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3D modeling of X-ray images using VR

Shruti Kore[1], Vaishnavi Kadam[2], Samiksha Shinde[3], Ms.S.D.Salunkhe[4]

Student, Department of HA, Rajarambapu Patil Institute of Technology,Islampur,India[1]

Student, Department of HA, Rajarambapu Patil Institute of Technology,Islampur,India [2]

Student, Department of HA, Rajarambapu Patil Institute of Technology,Islampur,India [3]

Guide, Department of HA, Rajarambapu Patil Institute of Technology,Islampur,India [4]

Abstract:Medical imaging has evolved significantly with the integration of 3D reconstruction and Virtual Reality (VR), allowing for enhanced visualization, diagnosis, and surgical planning. Traditional X-ray images provide only 2D projections, limiting spatial understanding of anatomical structures. This study presents a systematic approach for converting 2D X-ray images into detailed 3D models that can be visualized in a VR environment. The process begins with image pre-processing, including noise reduction, contrast enhancement, and segmentation using deep learning techniques such as U-Net and Mask R-CNN. Advanced 3D reconstruction techniques, including the Marching Cubes algorithm and Voxel Net, are employed to convert segmented X-ray images into volumetric data. For cases with multi-angle X-rays, shape-from-silhouette and generative adversarial networks (GANs) are leveraged to infer depth and generate accurate 3D structures. The reconstructed models are then optimized for real-time VR visualization using game engines like Unity and Unreal Engine, incorporating XR interaction toolkits to enable immersive manipulation. The integration of VR provides an interactive experience, allowing users to navigate, zoom, and annotate anatomical models with precision. This approach enhances medical diagnostics, facilitates surgical simulations, and improves medical education by offering a more intuitive understanding of complex structures. The research further discusses the challenges of data acquisition, computational requirements, and real-time rendering, paving the way for future advancements in AI-driven medical imaging and VR-assisted healthcare solutions.

Keywords: 3D Reconstruction, X-ray Imaging, Virtual Reality (VR), Medical Imaging, Deep Learning, Segmentation, Marching Cubes Algorithm

I. INTRODUCTION

Medical imaging plays a crucial role in diagnostics, treatment planning, and medical education. Traditional X-ray imaging provides 2D projections of internal structures, which, although effective, have limitations in depth perception and spatial understanding. Physicians and radiologists often rely on mental reconstruction or multiple imaging modalities, such as CT and MRI, to interpret complex anatomical structures. However, recent advancements in computational techniques and visualization technologies have enabled the transformation of 2D X-ray images into interactive 3D models, significantly enhancing medical diagnostics and surgical planning [1][2]. 3D reconstruction from X-ray images involves several key steps, including image pre-processing, segmentation, and volumetric rendering. Image pre-processing techniques, such as noise reduction and contrast enhancement, improve the clarity of anatomical structures [3]. Segmentation methods, including deep learning models like U-Net and Mask R-CNN, allow for precise extraction of bones, organs, and other regions of interest [4]. Once segmented, algorithms such as Marching Cubes and Voxel Net convert the 2D data into a 3D volumetric representation, ensuring accurate reconstruction of anatomical features [5]. Virtual Reality (VR) provides an immersive platform for interacting with these 3D models, allowing users to explore anatomical structures in a realistic environment. By integrating 3D models into VR frameworks such as Unity and Unreal Engine, medical professionals can manipulate, rotate, and zoom into structures for detailed examination [6]. This interactive approach aids in better understanding spatial relationships within the human body, making it particularly useful for surgical simulations, medical training, and patient education [7]. Additionally, VR-assisted diagnostics can improve decision-making by providing enhanced visualization compared to traditional static images [8]. Despite its potential, challenges exist in converting X-ray images to high-fidelity 3D models. The lack of depth information in single-view X-rays necessitates the use of advanced computational methods, such as shape-from-silhouette techniques and generative adversarial networks (GANs), to infer missing spatial details [9]. Furthermore, real-time rendering of complex anatomical structures in VR requires high computational power and optimized algorithms [10]. Addressing these challenges through AI-driven techniques and hardware acceleration will be critical for the widespread adoption of VR-based medical imaging. This study explores the methodologies for transforming 2D X-ray images into 3D models and their integration into VR environments. It discusses the technical aspects of image processing, 3D reconstruction, and VR interaction while highlighting potential applications in medical diagnostics, education, and surgery [11]. By leveraging deep learning and immersive visualization, this research aims to bridge the gap between traditional medical imaging and modern computational advancements, paving the way for more accurate and interactive medical analysis.

