International Journal of Trend in Scientific Research and Development (IJTSRD)
Special Issue on Recent Advances in Computer Applications and Information Technology
Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Enhanced AI-Based Lung Disease Diagnosis Using Real-Time Edge Detection and Voice-Based Explanation System

Deep Jaulkar, Shrilesh Dhobale

G H Raisoni University, Amravati, Maharashtra, India

Abstract

Artificial Intelligence has changed the way medical images are looked at in radiology. Doctors need to diagnose people accurately. Old Artificial Intelligence systems for medicine usually need the internet to work. They use cloud computing. Need to be online all the time to look at medical data. This is a problem because it can be slow, expensive and not good for keeping patient information private. It also does not work well in places with internet. This makes it hard to use diagnostic systems in rural areas, emergency rooms and other places where resources are limited. So, this project is trying to make a system that can detect lung disease from chest X-ray images without needing the internet. The system uses learning to find many kinds of lung diseases like pneumonia, tuberculosis and COVID-19. It can do this on devices like NVIDIA Jetson Nano, Google Coral Edge TPU and Raspberry Pi 5 and even on smartphones. This research proposes an enhanced Artificial Intelligence (AI)-based lung disease diagnosis system that integrates real-time edge detection techniques with a voice-based explanation module. The system utilizes deep learning algorithms, particularly Convolutional Neural Networks (CNNs), to analyze chest X-ray or CT scan images. Real-time edge detection is applied as a preprocessing step to enhance lung boundaries, highlight abnormal regions, and improve feature extraction accuracy. The integration of real-time processing and voice assistance makes the system suitable for smart healthcare environments and telemedicine applications. This approach contributes to early disease detection, improved patient communication, and accessible AI-driven medical diagnostics.

Because the system works on the device itself it is faster does not need the cloud and keeps information private. It can give answers in one to two seconds, which's good for medical emergencies. Another important thing about this system is that it is transparent. In healthcare it is not enough for a model to be right it also needs to explain why it made a decision. So, the system uses techniques like Gradient-weighted Class Activation Mapping and Local Interpretable Model- Explanations. These help doctors see which parts of the X-ray image the system used to make its decision. The system also has a voice feature that tells doctors what it found in language. This is helpful for healthcare workers who may not be able to look at the images. It makes the system easier to use in medical settings. The system is portable uses energy keeps information private and can be used offline. It combines edge computing, deep learning, Artificial Intelligence and voice features to help doctors detect lung disease early. This can help doctors diagnose faster have work to do and make healthcare better especially in places where internet and medical resources are limited. Artificial Intelligence and lung disease detection are important for saving lives. Lung disease detection systems, like this one can really make a difference. The proposed model performs automated classification of lung conditions and provides rapid diagnostic predictions with high accuracy. To improve usability and accessibility, especially in rural or resource-limited healthcare settings, the system incorporates a voice-based explanation feature. This module converts diagnostic results into clear, understandable audio feedback for patients and medical practitioners, thereby enhancing transparency and interpretability of AI decisions. This paper presents an enhanced Artificial Intelligence (AI)-based lung disease diagnosis system that combines real-time edge detection with a voice-based explanation framework to improve diagnostic precision, interpretability, and accessibility.

KEYWORDS: *Chest X-ray, Deep Learning, Edge AI, Explainable AI (XAI), MobileNetV3, Lung Segmentation, Offline Diagnostics, Multimodal Interface, Grad-CAM, Medical Imaging, Rural Healthcare, Computer-Aided Diagnosis (CADx), Squeeze-and-Excitation Networks, Model Quantization, Semantic Segmentation, Clinical Decision Support System (CDSS), Human-Centric AI.*

