced regions, where access to trained medical professionals, advanced diagnostic facilities, and appropriate treatment options is severely limited. Traditional diagnostic methods, including chest X-rays and laboratory tests, often require skilled radiologists and expensive equipment that may not be available in rural or low-income areas. This leads to delayed diagnoses, increased mortality rates, and a greater strain on healthcare systems. AI-driven solutions present an opportunity to bridge this healthcare gap by providing automated, cost-effective, and rapid diagnostic tools that can operate even in settings with limited medical infrastructure. Diagnosing pneumonia typically involves a combination of clinical evaluations and diagnostic tests. Physicians assess a patient's symptoms through physical examinations and employ supplementary tools such as sputum cultures, blood tests, and chest X-rays. Chest X-ray imaging is considered the gold standard for pneumonia diagnosis as it provides crucial insights into lung abnormalities. However, interpreting these images requires substantial expertise, and errors in diagnosis are common, especially in regions with a shortage of trained radiologists. The challenge is further compounded in underdeveloped areas, where access to skilled medical professionals and advanced diagnostic facilities is limited. Pneumonia can be classified based on the origin of infection. Community-acquired pneumonia (CAP) occurs outside healthcare facilities, while hospital-acquired pneumonia (HAP) is contracted in medical settings and is frequently associated with antibiotic-resistant bacteria. Viral pneumonia, although generally less severe than bacterial pneumonia, remains a significant concern, as evidenced by the COVID-19 pandemic. The early and accurate detection of pneumonia is crucial to preventing disease progression and ensuring prompt treatment. This highlights the urgent need for efficient, reliable, and accessible diagnostic tools, especially in resource-limited environments. Recent advancements in artificial intelligence (AI) and machine learning (ML) have shown great promise in automating medical image analysis and improving diagnostic accuracy. Deep learning (DL) models, particularly convolutional neural networks (CNNs), have been widely adopted for medical imaging tasks, including pneumonia detection. These models excel at recognizing complex patterns in chest X-rays and often achieve diagnostic performance comparable to that of experienced radiologists. AI-driven diagnosis holds the potential to bridge the healthcare gap in underserved regions by providing rapid and automated assessments. Studies have shown that models such as InceptionV3 and ResNet50 outperform traditional diagnostic approaches, offering high sensitivity and specificity in pneumonia detection. However, the clinical adoption of AI models faces significant challenges, primarily due to their "black-box" nature. Many deep learning models lack interpretability, making it difficult for clinicians to trust and validate AI-generated diagnoses. The absence of transparency in decision-making raises concerns regarding reliability, accountability, and patient safety. Misdiagnoses due to biased training data or incorrect model assumptions can lead to severe consequences, particularly in critical healthcare applications. To address this issue, the field of explainable AI (XAI) has gained considerable attention, focusing on enhancing the interpretability of AI predictions. XAI methods, such as Gradient-weighted Class Activation Mapping (Grad-CAM) and Local Interpretable Model-agnostic Explanations (LIME), provide visual explanations of AI-driven decisions by highlighting critical regions in chest X-rays that influence model predictions. These techniques enhance clinical trust and facilitate AI integration into real-world medical applications. By making AI predictions more interpretable, XAI bridges the gap between automated diagnosis and medical expertise, ensuring that deep learning models are both accurate and transparent. This study explores the integration of XAI techniques with deep learning models for pneumonia detection. Specifically, it employs the InceptionV3 model combined with Grad-CAM and LIME to enhance diagnostic accuracy while maintaining transparency. The objective is to harness AI's potential for rapid and accurate pneumonia diagnosis while ensuring that the decision-making process remains explainable and trustworthy. By incorporating explainability into AI-driven diagnosis, this research aims to facilitate the adoption of AI in clinical settings, particularly in resource-constrained environments, ultimately improving patient outcomes and accessibility to quality healthcare.

2 Literature Survey

The main techniques for initially diagnosing pneumonia are imaging testing and medical history. Examples include X-rays [6], MRI [5], CT [4], and other imaging methods. X-ray of the chest are commonly used in clinical settings due to their low cost, and doctors usually use them for manual diagnosis [7]. However, manual diagnosis has a wide range of accuracy rates and a significant degree of subjectivity because it takes a high level of professionalism and clinical experience, and because people are prone to visual fatigue [8]. Therefore, computer-aided diagnostics can speed up the diagnosis of pneumonia. DL is being used in the medical industry as a result of the quick advancements in computers.