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II. LITERATURE REVIEW

Medical imaging has seen significant advancements in recent years, particularly in the domain of three-dimensional (3D) reconstruction from X-ray images and the integration of Virtual Reality (VR) for enhanced visualization. Researchers have explored various techniques to improve the accuracy and efficiency of 3D medical imaging. Engel et al. discuss real-time volume rendering techniques using GPU-based acceleration, which is crucial for interactive visualization of volumetric data in medical applications. Their study highlights how real-time rendering enables seamless exploration of reconstructed 3D medical images in VR environments [12]. Similarly, Greenspan et al. provide an overview of deep learning applications in medical image analysis, emphasizing the role of convolutional neural networks (CNNs) in automating anatomical structure detection, a fundamental step in creating accurate 3D models from X-ray images [13]. The introduction of the U-Net architecture by Ronneberger et al. has further revolutionized biomedical image segmentation, allowing for efficient feature extraction necessary for 3D reconstructions [14]. One of the foundational algorithms for 3D medical imaging is the Marching Cubes algorithm, introduced by Lorensen and Cline. This algorithm is widely used for converting segmented 2D medical images into high-resolution 3D surface representations, making it essential for medical visualization software [15]. Collins and White investigate the use of VR in medical training, particularly for surgical simulations, demonstrating the advantages of VR-based learning environments for enhancing spatial understanding of complex anatomical structures [16]. Maier-Hein et al. explore AI-driven algorithms for surgical planning and navigation, integrating 3D medical images into VR-based surgical guidance systems, which significantly improve decision-making during medical procedures [17]. The application of immersive technologies in medical imaging is further explored by Wachs and Stern, who review Augmented Reality (AR) and VR methods for interactive visualization of 3D medical data. Their research demonstrates how these technologies enhance clinical workflows and patient diagnosis [18]. Deep learning-based techniques have also played a crucial role in X-ray-based 3D reconstruction. Litjens et al. discuss how CNNs and Generative Adversarial Networks (GANs) can infer depth information from 2D X-ray images, enabling automated 3D model generation [19]. Zhang et al. propose optimization methods for real-time rendering of medical images in VR, ensuring high-fidelity display of anatomical structures with minimal latency [20]. Similarly, Kersten-Oertel and Gerard compare different visualization techniques for medical data, emphasizing the advantages of immersive VR interactions in medical diagnostics [21]. Recent advancements have also introduced shape-from-silhouette techniques for X-ray-based 3D reconstruction. Barré and Hornegger demonstrate how multiple X-ray views can be combined to infer depth information, offering an alternative to more expensive imaging techniques like CT and MRI scans [22]. Moghari and Peters explore the use of GANs for generating synthetic 3D medical images from 2D X-ray datasets, showing how AI-generated volumetric models improve visualization and diagnostic capabilities [23]. Similarly, Iqbal and Hussain review deep learning models used for medical image segmentation, discussing how CNNs and transformer-based networks enhance feature extraction for 3D reconstruction [24]. O'Shea and Nash provide an in-depth review of CNN architectures used in image processing, highlighting their effectiveness in extracting meaningful features from X-ray images for 3D model generation [25]. Shen et al. further explore various deep learning techniques applied to medical image analysis, emphasizing their role in improving the accuracy of virtual 3D models derived from X-ray scans [26]. These studies collectively highlight the rapid advancements in 3D medical imaging, particularly the integration of deep learning and VR technologies. While AI-driven segmentation, real-time rendering, and immersive visualization have opened new possibilities for medical education and surgical planning, challenges such as computational efficiency, real-time interaction, and dataset limitations remain areas for further research.

III. PROPOSED SYSTEM

The proposed system aims to develop an efficient and accurate disease classification model using Convolutional Neural Networks (CNNs) while employing the Median Filter for noise removal in medical X-ray images. The system enhances image quality by eliminating noise before feeding it into the CNN model for classification, ensuring robust and reliable disease diagnosis. Additionally, integrating 3D reconstruction and Virtual Reality (VR) can provide an immersive visualization of affected areas, aiding medical professionals in better decision-making. The fig 1 shows the proposed system architecture.