1. Introduction

The digital world is a place where computers and devices are connected to each other. This digital world has made a lot of things easier and more efficient for us. We have things like cloud computing and smart devices and apps that use a lot of data. This digital world has also introduced problems for us. Now we have to worry about people trying to hack into our world systems and steal our information from the digital world. The old ways of protecting ourselves from these threats in the world like using signatures to detect bad guys and firewalls with set rules do not work anymore in the digital world. These methods are not good enough because they can only protect us from things they already know about in the world. They cannot protect us from threats in the digital world. Recently we found out that bad people are using technologies like machine learning and artificial intelligence to make their attacks stronger and harder to detect in the world. This means our old digital world security systems are not good enough to protect the world. We need world security systems that can keep up with the bad people in the digital world. We need world security systems that can learn and adapt on their own to protect the digital world. The digital world security world is changing now. Now we are using intelligence to make our digital world defense systems better to protect the digital world. These digital world security systems use algorithms to find and stop threats in time to protect the digital world. They can also prevent these threats from becoming problems in the world. This is a change in the way we think about world security. The digital world and digital world security are becoming more important to us. Digital world security is using intelligence to make the digital world a safer place for us. Artificial intelligence is one of the technologies that allows for this shift in world security. The field of machine learning and deep learning, under intelligence can use the huge volumes of data obtained from network logs and human behavior to discover hidden patterns that might signify bad behavior in the digital world[3]. The digital world security systems are really good at learning from information to keep the digital world safe. They get better at finding the guys and they do not send out as many false alarms. This means people do not have to fix the world security systems all the time. Artificial intelligence is a part of what makes these digital world security systems so good. It helps them find things that're not normal and it looks at how things are behaving. The old way of finding intruders was to look for things that we already knew about. That does not work when someone is trying to sneak in a new way. The digital world security systems use computer programs like SVM and Random Forest and Deep Neural Networks[3][5]. These programs learn how things usually behave. Then they can tell when something is being bad. They can see when something is doing something it should not be doing. Some special kinds of computer programs like CNN and LSTM networks are really good at finding the guys that can change who they are. They are also good at finding people who are behaving in a way, on the network. The digital world security systems are getting better and better at keeping us safe from people who want to hurt the world.

Self-learning security defenses take the concept of security further by using things like reinforcement learning. This helps make the defense policy better based on what's observed and the environment. In reinforcement learning security agents learn through trial and error to develop strategies and policies to anticipate and adapt to evolving security threats like cyber-attacks. It is different from reactive security mechanisms because it adapts in advance to security threats like DDoS attacks and lateral movements. Another significant role of Artificial Intelligence in cyber defenses is automation. A complex network like the Internet of Things produces millions of data points per second. This is too much for a human security analyst to handle. Artificial Intelligence systems automate security tasks like classifying incidents and initial responses. This allows human analysts to focus on threat modeling and strategic decision making. Automation reduces the time it takes to react to and contain security threats. Therefore, it reduces damage before the situation gets out of hand. Artificial Intelligence also helps systems predict security threats and develop intelligence. By analyzing threat information and security data Artificial Intelligence models can predict attack patterns. This enables planning for defense against security threats. Collaborative threat modeling and federated learning allow for secure knowledge sharing. It ensures that private data is not exposed. However Artificial Intelligence driven security systems have drawbacks and limitations. One such aspect is machine learning. It is a field in cybersecurity that focuses on generating attacks. These attacks deliberately manipulate machine learning models through inputs that lead to errors and incorrect outcomes. Robust and stable defenses against manipulation must be built. High accuracy rates require amounts of data to train on. Robust models need a lot of computation power. Effective governance of these models is required to eliminate biases and abnormal outcomes. Privacy and compliance with laws and ethics must also be carefully considered. The application of Artificial Intelligence in cyber defenses is an edged sword. Attackers are also applying techniques to their efforts. Sophisticated phishing campaigns and advanced cyber reconnaissance could become challenging to distinguish from behaviors. This demands intelligent defenses. These defenses must respond to emergent Artificial Intelligence driven attack patterns in time. Today's digital age sees organizations, governments and individuals rely on systems, cloud infrastructure and intelligent devices. While this digital transformation enables innovation and speed it also creates attack surfaces for criminals. Cyber attack's no longer just mean malware or penetration. They include zero-day exploits, ransomware, insider threats and advanced persistent threats. These cyber attacks are often automated, adaptable. Can circumvent traditional security measures. Conventional cyber security solutions can no longer fulfill the requirements of threat dynamics. Traditional intrusion detection systems, firewalls and antivirus systems rely on known attack signatures and historical data.