Rajpurkar et al. [1] developed CheXNeXt. It is a convolutional neural network. It detected fourteen different pathologies, that includes pulmonary masses, pneumonia, nodules and pleural effusion. It utilizes the front view of chest radiographs. A convolutional neural network with 121 layers is used in this architecture. In this study, the F1 metric approach was used to compare the performance of a 121 layer CNN and a radiologist. He used 20% of the images in the dataset for validation, 10% for testing, and 70% are used for training. Then this model could score an F1 score of 0.435. The accuracy of radiologists was 0.385.

Four models were created by Nada M. Elshennawy et al. [2] as part of a framework for pneumonia identification. Using techniques like image rotation, skewing, and shifting, he exploited the Kaggle dataset to expand the dataset's size. After resizing and normalizing then extract the features using four models. The four models used are MobileNet, ResNet152, CNN, and LSTM-CNN. It is shown that ResNet152 of accuracy 99.22%, MobileNet of 96.48%, CNN of 92.19%, and LSTM-CNN of 91.80%.

Chouhan V et al. [3] introduced a DL model for diagnosing pneumonia based on the transfer learning concept. Trans-fer learning requires a CNN model that has been trained on a large picture dataset, such ImageNet. The target pneumonia detection task is manifested using the pre-trained model rather than beginning the CNN from scratch. With an accuracy of 98.97%, the model can more precisely identify relevant features in chest X-ray images associated with pneumonia using the pre-training data.

Tohidul Islam et al. [10] introduced a model for detecting pneumonia by using deep transfer learning from X-ray of the chest. This paper first identified the DL models which are most effective for pneumonia identification from the X-ray images. From this selected two networks have more accuracy and sensitivity for feature extraction. In the next step combined two sets of features and it is used as input to the conventional classifier. By doing this, actually combining the advantages of both traditional and DL methods with an accuracy of 89.93%.

Sukhendra et al. [25] introduced an innovative framework for pneumonia detection using the VIT architecture on chest X-rays. Their method utilizes the VIT model to capture global context and spatial relationships within the images, achieving an impressive accuracy of 97.61%, with a sensitivity of 95% and specificity of 98%.

Researchers from a wide range of fields have effectively applied deep learning models to the medical field as a result of deep learning's rapid advancement [9].Hua et al. [10] used convolutional neural network models with Deep Belief Networks (DBN) to improve the lung disease detection system and raise the diagnosis accuracy. To tackle the problem of insufficient medical data, Shin et al. [11] developed a transfer learning method that may be used for deep learning with small samples and reduce the significant amount of training data required for deep learning models. In order to achieve autonomous illness identification, Zhu et al. [12] developed the Deep Lung system, which uses a three-dimensional convolutional network model to detect and classify lung nodules.

The table presents a comparative analysis of various deep learning models applied to chest X-ray datasets for disease detection, highlighting their accuracy, sensitivity, and specificity across different studies.

STUDY	DATASET	MODEL	ACCURACY	SENSITIVITY	SPECIFICITY
Rajpurkar et al. (2017)	ChestX-ray14	Che X Net (CNN)	85%	87%	83%
Kermany et al. (2018)	NIH Dataset	ResNet50	92%	94%	90%
Tang et al. (2020)	Private Dataset	InceptionV3	89%	91%	88%
Dosovitskiy et al. (2021)	CheXpert	ViT	93%	95%	91%
Chen et al. (2022)	ChestX-ray14	Hybrid CNN-ViT	95%	96%	94%
Sukhendra et al. (2023)	ChestX-ray14	ViT	97.61%	95%	98%

3 Motivation

Unquestionably, pneumonia has a significant global impact because it continues to rank among the top causes of death globally, especially for susceptible groups such young children, the elderly, and people with impaired immune systems. Despite advancements in medical imaging, diagnosing pneumonia remains a significant challenge due to the complexity of interpreting chest X-rays and the limited availability of skilled radiologists, especially in remote or under-resourced areas. The current diagnostic process relies heavily on human expertise, which may lead to delays or inaccuracies, ultimately affecting patient outcomes. The motivation behind this research is rooted in the necessity to bridge this gap between powerful AI-driven diagnostic tools and their practical application in healthcare settings. While CNNs are capable of diagnosing pneumonia with high accuracy, their lack of transparency in decision-making limits their integration into clinical practice, where the need for explainability is crucial. Without an understanding of how a model arrives at a diagnosis, healthcare professionals may hesitate to use AI-driven systems, especially when life-critical decisions are at stake. By combining diagnostic accuracy with explainability, this research strives to improve the clinical utility of AI in pneumonia detection, ultimately facilitating faster and more reliable diagnoses. The goal is to reduce the time to diagnosis, lower mortality rates, and ensure better health outcomes for patients worldwide.