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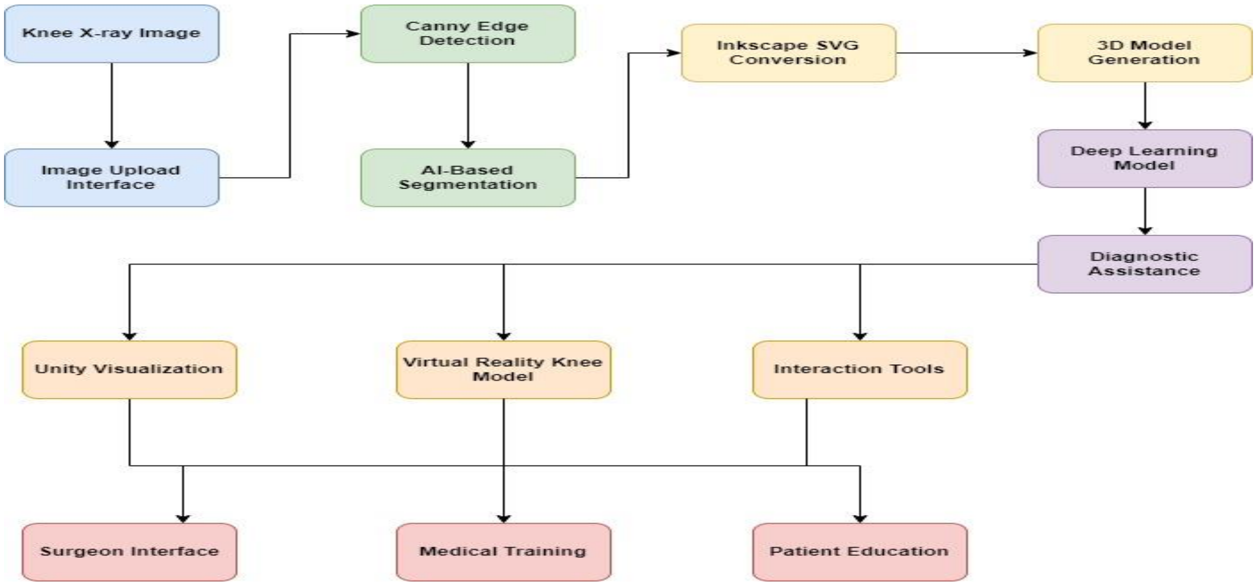

Fig. 1 Proposed System Architecture

Data Acquisition & Pre-processing:

- X-ray images are collected from medical datasets or hospital repositories.
- Image quality is improved by applying the Median Filter to remove salt-and-pepper noise and enhance edges.
- Normalization and resizing of images to ensure uniformity before passing them to the CNN model

Feature Extraction & Classification (CNN Model):

- A deep CNN architecture (e.g., ResNet, VGG16, or custom-built CNN) is used to automatically extract patterns and features from X-ray images.
- The CNN is trained to classify different diseases such as pneumonia, tuberculosis, lung cancer, or bone fractures based on the extracted features.
- A softmax layer is used to assign probability scores for classification.

3D Reconstruction & VR Visualization (Optional for Advanced Systems):

- After classification, 3D models of the affected region can be generated using multiple X-ray images.

Output & Diagnosis:

- The model provides a classification output indicating the presence of a disease along with a confidence score.
- The results can be displayed using heat maps (Grad-CAM) to highlight affected areas in X-ray images.

Dataset Used
https://www.kaggle.com/datasets/tolgadincer/labeled-chest-xray-images

This dataset contains labelled chest X-ray images for disease classification, primarily focusing on pneumonia detection. It is widely used for training and evaluating deep learning models, particularly CNNs, in medical image analysis.

2. Dataset Structure

The dataset is structured into three main folders:
Train: Images used for training the CNN model.
Test: Images for evaluating model performance.

Validation: A small set of images for fine-tuning and preventing overfitting.
Each folder contains two categories of images.

Normal: Chest X-ray images of healthy individuals.
Pneumonia: X-ray images showing pneumonia-infected lungs.

3. Data Statistics

Total Images: Approximately 5,856 images.
Image Format: JPEG (.jpeg)
Resolution: Varies but mostly 1024×1024 pixels.