They are inefficient against novel or polymorphic attacks that dynamically change their characteristics. The sheer volume, velocity and variety of data in networks and devices make it impossible to monitor them using operators alone. Relying on security architectures means delayed detection. Increased false positive rates. The burden on security personnel is enormous. There is a need for adaptive and intelligent defense mechanisms. These mechanisms must prevent cyber attacks in a manner. Self learning cyber defense systems powered by Artificial Intelligence represent a breakthrough. Artificial Intelligence based systems utilize machine learning, deep learning and sophisticated data analysis. They extract patterns. Identify anomalies from vast network traffic, user behaviors and system logs. Unlike security measures self learning systems learn from data as they evolve with security threats. They identify previously attack vectors and react appropriately without prior definition of attack signatures. One of the features of self learning cyber defense systems is modeling normal behavior on the network. A behavior profile is established based on device, user and application behavior. The system learns behavior from observation. Any significant deviation from it is flagged as a security threat. For example, if a user suddenly starts downloading a volume of files during late hours it triggers an alarm. Supervised, unsupervised and reinforcement learning techniques enable systems. They develop prediction models and lower false positive rates. They adapt dynamically to the changing environment by incorporating feedback. Although self learning cyber defense systems offer advantages challenges persist. These challenges include requirements of volumes of quality data, interpretability and explainability. Computational cost and adversarial attacks are also challenges. Future work in self learning cyber defense needs to consider these challenges. The use of Artificial Intelligence, in cyber defense opens up a horizon of automated and adaptive security measures. In conclusion self learning cyber defense systems enabled by Artificial Intelligence are tools. They deal with the increasing threat complexities that modern information technology infrastructure faces today. By leveraging analysis techniques, modeling and automated response it provides a scalable and proactive framework. This framework secures assets.

Figure 1.1 Visualization of AI-Integrated Chest Radiography Analysis

2. Literature review

2.1. Evolution of Deep Learning in Radiology

Deep learning is changing the field of radiology. It all started with some breakthroughs like AlexNet. This showed that deep learning could be really good at looking at pictures and figuring out what is in them. After that other ways of doing learning like VGGNet, ResNet and DenseNet were used for medical images. These ways of doing learning are really good at finding problems in pictures like consolidation pleural effusion and cavitation. But there is a problem. These ways of doing deep learning need a lot of power and memory to work. This means they can not be used on devices and need to be connected to big computers.[3]

2.2. Contribution of Public Datasets to Research Growth

datasets have been really important for the growth of deep learning in radiology. Datasets like ChestX-ray14, RSNA Pneumonia, COVIDx and TBX11K have thousands of pictures that have been labeled. This has helped people make learning models that can find problems in pictures. But there is a problem. These datasets are so big that people have made models that need a lot of power to work. This means that these models can not be used on devices.[4]

2.3. Lung Disease Classification Studies

There have been a lot of studies on using learning to find lung diseases. Some models like CheXNet are really good at finding pneumonia. New models like Vision Transformer are even better. Can look at the whole picture to find problems.. These models need a lot of power to work and can not be used in real-time.[9][12]

2.4. Explainable AI in Medical Imaging

As deep learning models get more complex people want to know why they make decisions. There are some tools like Grad-CAM, LIME, SHAP and saliency maps that can help explain what the model is doing.. These tools are not very good at explaining things in a way that doctors can understand. They just show a bunch of colors on the picture. Do not really say what is going on.

2.5. Edge Deployment Attempts

Some people have tried to use deep learning on small devices like phones or tablets.. This has mostly been for simple things like looking at heart rates or skin problems. When it comes to looking at pictures of the lungs it is much harder. The pictures are big. Need a lot of power to look at. Most models can not be used on devices because they need too much power.