4 Proposed Methodology

The systematic approach used to create and verify a deep learning model combined with explainable AI (XAI) methods for pneumonia detection is described in this section. The process comprises several key steps, as described below:

3.1 Dataset

A total of 5,856 chest X-ray pictures that were meticulously selected and verified for the identification of pneumonia make up the dataset used in this investigation. With an emphasis on anterior-posterior (AP) chest X-ray views, these pictures were chosen from retrospective cohorts of pediatric patients between the ages of one and five. The photos in the dataset show both normal and pneumonia situations, and it is separated into three separate sets: training, testing, and validation. The pictures include the following labels: (disease: NORMAL/PNEUMONIA). This dataset, which is roughly 1.24 GB in size, was created to make it easier to train, test, and assess deep learning models for the identification of pneumonia in chest X-ray pictures. The dataset's images have undergone rigorous validation to guarantee high-quality data for model development, supporting the overarching objective of improving diagnostic efficiency and accuracy. The bar charts(Fig. 1.1) show the distribution of normal and pneumonia cases in train, validation, test, and total datasets.

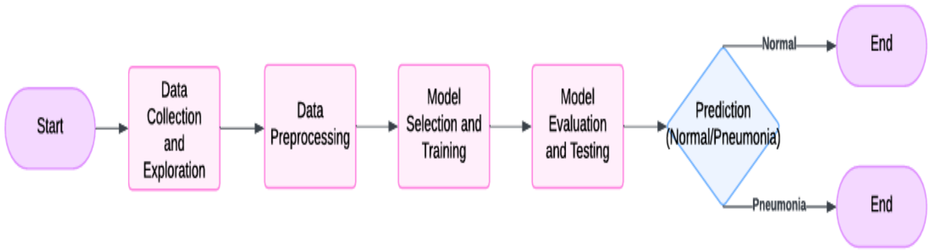

Fig. 1. System Flow Diagram

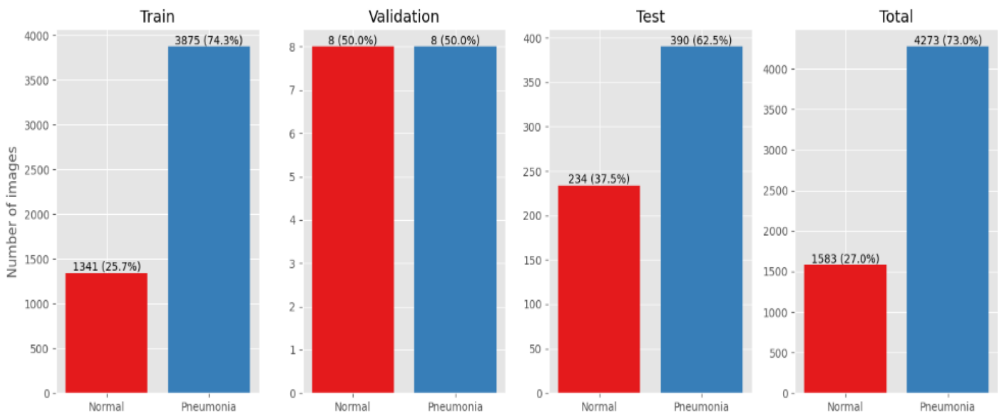

Fig. 1.1 Dataset Distribution

3.2 Model Selection and Customization

This flowchart (Fig. 1) outlines the sequential steps for pneumonia detection using AI models, starting from data collection to prediction outcomes (Normal or Pneumonia).