IV. RESULT & DISCUSSION

1. Main UI Part of System

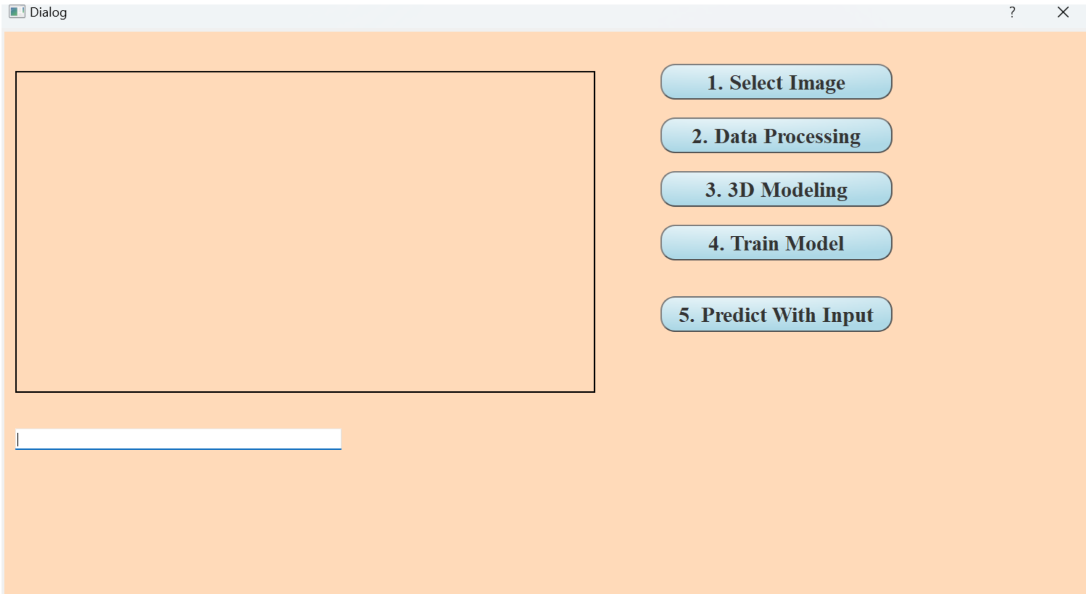

Fig 2 Main UI of system

The fig2 shows the main UI of system. User have serval options like select image, data processing and train model and predict input.

2. Erosion and Dilation

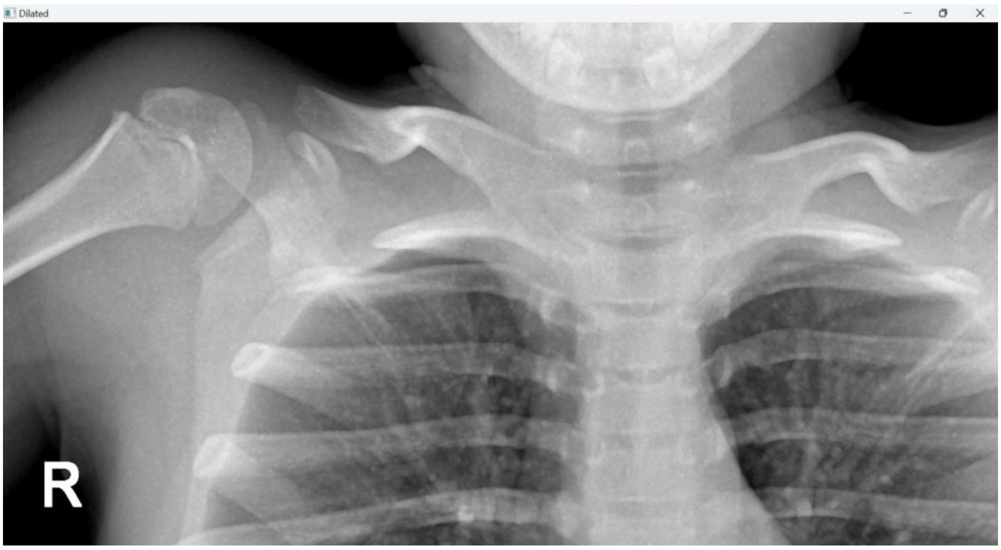

Fig 3 Dilated Image

Erosion and dilation are fundamental morphological operations in image processing, commonly used for noise reduction, shape analysis, and object detection. Erosion works by removing pixels on the boundaries of objects, effectively shrinking the foreground (bright areas) and expanding the background (dark areas). This is useful for eliminating small noise, separating connected objects, and refining boundaries. In contrast, dilation adds pixels to object boundaries, expanding the foreground and reducing gaps in structures. This helps in filling small holes, connecting broken components, and enhancing object visibility. Both operations rely on a structuring element (kernel), which defines how the transformation affects the image. When used together in processes like opening (erosion followed by dilation) and closing (dilation followed by erosion), they help in tasks like feature extraction, edge detection, and medical image processing.