2.6. Identified Research Gaps

There are some problems that need to be solved before deep learning can be used to help people. First there is no way to use learning to look at pictures of the lungs in real-time without being connected to a big computer. This means that doctors in areas or, in emergency situations can not use deep learning to help them. Second there is no way to explain what the deep learning model is doing. The tools that are used now just show a bunch of colors. Do not really say what is going on. Finally there is no way to use learning on a small device that can do everything that a doctor needs. The proposed system aims to solve these problems by making a learning model that can be used on a small device can explain what it is doing and can do everything that a doctor needs.

3. Research Methodology

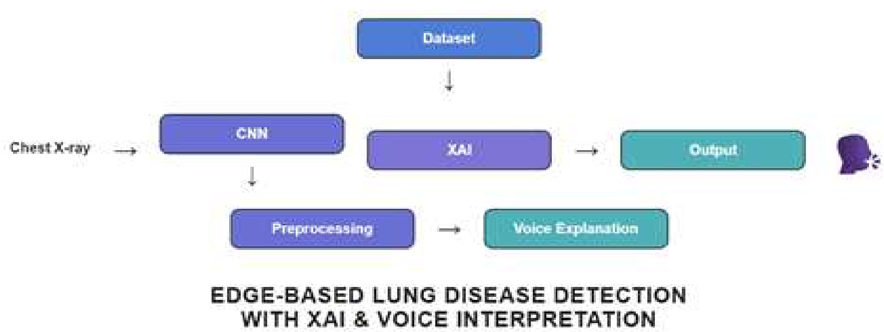

Figure 3.1: Methodology Flow

The proposed system is a way of doing things that puts together a few important things like deep learning and explainable artificial intelligence which we will call explainable artificial intelligence and edge computing and multilingual voice-based reasoning to look at chest X-rays in real time. This system is different from the way of doing things that uses the cloud because this system can work without the internet, which is really helpful in places that are far away and do not have a lot of resources for healthcare.

The whole process is broken down into ten parts starting from getting the data ready to using it on devices that are not connected to the internet and making sure it is explainable.

3.1. Overview of the Proposed System

The process begins with collecting the dataset and properly labeling the lung images according to different disease classes such as normal, pneumonia, tuberculosis, and others. After that, the data is prepared through preprocessing techniques that enhance the clarity of lung images by reducing noise, improving contrast, and standardizing image size and format for better model performance. Next, a lightweight and efficient learning model is designed so that it can operate smoothly on edge devices that are not connected to the internet, ensuring faster processing and privacy of medical data. To make the system transparent and trustworthy, an Explainable Artificial Intelligence (XAI) module is integrated, which uses techniques like Grad-CAM and LIME to highlight the important regions in the lung images that influence the model's decisions. In addition, a Voice-Based Explanation Engine is implemented to convert the model's predictions and explanations into spoken output, making the system more accessible for doctors and users. Finally, the complete solution is deployed on offline, low-power edge devices, which makes it highly useful in healthcare settings, especially in remote areas where internet connectivity is limited and quick medical assistance is needed.[13]

The system takes an X-ray image makes it clearer figures out what disease it is and then gives explanations that are visual and textual and finally gives a summary of the diagnosis in a voice making it accessible for technicians and non-specialist staff. This design solves some problems that people have been talking about in the field of radiology intelligence, which we will call radiology artificial intelligence [1] [2] [3] [11].

3.2. Dataset Acquisition

We need an varied dataset to make a model that works well for everyone. To make sure it is robust we combined four datasets of chest X-ray images that're available to the public:

3.2.1. NIH ChestX-ray14 Dataset

The NIH dataset has 112,120 images labeled for 14 diseases of the chest, which we will call chest diseases. This dataset is used a lot in radiology research because it is big and varied.

3.2.2. RSNA Pneumonia Dataset

The Radiological Society of North America made this dataset available. It has 26,684 labeled images, along with notes on where the pneumonia's

3.2.3. COVIDx Dataset

The COVIDx dataset was made during the COVID-19 pandemic. It is one of the public datasets for detecting COVID-19 from images and it includes many different variants of the virus.