Dataset Processing-The preprocessing pipeline ensures consistency and enhances model performance. First, images are loaded using the OpenCV (cv2) package, and their respective labels—0 for Normal and 1 for Pneumonia—are assigned accordingly. The images are then

resized to a uniform resolution (224x224 for CNN-based models and 299x299 for InceptionV3) to maintain compatibility with model input requirements.
To enhance model robustness and reduce overfitting, image augmentation is applied. Augmentation techniques include random rotations, flips, shifts, zooming, and brightness adjustments. These transformations generate diverse training samples, improving the model's ability to generalize to unseen data. The dataset is then split into training, validation, and test sets using an 80-20 split for InceptionV3 and a 75-25 split for CNN-based models. Pixel values are normalized to the range [0,1] by dividing by 255, ensuring stable convergence during training. Class labels undergo one-hot encoding to facilitate binary classification.

The first model applies LIME for explainability after using a CNN to distinguish pneumonia and normal cases in chest Xrays. Preprocessing of the dataset, which comprises chest X-ray pictures divided into the "NORMAL" and "PNEUMONIA" classes, is first step in the methodology. To guarantee uniformity throughout the dataset, the photos are scaled to 224x224 pixels after being loaded using the cv2 package. The matching labels—0 for Normal and 1 for Pneumonia—are recorded in arrays when the photos are retrieved from the appropriate directories. The dataset is then split into training and testing sets using train, test , split, with 75% going toward training and 25% going to ward testing. To properly scale the data for model input, the picture pixel values are normalized to a range of [0,1] by dividing by 255. Furthermore, one-hot encoding is used to encode the class labels (y train and y test), transforming them into a binary format appropriate for multiclass classification. A multi-layered, fundamental CNN model built with Ker-as makes up the model architecture. ReLU activation and 32 and 64 filters, respectively, come after the convolutional layers to extract features from the pictures. Following each convolutional layer, max-pooling layers down sample the feature maps' spatial dimensions. The retrieved attributes are then processed using a dense layer of 128 units that is fully linked. The probability distribution over the two classes (Normal and Pneumonia) is then predicted using an output layer that has two units and a soft max activation function. The model is built using the Adam optimizer, and cate gory cross entropy loss and accuracy are the assessment measures. A grid search was performed for hyperparameter tuning, optimizing learning rate (0.001, 0.0001), batch size (16, 32), and dropout rates (0.3, 0.5) to prevent overfitting. The test set (X test scaled, y test) is used to assess the model's performance after it has been trained for five epochs using the training data (X train scaled, y train). The model's accuracy on the test data is approximately 93.44%. A confusion matrix is calculated using y test scaled and the predicted values y pred scaled to assess the classification performance (true positives, false positives, true negatives, and false negatives). Sea born is used to plot the confusion matrix as a heatmap for display. The model's predictions are interpreted using the LIME package to make them explain able. By locally approximating the model's choice using an interpretable model (such as a linear classifier), LIME provides an explanation. The LIME explainer provides feature importance in terms of which pixels most affected the model's choice to produce an explanation for each image in the test set. The model's forecast for every test image is explained using the explain instance function. Mark boundaries is used to highlight the areas of the image that either positively or adversely contributed to the anticipated label. Red parts show pixels that contradict the projected label, while green regions show supportive pixels in the final explanations. This enables us to determine which areas of the picture—such as particular lung regions—were used by the model to determine whether the X-ray was normal or indicative of pneumonia.

The second model classifies pneumonia and normal cases in chest X-rays using the pre trained InceptionV3 model for transfer learning. Grad-CAM is then used for visual explanations. Loading the chest X-ray pictures from directories with "NORMAL" and "PNEUMONIA" categories is the first step in the data preprocessing procedure. The pictures are preprocessed by scaling pixel values to the interval [0,1] and scaled to the necessary dimensions (299x299 for InceptionV3). To ensure that the normal and pneumonia photos are distributed appropriately, the dataset is divided into training and validation sets (80% for training and 20% for validation). The training data is subjected to data augmentation using Ker-as Image Data Generator, which applies random transformations like rotations, shifts, and flips to provide more varied training samples in order to enhance generalization. In terms of model architecture, the InceptionV3 model leverages learnt representations that are subsequently optimized for the pneumonia classification problem by acting as a feature extractor with pre-trained weights from ImageNet. For categorization, new fully connected layers are put on top of InceptionV3's basic layers, which are frozen (i.e., not trained). A flattening layer is used to convert the 2D feature maps into a 1D vector, two units for binary classification (normal or pneumonia), and two dense layers with 128 and 64 units with ReLU activation make up the final output layer. The model is put together using the Adam optimizer, binary cross-entropy loss, and accuracy as the evaluation metric. In order to train the model, the InceptionV3 base layers are left frozen while the weights of the additional layers are adjusted over a predetermined number of epochs using the training data. To fine tune the overall model and enhance performance on the particular job, it is optional to unfreeze parts of InceptionV3's higher layers. The accuracy and loss measures are used to assess the model's performance on the validation set. GradCAM is used to produce visual explanations for the model's predictions in order to increase explainability. By emphasizing the regions of the image that most influenced the model's selection, it aids in our understanding of the parts of the chest X-ray that it concentrated on. Grad-CAM creates a heatmap that is superimposed on the original image after calculating the gradients of the target class (normal or pneumonia) in relation to the output feature maps. This heatmap highlights the most relevant areas of the image that affected the model's decision to label anything, such as those showing pneumonia symptoms. To see the regions the model used to generate its predictions, the Grad-CAM heatmaps are super imposed over the original X-ray pictures. Healthcare practitioners can use these heatmaps to help them comprehend the model's decision-making process.