3. 3D Modeling of image

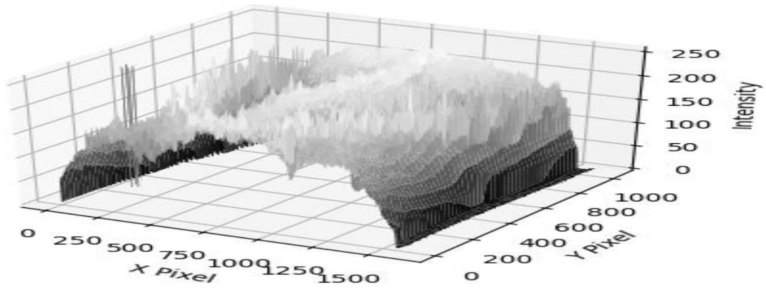

Fig 4 3d Modeling of image

The fig 4 is a 3D surface plot representing pixel intensity variations across an image. The X and Y axes correspond to pixel coordinates in the image, while the Z axis (intensity) represents grayscale values, where higher values indicate brighter regions and lower values correspond to darker areas. The grayscale shading in the plot visually emphasizes these variations, with peaks showing regions of high intensity and valleys representing darker areas. Such plots are useful in image processing and computer vision for analyzing brightness distribution, detecting patterns, and performing edge detection or feature extraction in images.

4. Training & Validation Accuracy

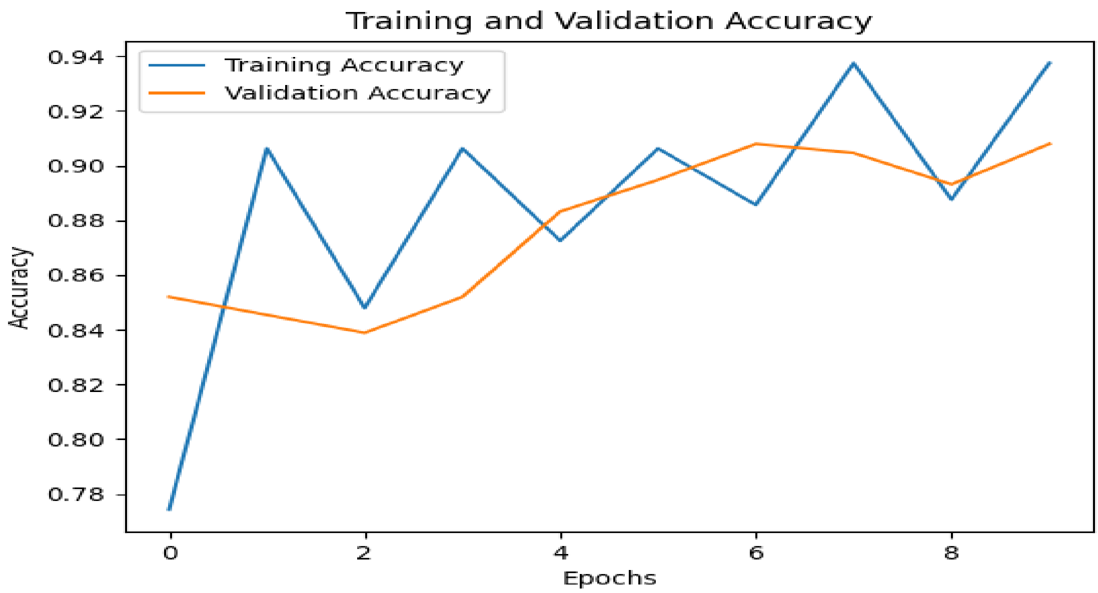

Fig 5 Training and validation accuracy

The graph fig5 illustrates the relationship between training accuracy and validation accuracy over multiple epochs during a machine learning model's training process. Training accuracy (blue line) represents how well the model learns from the training data, typically increasing as the model adjusts its parameters.

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Validation accuracy (orange line) measures how well the model generalizes to unseen data, providing an estimate of real-world performance. Initially, both accuracies improve, indicating effective learning. However, as training progresses, the training accuracy continues rising while validation accuracy stabilizes, suggesting potential overfitting—where the model memorizes training data instead of learning generalizable patterns. The fluctuations in training accuracy towards the later epochs may indicate instability in learning, possibly due to an overly complex model or suboptimal hyper parameters. A smaller gap between training and validation accuracy signifies better generalization, while a large gap may require techniques like regularization, dropout, or early stopping to improve performance.