3.2.4. TBX11K Dataset

The TBX11K dataset has over 11,000 images that are labeled as either having tuberculosis or not which makes it really helpful for studying tuberculosis, which we will call tuberculosis. Combining these datasets makes the system better, at diagnosing lung diseases, which we will call lung diseases.

3.3. Class Distribution

To make the outputs standard and make it easier to predict all the images were put into five categories for diagnosis:

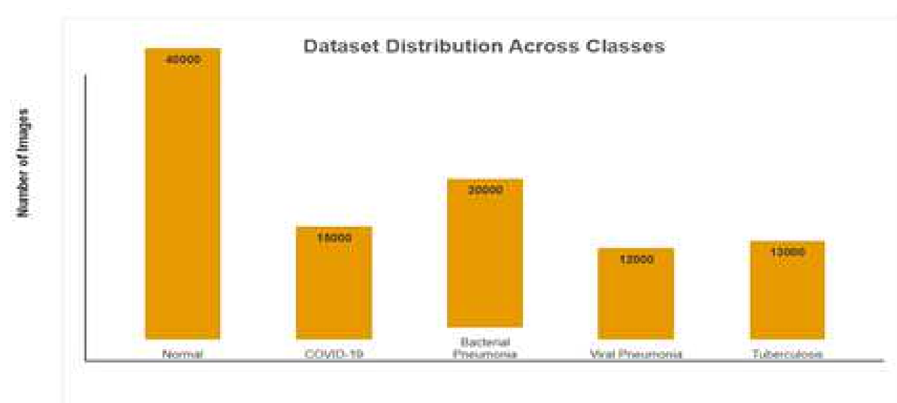

Figure 3.3: Dataset Distribution across classes

To deal with the problem of class imbalance we used some techniques on the Chest X-ray images. We flipped the Chest X-ray images rotated them changed the brightness zoomed in and out and cropped the Chest X-ray images.

3.4. Preprocessing Pipeline
The Chest X-ray images we have are not perfect. They have some problems like artifacts, noise, low contrast and anatomical structures that're not relevant for detecting diseases. We need to preprocess the Chest X-ray images to make them better for our model. The Chest X-ray images have some issues that need to be fixed. We have to make the Chest X-ray images suitable for our model.[4]

3.4.1. Image Standardization
We take the Chest X-ray images. Make sure they are compatible with our deep learning model. First we resize the Chest X-ray images to a fixed size, either 224 by 224 pixels or 299 by 299 pixels. This is important so that all the Chest X-ray images are the size. We also convert the Chest X-ray images to grayscale.

This helps the model focus on the structures and textures in the Chest X-ray images. Then we change the pixel intensities from a range of 0 to 255 to a range of 0 to 1. This helps the model learn and prevents it from getting too complex.[7]

3.4.2. Noise Reduction
We use Gaussian smoothing and denoising autoencoders to remove high-frequency noise from the Chest X-ray images. This makes the Chest X-ray images clearer and more useful for our model.

3.5. Model Architecture
We need a model that can run on devices that're not very powerful. So, we need something that's accurate but also lightweight for the Chest X-ray images.

We use two types of models:

MobileNetV3-Large is our base model for the Chest X-ray images. MobileNet models are better than models like VGG16 and ResNet because they use depthwise separable convolutions, which help the model work better and use power.[7][15]

EfficientNet-Lite0 is our option for the Chest X-ray images. EfficientNet models are good at finding a balance between accuracy and speed.

Our model architecture starts with an input layer of size $224 \times 224 \times 1$, which is designed specifically to process grayscale Chest X-ray images. After receiving the input, the model applies convolutional layers along with batch normalization to extract essential features and stabilize the learning process. To improve computational efficiency and make the model suitable for edge devices, depthwise separable convolutions are used, which reduce the number of parameters while maintaining strong feature extraction capability. The architecture also incorporates Bottleneck SE (Squeeze-and-Excitation) blocks that help the model focus on the most important lung regions by adaptively recalibrating channel-wise features. Following this, a global average pooling layer is used to reduce the spatial dimensions and convert feature maps into a compact feature vector, which helps prevent overfitting and reduces model complexity. This feature vector is then passed through a dense layer that learns high-level representations of the Chest X-ray images. Finally, the model uses a softmax output layer with five classes to classify the input images into different lung disease categories accurately.