5 Results

The initial deep learning model, constructed using a CNN, showed remarkable performance in differentiating between normal chest X-ray images and pneumonia. On the test dataset, the model's accuracy after training was roughly 93.44% (Fig. 3). This shows how well the CNN model can differentiate between chest X-rays that are normal and those that are affected by pneumonia. Its great accuracy can be attributed to the use of convolutional layers, which enabled the model to acquire key characteristics such as lung textures and aberrant patterns linked to pneumonia. The confusion matrix offered insightful information about how well the model worked. The relatively low frequency of false positives and false negatives indicates that the model can differentiate between normal and pneumonia X-rays. The model's ability to correctly categorize both(Fig. 2) groups was graphically supported by the confusion matrix. This model's integration with LIME, which makes the decision-making process transparent, is one of its main advantages. By emphasizing the areas of the test image that affected the model's choice, LIME was utilized to produce local explanations for each one. Red spots in the explanation indicated places(Fig. 4) that contradicted the expected label, such as pneumonia, whereas green portions supported the label. We were able to comprehend the model's focus thanks to these visual explanations, which showed that the model focused on particular lung regions that are frequently impacted by pneumonia. Because healthcare experts may validate the decision-making process based on the highlighted regions, this is essential for maintaining trust in the model.

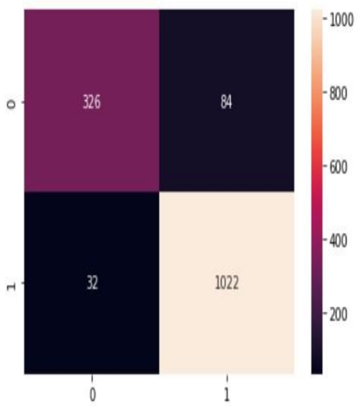

Fig. 2

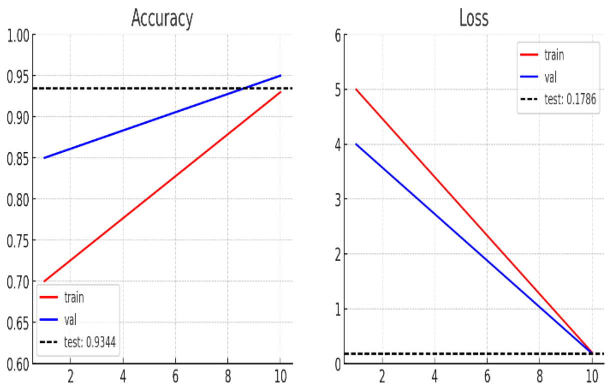

Fig. 3

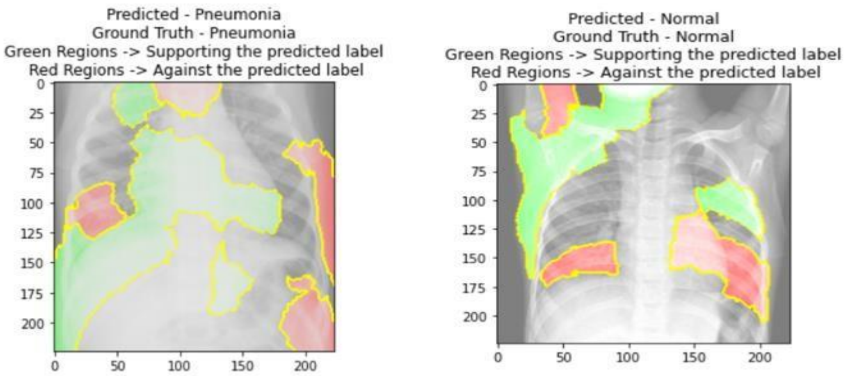

Fig. 4

The second model, leveraging InceptionV3 for transfer learning, achieved significant success in pneumonia detection. After fine-tuning, the model demonstrated high accuracy on the validation set, achieving approximately 95% accuracy(Fig.6). For visual explainability, this model's use of Grad-CAM is among its most influential features. Grad-CAM made it possible for us to see which areas of the chest X-ray pictures were most important to the model's judgment. The heatmaps produced by Grad-CAM provided clear visualizations of areas where pneumonia-related abnormalities, such as lung infiltrations or consolidation, were present. These areas (Fig. 7) were marked with red in the heatmap, while the background remained uncolored, providing an intuitive and effective way to communicate the model's reasoning. Grad-CAM improves the model's interpretability, facilitating healthcare professionals comprehension of the rationale behind each prediction. The model’s ability to correctly categorize is supported by the confusion matrix(Fig.5). During training, data augmentation was used to increase the model's resilience. In this