5. Epoch Wise Accuracy

Table 1 Epoch Wise Accuracy

Epoch	Accuracy
10	0.91
20	0.92
50	0.96

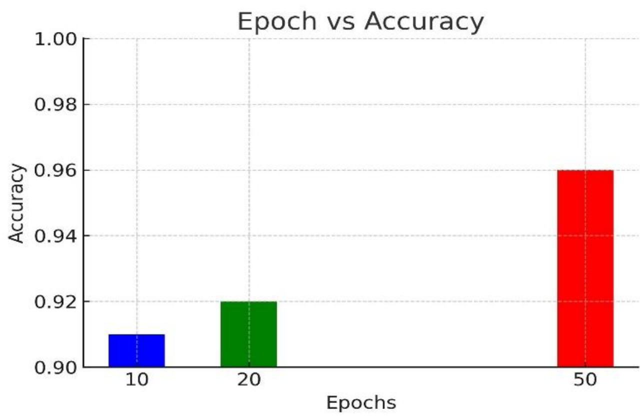

Fig 6Epoch VS Accuracy

A bar graph in fig 6 is a visual representation of data using rectangular bars, where the height or length of each bar corresponds to the value it represents. In the Epoch vs. Accuracy bar graph, the x-axis represents the number of epochs (10, 20, and 50), while the y-axis represents the accuracy achieved at each epoch. The increasing height of the bars indicates that as the number of epochs increases, the accuracy also improves. At 10 epochs, the model achieves an accuracy of 0.91, which slightly increases to 0.92 at 20 epochs and reaches 0.96 at 50 epochs. This suggests that training the model for more epochs leads to better performance. However, after a certain point, further training may lead to overfitting, where the model memorizes the training data instead of generalizing well to new data.

6. Prediction of disease with input disease

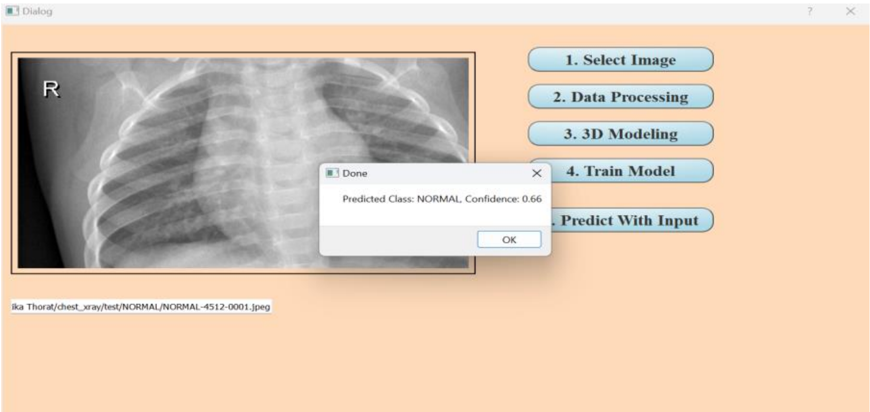

Fig:7 Prediction with input image

The fig7 shows the prediction with input image. It displays the disease with confidence score.

V. CONCLUSION

In this study, we proposed a CNN-based disease classification system for chest X-ray images, incorporating a Median Filter for noise removal to enhance image quality. The Labeled Chest X-ray Images dataset from Kaggle provides a valuable resource for training and evaluating deep learning models for pneumonia detection. By preprocessing images using Median Filtering, we improve feature clarity, enabling CNN models to achieve higher accuracy in disease classification. The integration of CNN for automated diagnosis significantly reduces the dependency on manual interpretation, providing fast, accurate, and reliable results for medical professionals. Furthermore, the potential extension of 3D reconstruction and VR-based visualization can enhance clinical decision-making by offering interactive and detailed analysis of affected regions. Despite the dataset's advantages, limitations such as class imbalance and the absence of other lung diseases must be addressed for real-world applicability. Future improvements could involve transfer learning with larger medical datasets, multi-class disease detection, and real-time deployment in clinical settings. Overall, our system demonstrates a promising approach to AI-driven medical imaging, enhancing diagnostic efficiency and accuracy.

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