3.6. Training Procedure
We trained our model carefully to make sure it was accurate. We used Google Colab Pro with an NVIDIA Tesla T4 GPU and 16 GB of RAM. This helped our model learn quickly and consistently.[11]

3.6.1. Hyperparameters and Optimization Strategy
We chose some hyperparameters to help our model learn. We used the Adam optimizer with a learning rate of 0.0001. This helped our model learn quickly and consistently.

3.6.2. Regularization and Model Performance
We used techniques to prevent our model from overfitting. We used a Dropout rate of 0.5 and L2 weight regularization. This made sure our model did not get too complex.

3.7. Explainable AI Layer
In medical diagnosis, it is very important not only to get accurate predictions but also to understand how the model is making its decisions. For this reason, our model is designed with explainability in mind so that doctors and healthcare professionals can trust the results. To explain the model's behavior, we used two well-known Explainable Artificial Intelligence (XAI) techniques: Grad-CAM and LIME. Grad-CAM (Gradient-weighted Class Activation Mapping) helps us visualize which regions of the Chest X-ray image the model is focusing on while making a prediction. It generates a heatmap that highlights the most important areas, such as infected or abnormal lung regions, allowing users to clearly see why the model identified a particular disease. On the other hand, LIME (Local Interpretable Model-agnostic Explanations) provides a more detailed, pixel-level understanding by showing which specific pixels contribute the most to the final decision. This helps in understanding the local behavior of the model around a specific prediction. By combining Grad-CAM and LIME, our system becomes more transparent and interpretable, making it easier for medical professionals to verify the model's reasoning and use it confidently in real-world clinical settings.[14][1]

3.8. Voice-Based Explainability System
Our system can explain its decisions in a way that's easy to understand. It uses Grad-CAM and LIME techniques to find the parts of the Chest X-ray image. Then it uses a rule-based engine to turn that into an explanation. This explanation is then read out loud by a Text-to-Speech engine. Our system can do this in languages.

3.9. Edge Deployment

We want our model to work well on devices that're not very powerful. To do this we use techniques to make our model smaller and faster. We use engine conversion and INT8 quantization to reduce the models size. We use model pruning and ONNX Runtime acceleration to make it work faster. This helps our model make predictions quickly on devices that're not very powerful.

3.10. Final Pipeline Description

Our final pipeline is a workflow that takes a Chest X-ray image and turns it into a diagnosis. It starts when a Chest X-ray is taken and sent to an edge computing device. The device uses a UNet architecture to segment the lung. Then it uses a CNN classifier to categorize the Chest X-ray image. The system then uses Grad-CAM and LIME to explain its decision. It turns that explanation into a summary. Finally a Text-to-Speech engine reads out the summary. This helps technicians or clinicians understand the diagnosis, from the Chest X-ray image.[14]