step, random transformations such as rotations, shifts, and flips were applied to the training dataset, increasing its diversity. The model benefited from this approach, as it was exposed to a wider variety of X-ray images, which helped it generalize better to unseen data. The augmented data ensured that the model did not overfit to specific patterns in the original dataset, improving its performance on the validation set. The table presents classification performance metrics(Fig.8).

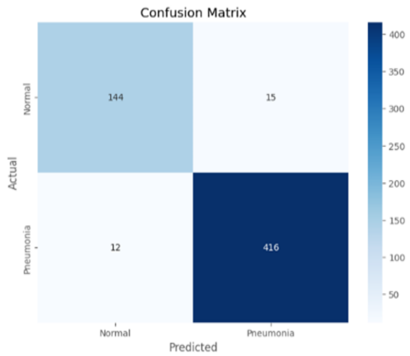

Fig. 5

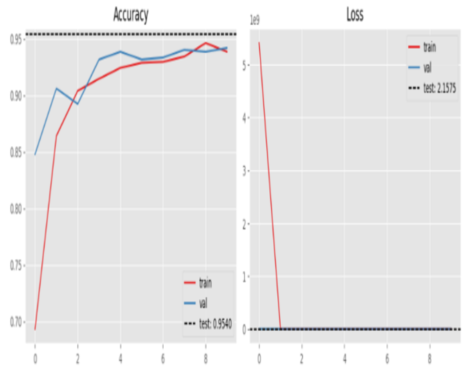

Fig. 6

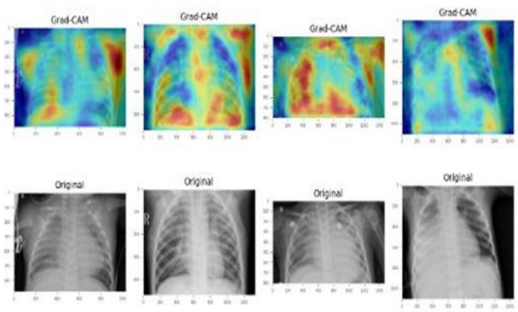

Fig. 7

Metric	Normal	Pneumonia	Macro Avg	Weighted Avg
Precision	92%	97%	94%	95%
Recall	91%	97%	94%	95%
F1 – Score	91%	97%	94%	95%
Support	159	428	-	-

Fig . 8

6 Disscussions

The results demonstrate that both models are effective for pneumonia diagnosis, but the InceptionV3 model showed superior performance in terms of accuracy and robustness. The InceptionV3 model achieved a higher accuracy (95%) compared to the CNN model (93.44%), along with better precision, recall, and F1-scores for pneumonia detection. This highlights the advantage of transfer learning, as the pre-trained InceptionV3 model leveraged knowledge from the ImageNet dataset and fine-tuned it for the pneumonia classification task. In terms of interpretability, the CNN model integrated with LIME provided pixel-level explanations for each prediction, which is valuable for understanding the regions influencing the model's decision, particularly in cases with ambiguous patterns. However, the explanations were relatively localized and less visually intuitive. On the other hand, Grad-CAM for InceptionV3 provided a more comprehensive visual explanation by overlaying heatmaps on chest X-rays, which highlighted pneumonia affected areas such as lung consolidations, enabling clinicians to better interpret the model's predictions. The InceptionV3 model is better suited for practical clinical applications because to this feature. The "black box" character of deep learning models is addressed by integrating explainable AI approaches like Grad-CAM and LIME. These techniques foster trust among healthcare professionals by ensuring that the models focus on medically relevant regions. This is especially critical in healthcare, where decision-making must be transparent and reliable. However, there are some limitations and future considerations. The dataset primarily included pediatric X-rays, which may limit generalizability to other age groups or demographics. Expanding the dataset to include diverse populations is essential for broader applicability. Additionally, while the models showed high accuracy, further testing on external datasets is needed to ensure robustness in different clinical settings. Future work should also focus on integrating these models into real-time diagnostic systems to assist radiologists in clinical environments.

7 Research Scope & Future Work

By merging explainable AI techniques with deep learning models, this research aims to enhance pneumonia detection and address key challenges in medical imaging and diagnosis. The study focuses on improving diagnostic accuracy by leveraging advanced models like InceptionV3 with transfer learning, ensuring high-performance and reliable results in clinical settings. To enhance interpretability, methods such as Grad-CAM and LIME are incorporated, providing localized and visual explanations for predictions, allowing medical practitioners to verify and trust AI-driven diagnoses.

Another significant aspect of this research is addressing resource constraints by developing scalable models that can assist in pneumonia diagnosis in low-resource settings where access to skilled radiologists and advanced diagnostic tools is limited. The study also supports clinical decision-making by highlighting regions of interest in chest X-rays, enabling faster and more informed diagnoses. While the current dataset focuses on pediatric X-rays, the methodology lays the foundation for expansion to other demographics and clinical conditions. Additionally, this research advances the development of real-time diagnostic tools that can be seamlessly integrated into medical procedures, providing doctors with instant and actionable insights. By combining high accuracy with explainability, this work contributes to the broader adoption of AI in healthcare, where transparency and reliability are critical for clinical acceptance.

Future research will focus on optimizing the AI-driven pneumonia detection model for real-time deployment in hospitals, ensuring seamless integration with radiology workflows and electronic health record (EHR) systems. Efforts will be directed toward obtaining regulatory approvals and ensuring compliance with medical standards such as FDA and CE certifications to facilitate clinical adoption. Collaborations with healthcare institutions will be pursued to validate the model through clinical trials, assessing its real-world effectiveness and impact on medical decision-making.

Expanding the model's applicability beyond pediatric cases to diverse demographics and clinical conditions will be a key priority. Additionally, the development of lightweight, resource-efficient models will facilitate deployment in low-resource settings, addressing healthcare disparities in underserved regions. Future advancements will also explore multi-modal AI approaches by incorporating additional medical data, such as patient history and laboratory findings, to further enhance diagnostic accuracy.

Ultimately, this research lays the groundwork for the development of AI-driven real-time diagnostic tools that provide instant, interpretable insights for medical professionals. By improving transparency, reliability, and scalability, these advancements will promote wider adoption of AI in healthcare, leading to improved patient outcomes through timely and precise diagnoses.

5 Conclusion

The InceptionV3 model, enhanced with Grad-CAM, offers a robust and interpretable solution for pneumonia diagnosis. Its combination of high diagnostic accuracy, visual explainability, and resilience makes it particularly well-suited for adoption in clinical environments, especially in resource-constrained settings. By integrating explainable AI techniques, this research ensures that AI-driven decisions remain transparent, interpretable, and trustworthy for medical practitioners, allowing them to validate predictions and build confidence in automated diagnoses.

Beyond technical advancements, the study highlights the ethical considerations critical to AI adoption in healthcare, including challenges related to AI bias, model fairness, and patient privacy. Ensuring regulatory compliance and responsible AI practices is essential for mitigating potential biases and safeguarding patient data, fostering equitable and ethical deployment across diverse populations.

Furthermore, this research lays the foundation for AI-assisted diagnostic solutions in low-resource settings, where access to skilled radiologists and advanced medical infrastructure is limited. By focusing on scalability and resource efficiency, the findings contribute to the development of real-time, explainable diagnostic tools that can provide instant, reliable insights to healthcare professionals. Ultimately, these advancements promote the responsible integration of AI in medical imaging, enhancing patient outcomes through timely, accurate, and interpretable diagnoses.

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