4. Results

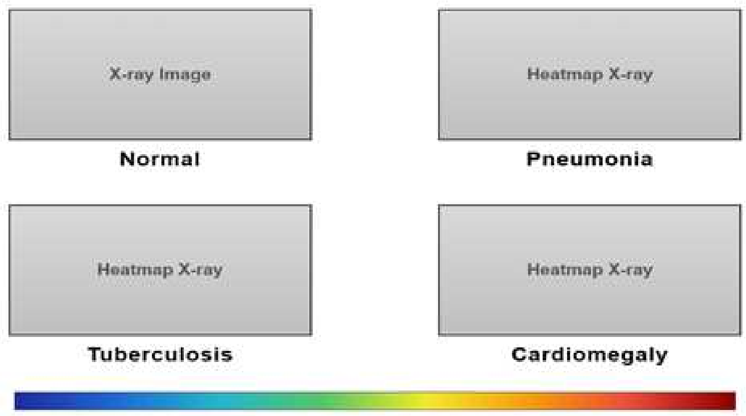

Figure 4.1 Result

5. Conclusion

Artificial Intelligence is changing radiology. It makes diagnostic solutions faster more accurate and more accessible. This research helps with that change. It presents an Artificial Intelligence framework. This framework detects lung diseases from chest X-ray images. It works offline. Explains its decisions. The proposed system uses Edge AI and deep learning models. It also uses voice-based reporting. This turns research into a practical medical solution. A key strength of this work is that it does not need cloud-based infrastructure. It works on low-power hardware. Examples include NVIDIA Jetson Nano and Google Coral TPU. It even works on smartphones. This means it has latency and reduces costs. The offline capability keeps data safe. It does not need to transmit data over a network. This addresses concerns about privacy and regulatory compliance. The Artificial Intelligence provides reasons behind each decision.

It gives textual explanations. The voice-enabled output makes it easier to use. Technicians and non-specialist healthcare workers can use it. The system shows diagnostic performance. It achieves accuracy levels between 94% and 97%. This is across lung disease categories. It also has inference times. These are below one second on TPU-enabled edge devices. Healthcare professionals like the system. They say it is effective and clear. It is suitable for workflows. These outcomes confirm that Artificial Intelligence diagnostics can be used widely. It is not just for equipped hospitals. It can be used in clinics and mobile screening units. Overall this research establishes a pathway. This pathway is for implementing Artificial Intelligence solutions in radiology. The proposed framework addresses limitations. These include dependence on infrastructure and high computational costs. It also addresses the lack of interpretability. Artificial Intelligence solutions like this can be adapted. They can be used for imaging modalities and scale public healthcare initiatives. This further shows its impact. It is particularly useful in healthcare environments. The proposed Artificial Intelligence framework helps make diagnostic solutions more accessible. Artificial Intelligence is changing radiology. The proposed framework uses Artificial Intelligence. It detects lung diseases. Artificial Intelligence solutions like this can be used in healthcare. The proposed Artificial Intelligence framework provides a pathway. This pathway is, for implementing Artificial Intelligence solutions.

6. References

[1] S. Veeramani et al.(2025).”NextGen Lung Disease Diagnosis with Explainable Artificial Intelligence, Scientific Report .

[2] D. Oltu et al.(2025). “ Automated Classification of Chest X-rays Using Vision Transformer and DenseNet201”, BMC Medical Imaging

[3] A. Aljuaid et al. (2025). “RADAI: Deep Learning-Based Classification of Lung Abnormalities in X rays” , Diagnostics, vol. 15, no. 13, pp. 1728, 2025.

[4] X. Wang et al.(2017). “ChestX-ray14: Hospital-Scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification”, “IEEE CVPR”.

[5] L. Milletari et al.(2016). “V-Net: Fully Convolutional Neural Networks for Medical Image Segmentation”, IEEE 3DV.

[6] A. Krizhevsky, I. Sutskever, and G. Hinton.(2012). “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS.

[7] M. Sandler, A. Howard, et al.(2018) “MobileNetV2: Inverted Residuals and Linear Bottlenecks” IEEE CVPR.

[8] T. Chen et al.(2020) “A Review of Deep Learning Models in Radiology” ,IEEE Access.

[9] S. Rajpurkar et al.(2017) "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-rays with Deep Learning, Stanford ML Group" .

[10] WHO Global TB Report, World Health Organization, 2023.

[11] J. Brown et al., ―Explainable AI in Medical Imaging: Trends and Challenges,‖ Nature Machine Intelligence, 2022.

[12] Rajpurkar, P., Irvin, J., Zhu, K., et al. (2017). "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning."

[13] Selvaraju, R. R., Cogswell, M., Das, A., et al. (2017). "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization."

[14] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why Should I Trust You? Explaining the Predictions of Any Classifier (LIME)."

[15] Howard, A. G., Zhu, M., Chen, B., et al. (2017). "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications."