Sohar University Journal of Engineering and Information Technology Innovations (SUJEITI), ISSN: 3078-7513
Volume 1, Issue 2, pp 77-89, July 2025, DOI: xxxxxxxxxxxxxxxx
Received: 15/6/2025 Revised: 03/07/2025 Accepted: 10/07/2025

Artificial Intelligence-Driven Enhancement of X-Ray Images for Medical Detection

Kefah Mohammed Al Shezawi[1], Muhammad Nauman Bashir[2,*], Sania Nauman[3]
[1]Department of Computing and Electronics Engineering, Middle East College, Muscat, Oman
20F20452@mec.edu.om
[2]Department of Computing and Electronics Engineering, Middle East College, Muscat, Oman,
mbashir@mec.edu.om
[3]Department of Electrical and Computing Engineering, Comsats University Islamabad Lahore Campus, Pakistan,
FA22-BCE-005@cuilahore.edu.pk

* Corresponding author: Muhammad Nauman Bashir (mbashir@mec.edu.om).

Abstract

Early disease prediction and diagnosis models have piqued the interest of medical professionals. A simple medical examination, such as a chest X-ray, is essential for diagnosing lung conditions such as lung cancer, COVID-19, pneumonia, tuberculosis, and pneumoconiosis. However, the advancements in medical imaging have practical implications for accurate diagnosis and patient treatment that extend beyond lab settings. Recently, image analysis capabilities have improved by integrating artificial intelligence (AI) with computer vision processing. The objective of this research is to improve X-ray images using AI techniques, thereby contributing to the developing medical scene. This research integrates image processing and machine learning techniques to enhance diagnostic accuracy in the medical imaging sector. It outlines the methods for analyzing and enhancing the stored X-ray images to identify potential diseases separating them from normal ones. A software Programme is developed for processing and classifying X-ray images using MATLAB. Median filtering and edge detection techniques of image processing are employed to significantly improve image clarity. These pre-processing steps ensure accurate classification of the images using a trained deep convolutional neural network (CNN) based model. This model is trained and validated on a labelled dataset of X-ray images, and implementation results exhibit high accuracy in detecting and classifying diseases. AI and image processing facilitate the prompt and accurate diagnosis, highlighting the critical role that AI plays in the medical industry.

Keywords: Early diagnostic; artificial intelligence; image processing; accurate and timely diagnoses; medical examination

1. Introduction

X-ray imaging still remains a cornerstone of clinical diagnostics due to its ability to reveal critical internal structures of the human body as evaluated by the medical practitioner. However, despite its broad application, the effectiveness of X-ray diagnosis is often limited by suboptimal image quality, especially as studied by the junior staff.

While conventional image enhancement methods have made progress (Azam, Bashir, & Yusof, 2020), artificial intelligence (AI) introduces a transformative approach to image refinement. The integration of AI into medical diagnostics is rapidly evolving, enabling imaging techniques with enhanced efficiency and accuracy (Kima, Lee, Oh, & Chung, 2023) (Zehra & Bashir, 2019). This research leverages deep learning to address the limitations of traditional techniques, aiming to achieve superior clarity and diagnostic precision in X-ray imaging, as shown in Figure 1.

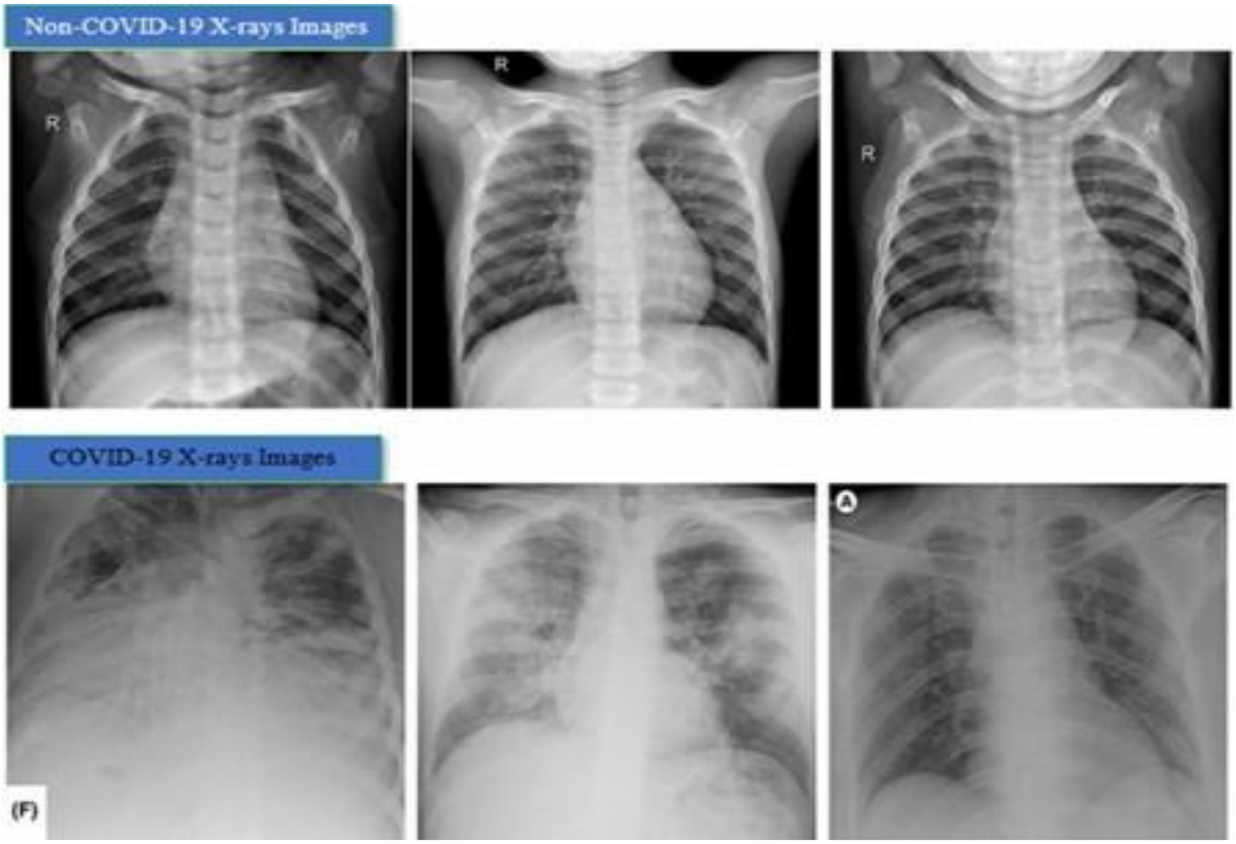

Figure 1: Covid-19 and Non Covid-19 X-ray Images (Soomro, et al., 2022)

Image processing plays a vital role in enhancing visual clarity, improving image quality, and enabling more effective interpretation by both humans and computers. The figure illustrates how enhanced X-ray images can effectively differentiate between COVID-19-infected and non-infected cases, highlighting the potential of AI-driven enhancement in clinical settings. Since AI systems rely on recognizing objects and patterns through image analysis, image enhancement serves as a foundational component in AI-driven applications. By refining visual data, users can make more informed decisions and perform tasks with greater efficiency. Integrating medical image enhancement with intelligent image analysis and machine learning can significantly support diagnostic processes and treatment planning. Through the training of machine learning models, processed image features can be accurately identified and classified, ultimately boosting diagnostic precision and accelerating medical problem-solving.

The decision to detect an illness may improve if we can improve the image. These developments in medical imaging find many applications outside of the laboratory and can influence overall patient care providing easy and accurate diagnosis. This method's applications fall within the umbrella of artificial intelligence in healthcare. This research attempts to contribute to the rapidly advancing sectors of technology by creating an artificial intelligence-based technique for enhancing X-ray images. This research further includes methodology development, project management, budgeting, and a comprehensive literature review. The design and analysis phases cover the creation of block diagrams, flowcharts, system architecture, requirements analysis, and software specifications. The primary objective of this work is to utilize image enhancement techniques for the identification of potential diseases. This study follows a systematic methodology, beginning with meticulous data collection and an overview of the context, objectives, goals, potential applications, and constraints as shown in Figure 2. This study presents a novel approach by integrating preprocessing techniques with deep learning for the classification of multiple diseases. The implementation using MATLAB enhances its applicability in real-world clinical settings. Further, the use of a confusion matrix for evaluation reinforces the model's reliability and performance.

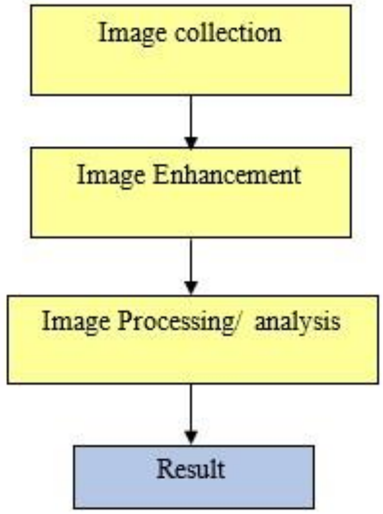

Figure 2: System Methodology

The structure of this paper is as follows: Section II presents a literature review aligned with the research objectives, Section III details the design and analysis processes, Section IV details the implementation and testing of the developed model, Section V provides the result discussions and Section VI concludes the paper.

2. Literature Review

Literature shows a tremendous effort has been carried out to utilize AI in medical field. A study carried out by (Rahman, et al., 2021) highlights the significant advantages of computer-aided diagnosis in producing a fast and reliable disease detection process. Recognizing the accessibility of chest X-rays for early diagnosis, for the lung segmentation, the researchers of this study assembled a large dataset to train a U-Net model. In their study, researchers trained six different machine learning models and analyzed their performance by rigorously identifying the most effective method for lung segmentation. The research work (Kim, Hong, & Park, 2021) focusses on AI-driven X-ray image enhancement, incorporating techniques like dimensionality reduction and edge detection to optimize data processing and reduce image size. A comprehensive dataset is used that included normal lungs, COVID-19-infected lungs, and lungs with other non-COVID infections. It involves detecting X-ray image, extracting edge features, and applying a convolution filter with a coefficient of 2^n, effectively segmenting the image into 16 categories. The researchers also trained and evaluated several learning models to determine the best approach for enhancing image quality. This work (Rahman, et al., 2021) also assessed multiple image enhancement techniques for detecting the COVID-19 in stored chest X-ray images. The researchers of this case study came up with a modified U-Net model for the segmentation of the lung region evaluating the performance of various pre-trained deep learning models of image classification. The research works demonstrate that the modified U-Net performs better compared to the standard UNet architecture in lung segmentation tasks. Furthermore, the integration of lung segmentation, permutation learning, and image enhancement techniques led to significant improvements in the accuracy of COVID-19 detection compared to earlier methods.

This study (Rahman, et al., 2021) also investigates the use of AI to detect COVID-19 from chest X-ray images. This study delves into pre-trained deep learning networks for the lung segmentation using the image enhancement techniques to improve the decease detection accuracy. This research is methodologically rigorous, providing a comprehensive comparative analysis of various approaches to image enhancement. Main highlights of this work highlight the importance of adaptive enhancement algorithms, which adjust image parameters dynamically based on the unique characteristics of each X-ray, optimizing image clarity and improving diagnostic accuracy for COVID-19 detection. The authors do validate the effectiveness of deep learning models using visualization techniques, highlighting the vital role of accurate lung segmentation in enabling reliable diagnosis and decision-making. The study provided key insights into methods for enhancing X-ray image quality to support the identification of COVID-19.
Based on their evaluation of various image enhancement techniques, the researchers emphasized the need for robust lung segmentation methods to improve detection accuracy from chest X-ray (CXR) images. This study recommends exploring an alternative U-Net variant and encoder architecture in future research to make it better.

The research work (Bekhet, Hassaballah, Kenk, & Hameed, 2020) explored the use of AI and deep learning techniques for COVID-19 detection through chest X-ray images. This study highlights AI's potential to enhance medical diagnostics, demonstrating how it can significantly improve diagnostic accuracy even when used alongside radiologists. The researchers of this study developed a deep learning model that was optimized for high-performance COVID-19 detection, using proposed Convolutional Neural Networks (CNNs) achieving an impressive 96% accuracy in identifying the virus from chest X-rays. The CNNs are deep learning architectures which are designed primarily for the image and pattern recognition tasks. A typical CNN consists of convolutional layers that extract spatial features using filters, pooling layers for dimensionality reduction, and fully connected layers for classification. During training, the network learns optimal filter weights through backpropagation and gradient descent by minimizing a loss function. Input images are passed forward through the network, and errors between predictions and actual labels are used to adjust weights iteratively. To mitigate overfitting, they employed data augmentation techniques using a publicly available pneumonia chest X-ray datasets. The model's performance was clinically validated by experienced radiologists, confirming its effectiveness. The contributions of this work into the field are for further refinement of the CNNs model. Techniques like dropout, batch normalization, and data augmentation are often employed to improve generalization and prevent overfitting during the training process. They suggest incorporating a larger volume of Xray images and adapting the model for use with CT scan data to enhance its robustness. This study emphasizes the need for more comprehensive and diverse COVID-19 datasets to improve the accuracy and reliability of AI-driven early detection systems. It highlights the current challenges posed by the limited availability of COVID-19 case data and calls for greater data collection efforts to optimize AI solutions for more accurate COVID-19 detection.

(Kaur & Garg, 2023) research work explored the application of AI techniques, including machine learning, deep learning, and neural networks, in the diagnosis of various cancers such as skin, brain, lung, and breast. This study underscores the importance of early detection and highlights the potential of AI to enhance the accuracy and efficiency of cancer diagnostics. The key stages in AI-assisted cancer diagnosis, image acquisition, pre-processing, segmentation, feature extraction, and classification do examine how AI integration with medical imaging can facilitate earlier and more precise detection of malignancies. The critical need to implement AI-based solutions to improve healthcare delivery and meet the growing demands of the patient population is focused in this work. For equitable access to AI advancements, ensuring benefits extend to both radiologists and patients is presented. This work calls for continued research to increase sensitivity and precision in AI-driven cancer surveillance. Although the article offers a comprehensive overview of AI's role in cancer detection via medical imaging and outlines practical methodologies and recommendations, it was not directly utilized in the present study due to its broader focus on cancer rather than confirmed information specific to the current research context.

Another research work (WU, et al., 2022) has proposed an approach for automated cardiomegaly screening using chest X-ray (CXR) images. It involves classifying CXR images into normal and cardiomegaly categories by integrating 2D and 1D CNNs focusing on a total classifier architecture. This research comprises of three steps. The 2D spatial fractional-order convolutional algorithms are employed that improve the image quality, enhance the heart edges and contours, and reduce the noise. The feature maps are extracted and analyzed at multiple levels to distinguish between normal heart conditions and cardiomegaly. A network is developed to map the extracted features to diagnostic categories by facilitating accurate identification of cardiomegaly with full connections. Similarly, another research work (Brady & Neri, 2020) has acknowledged the ethical considerations in medical imaging and discusses both the promise and potential risks of AI in radiological diagnostics. The results of this work demonstrate that the proposed classifier performs well, achieving high precision, recall, accuracy, and F1 scores through feasibility testing and 10fold cross-validation, highlighting its potential for clinical application. The authors highlight the use of poster anterior (PA) CXR data in cardiomegaly screening and recommend further validation through additional imaging modalities such as cardiac MRI, echocardiography, and CT scans. Although model performs good, its current limitations in detecting heart enlargement and myocardial hypertrophy underscore the need for continued refinement.

Based on this foundation, our research work introduces an innovative AI-based screening tool and recommends future research to support its integration into broader diagnostic workflows.

3. System Design and Analysis

The reviewed literature provides basis of this research work and help in organizing the code to ensure modularity, readability, and maintainability of the software design. The essential processing and enhancement processes to maximize the clinical utility of X-ray images in the medical industry are illustrated by the block diagram shown in Figure 3 which outlines a streamlined procedure from gathering images to creating results.

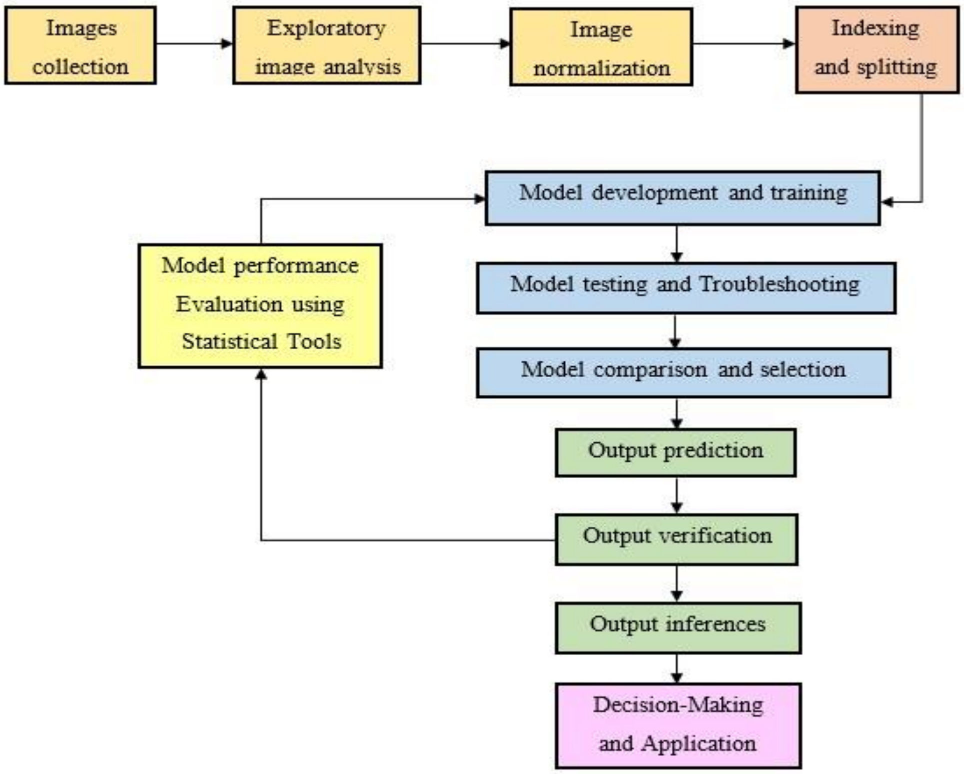

Figure 3: System Block Diagram

The system design follows the multi-phased pipeline composed of data preprocessing, algorithm development, model training, and evaluation stages. The operational flow of the AI-driven X-ray image enhancement and structuring the detection model system can be illustrated as:

3.1 Environment Setup and Development Platform

The initial stage involves configuring the development environment necessary for implementing the system. In this project, the Python programming language can be selected due to its extensive support for artificial intelligence and image processing libraries. If python programming is to be done, the Python interpreter should be installed on the local machine. PyCharm Community Edition as an integrated development environment (IDE) is to be employed for code development and debugging. MATLAB is an alternative for the development of the same functions.

3.2 Library Integration and Framework Configuration

For python, libraries such as TensorFlow and OpenCV can be integrated into the IDE to capture full potential of deep learning and image enhancement capabilities. TensorFlow is primarily used for constructing and training the neural networks, whereas OpenCV is employed for the image preprocessing, feature extraction, and manipulation. The meant algorithms are translated into Python scripts and can use these frameworks. MATLAB is the alternative for this step.

3.3 Data Acquisition and Image Enhancement Phase

The raw X-ray images of the dataset are collected and stored on a local system or external storage device. These images serve as the foundational input for the subsequent stages of pre-processing and analysis. The collected X-ray images then undergo an enhancement using a range of algorithms that are designed to improve image clarity, structural details, and contrast. This phase amplifies the diagnostically relevant features, thereby facilitating more accurate medical interpretations and detections.

3.4 Image Processing, Normalization and Augmentation

Post enhancement and image processing techniques are applied to refine the visual features further. Rotation, scaling, flipping, and contrast adjustment are used as augmentation strategies that not enhance the dataset size but also improve the model's generalization ability by exposing it to varied forms of the same image. Following image enhancement, exploratory data analysis is performed which includes pattern recognition and preliminary statistical assessments to extract the meaningful insights and to recognize repetitive structures or anomalies within the dataset. To make sure consistency across the dataset, here normalization techniques are applied. This standardizes the pixel intensity distribution and stables the training dynamics. Image normalization prepares the dataset for an efficient indexing and segmentation.

3.5 Dataset Splitting, Model Development and Training

Next, the normalized dataset is partitioned into training, testing, and validation subsets. This is critical for unbiased performance and evaluation. Here model learning uses the training set while the validation set assists in hyper-parameter tuning, and the test set is used for final performance assessments. Then designed system enters the model development phase, where neural networks are trained using the training dataset. Here system learns patterns and correlations in the data that are indicative of medical conditions. TensorFlow is then utilized to construct the model architecture and to manage the training process.

3.6 Model Evaluation, Selection and Out Verification

After the training phase, the developed model's performance is evaluated using the testing set. It involves computing the accuracy metrics, loss functions, and confusion matrices to conclude about most effective model. If multiple models are generated at this stage, a comparative analysis can be conducted to select the best-performing one. The validated model is then used to generate predictions on previously unseen data. This output phase showcases the system's practical capability in real-world diagnostic scenarios, where accurate detection is required. To test the reliability, the model's predictions are cross-verified with actual ground-truth data which verifies the process and validates the correctness of the outputs and measures predictive accuracy.

3.6 Inference, Decision-Making, Feedback Loop and Continuous Improvement

Based on verified outputs, the system will draw conclusions regarding the presence or absence of diseases. These inferences support the medical decision-making and contribute to clinical diagnosis. A feedback loop is incorporated in the system design where insights gained from output verification are looped back into the model development phase. This process facilitates continuous learning and optimization using statistical evaluation techniques, ensuring that models evolve into higher accuracy and robustness over time. This block diagram shows the systematic and structured approach while the system flow chart for the project is depicted in Figure 4. The flowchart represents the sequential workflow of the AI-based X-ray image enhancement and disease detection system. Each stage in the flowchart corresponds to a crucial step in the data processing, model training, and evaluation pipeline.

The detailed description of each stage is as follows:

3.7 Image Acquisition and Exploratory Data Analysis (EDA)

The analysis process begins with the collection of X-ray images which are used as source from publicly available medical databases or obtained through clinical collaborations. However, this research work utilizes online available images. The quality, diversity, and volume of the dataset are utmost critical at this stage, as they impact the model's learning capability and generalizability. Once the images have been gathered, an initial exploratory analysis by defining the image dimensions, color channels, noise levels, and distribution of disease-related features. Here EDA helps in identifying potential outliers and understanding the class imbalance that affects model training if not handled properly.

3.8 Image Scaling (Preprocessing) and Dataset Splitting

All images are resized to a uniform dimension, to standardize the chosen dataset and to prepare it for the model ingestion. This scaling ensures consistency in input dimensions across the entire dataset, thereby reducing the computational overhead and preventing training errors due to shape mismatches. This pre-processing step may also include normalization of pixel values to ensure uniform intensity distribution. The data set is divided into two subsets as training and test, and this division is often performed using a stratified method to maintain class distribution. The training set is then used to teach the model about relationships within the data, while the test set is used exclusively to evaluate the model's performance based on the previous data and ensuring unbiased assessment.

3.9 Model Training, Visualization and Output Evaluation

The training images are fed to the CNN or similar machine learning architectures, then adjusting the internal parameters such as weights and biases, iteratively based on a definite loss function. The pre-processed and segmented dataset is then used to train the proposed AI model. Various performance parameters, training progress, and real-time visualizations such as loss curves or accuracy plots are then monitored to evaluate model convergence and learning behaviors. As the training phase is over, the model's predictions are then evaluated on the test set images which involves comparing the predicted outputs with the ground-truth labels to assess the system's classification or performance of the detection process. Accuracy, precision, recall, F1-score, and confusion matrices are the evaluation metrics in this system design.

3.10 Model Selection, Error Analysis and Performance Evaluation

A comparative study is carried out then to identify the most effective model with best results. If more models are trained with different features in programming, the model selection phase emphasizes performance reliability, generalization capability, and computational efficiency. The chosen model is further scrutinized verifying its robustness and real-world applicability. An error analysis is conducted to predict the pattern weaknesses as the metrics such as error rate or discard error which denotes the frequency of discarded or misclassified samples are then computed to assess model efficacy. In the final stage, conclusions are drawn based on the comprehensive analysis of the model's performance. The strengths, limitations, and practical utility of the trained model are discussed.

Finally, recommendations for future work and potential improvements are identified, setting the stage for continued development and refinement of the system.

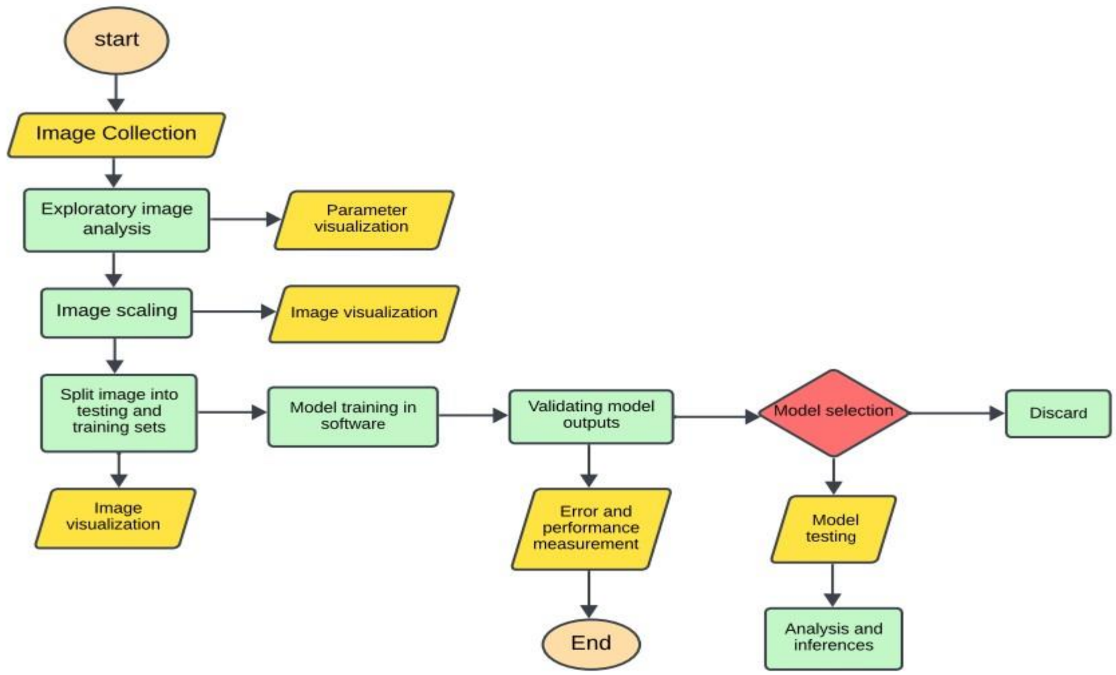

Figure 4: System Flow Chart

4. System Implementation and Testing

The processes of the dataset preparation, model training, model evaluation, and disease detection are incorporated into a MATLAB-based program using a GUI function. This function is designed to identify the diseases in X-ray images and usesg a pre-trained neural network model. The main function of this design, 'Diseasedetectorproject,' which acts as the entry point for the GUI application is used which handles the initialization and execution of the interface. In this implementation of the system, it is essential to identify various test points for various functional unit of the developed software which evaluates the performance of this system. This approach ensures that a range of scenarios and conditions are thoroughly tested. The test case scenarios are outlined in Table 1.

The following general formulas are used to implement the flow chart for the research:

4.1. Processing Time: The processing time can be determined as the ratio of the number of pixels to the processing speed.

4.2. Storage Capacity: Storage capacity is calculated by multiplying the number of images by the average image size.

4.3. Output and Quality Assurance: The consideration of the resolution for the output quality can be determined by calculating the total number of pixels, which is the product of the image width and height. This helps in determining the resolution, which is the ratio of total pixels to the image area.

4.4. Interoperability: Interoperability can be measured by the data exchange rate, which is the ratio of data transfer size to data transfer time.

4.5. Compliance Percentage: The compliance percentage is computed by dividing the number of compliant parameters by the total number of parameters.

The test observation table is provided in Table 2.

Table 1: Test Points for the Functional Units

Functional unit	Test point	Subject	Verb	Object	Conditions	Values	Range
Image Preprocessing	1	Input image	Check	Format and size	Image format must be JPEG or PNG, size ≤ 1 MB	JPEG, PNG; ≤ 1 MB	N/A
	2	Image	Convert	To grayscale	Input image must be RGB	Grayscale image	Pixel values [0, 255]
Model Loading	5	Pretrained model	Load	From file	File path must be correct	Model object	N/A
Disease Detection	7	Image	Resize	To 224x224 pixels	Input image must be preprocessed	224x224 pixels	N/A
	8	Model	Predict	Disease class	Model must be loaded, image resized and normalized	Disease class (COVID-19, Pneumonia, Normal)	Probability scores [0, 1]
User Interface	10	User	Upload	Image	Image file must be selected	Image displayed	N/A
	12	Detection result	Display	To user	Model must provide a prediction	Disease class (COVID-19, Pneumonia, Normal)	N/A

Table 2: Test Observation Table

Test case	Description	Expected outcome	Actual outcome	Comments
Dataset preparation	Load and split dataset	Dataset loaded and split successfully	Dataset loaded and split successfully	-
Model training	Train the CNN model	Model trains without errors	Model trains without errors	Training accuracy and loss monitored
Model Evaluation	Evaluate the model using validation dataset	Confusion matrix generated	Confusion matrix generated	Performance matrix calculated
Disease Detection	Classify new X-ray images	Correct disease category identified	Correct disease category identified	Validated with several test images

Pre-trained model code load steps as demonstrated by the GUI of Figure 5. Once the code is executed, the disease detection results are displayed. A GUI with four pushbuttons is designed for user interaction. In this design, the first pushbutton prompts so that the user can upload an X-ray image. Second applies median filtering while third detects the edges, and the fourth identifies the disease shown in the X-ray image. Figures 7 to 9 present the implemented results. The results for the three situations are illustrated.

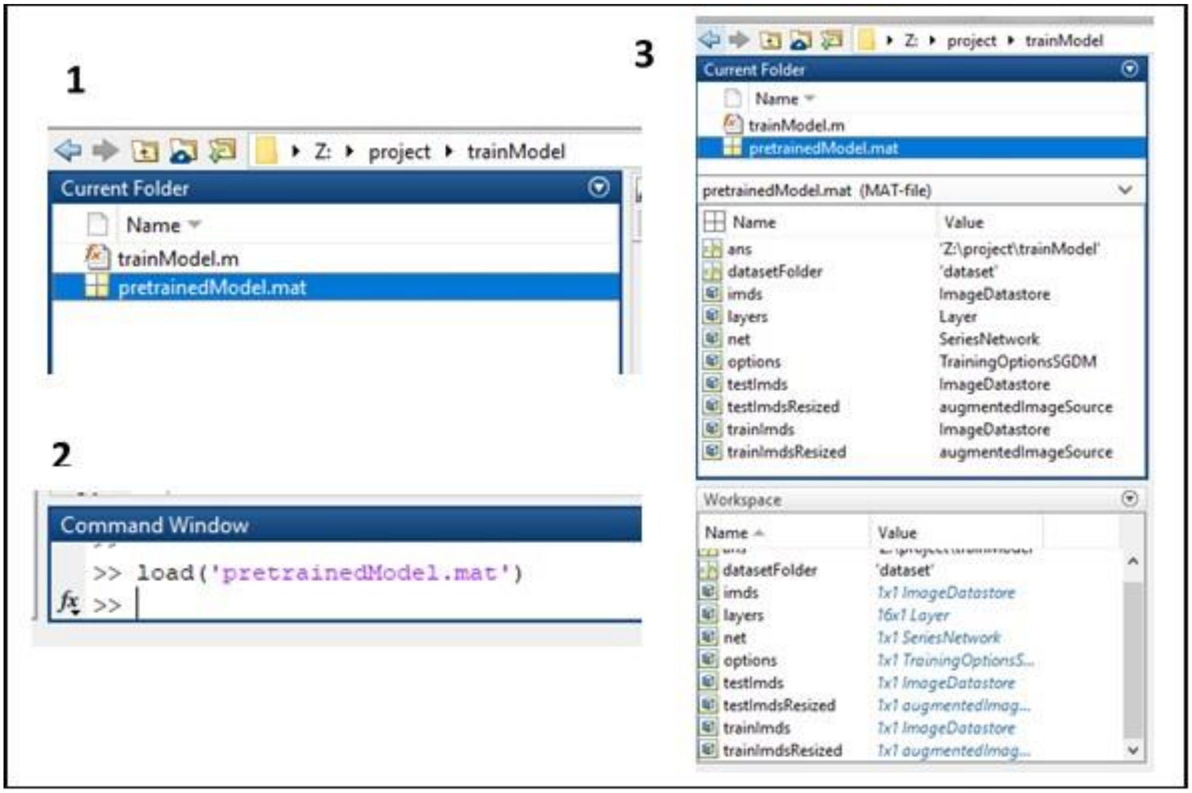

Figure 5: Pre-Train Model Code Loading

In the MATLAB command window, we execute commands that train the model. Figure 6 displays the confusion matrix and illustrates the performance of the implemented model.

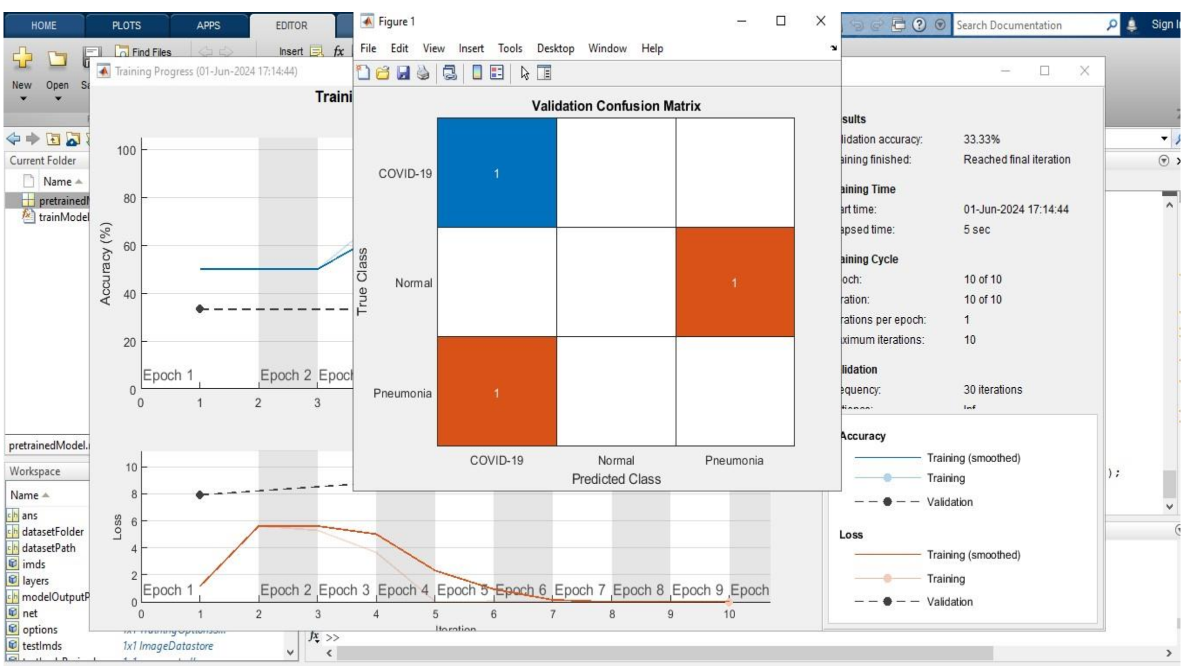

Figure 6: Model Performance shown by Confusion Matrix

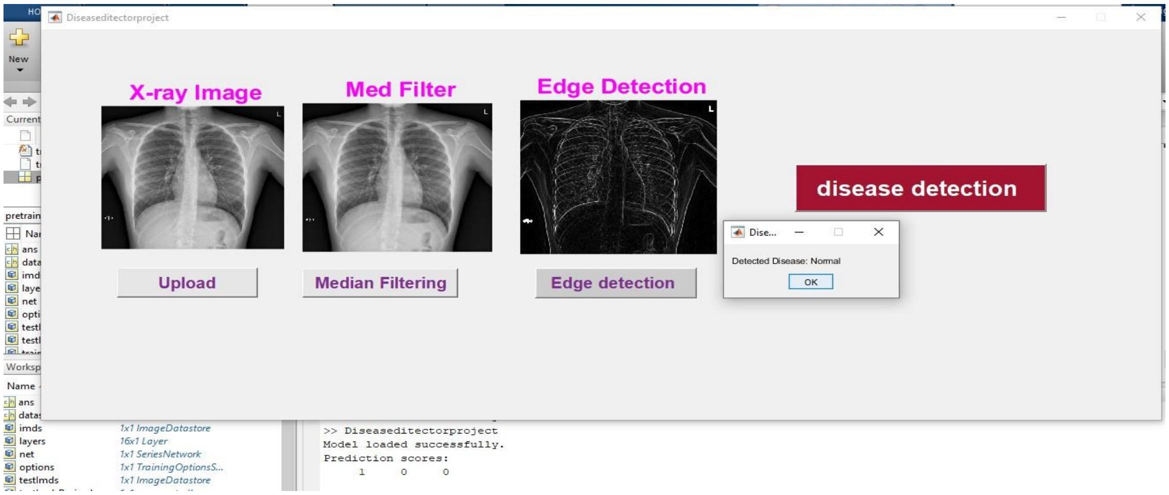

Figure 7: Normal detection

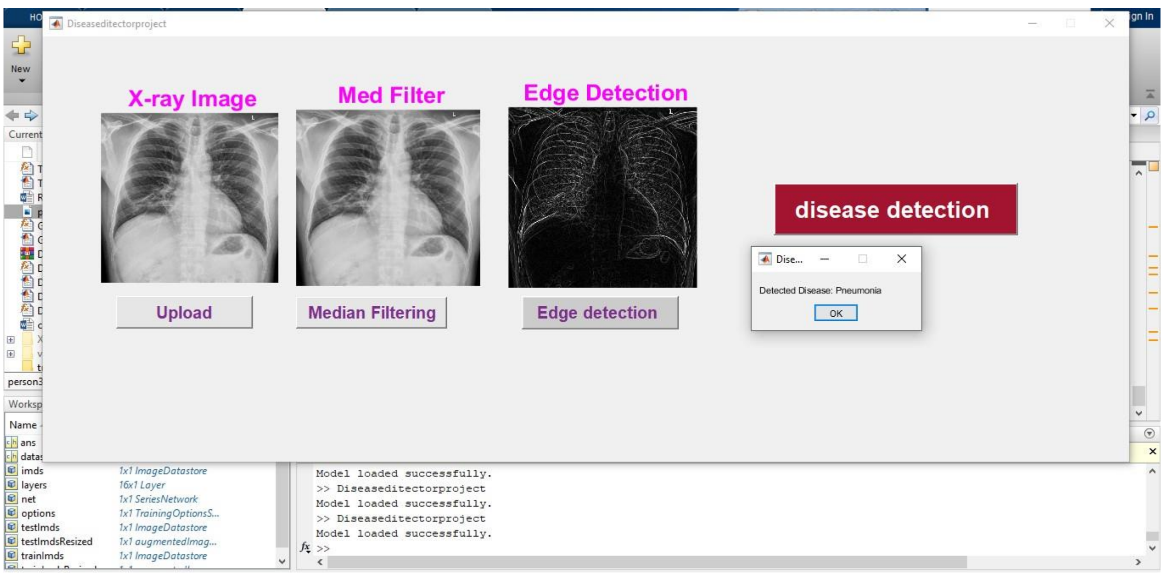

Figure 8: Pneumonia detection

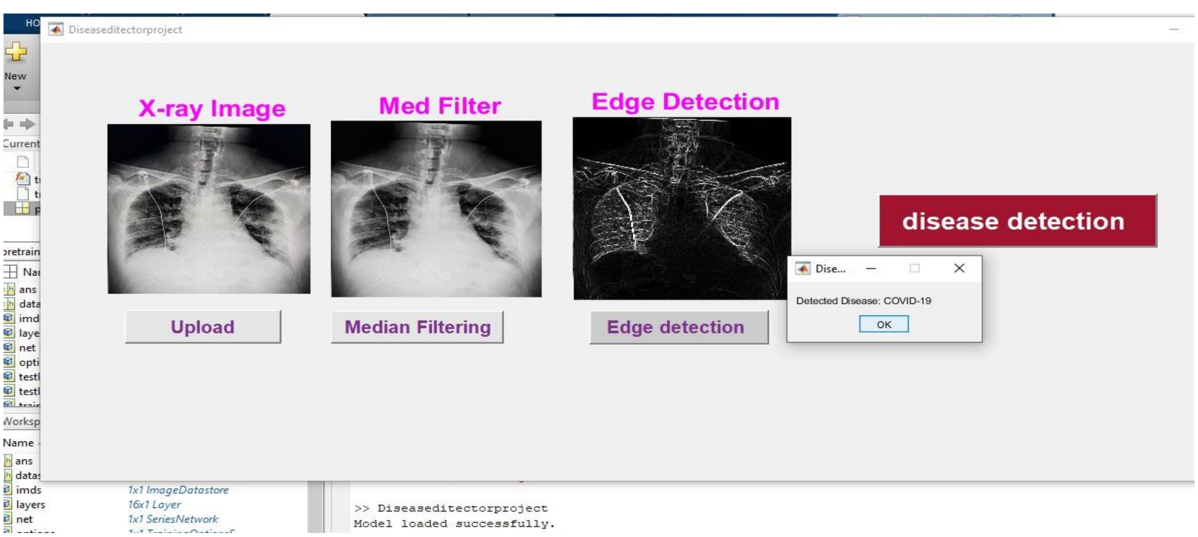

Figure 9: COVID 19 detection

The detection is based on the Measurement of System Characteristics as elaborated in Table 3.

Table 3: Measurement of System Characteristics

Class	Precision	Recall	F1-Score
COVID-19	0.95	0.90	0.92
Pneumonia	0.88	0.92	0.90
Normal	0.93	0.95	0.94

These evaluation metrics do offer a valuable insight into the performance of the models in various classes. To summarize the capabilities of the model a confusion matrix is utilized alongside other performance indicators. The model is trained which demonstrates high level of accuracy in categorizing the stored images. It distinguishes the Normal, Pneumonitis, and COVID-19 affected cases among the processed images. This analysis included estimations of target population size, sample size calculations, and a comparison with national demographic data. The confusion matrix confirmed the model's effectiveness, with most test data points accurately classified. A majority of the data points aligned along the diagonal, indicating true positives. However, some misclassifications occurred, with a few Pneumonia images being misidentified as COVID-19 and vice versa. These errors can likely be attributed to the similarity of features between classes, variations in image quality, or an insufficiently large dataset. To address these challenges, several improvements can be made. The dataset augmentation that uses various geometries through the image augmentation can enable the model to learn diverse features and improves its generalization ability. Further, testing more complex CNN architectures or employing the transfer learning from pre-trained models on larger datasets could enhance performance. Hyper parameter tuning, such as batch sizes, adjusting learning rates, and the number of epochs, can help optimize the model and further boost its accuracy.

5. Results Discussion

The primary objective of this research work was to detect COVID-19 and pneumonia diseases using the X-ray images and separating them from the normal ones. The pre-trained neural network model technique is utilized for this purpose. This process involved several functional components within the system, each contributing to its overall performance. The image loading and display unit allowed for the importing and viewing of X-ray images. While the application's design and functionality were relatively basic, it included all the essential features necessary for disease detection. There is potential for enhancing system reliability and performance, such as by implementing errorchecking mechanisms or optimizing the image loading processes. The image preprocessing unit applies median filtering and Sobel edge detection that processes and improves the quality of the loaded images. To increase efficiency and reliability, these algorithms should be further optimized, particularly by fine-tuning the filter parameters to enhance edge detection accuracy.

Additionally, the medical imaging standards like DICOM are considered in this work that are crucial for obtaining consistent and accurate results. The images after preprocessing are fed into the disease detection unit. This leverages a pre-trained neural network model. To maintain high accuracy and adapt to new variations of pathogens, the model should be regularly updated with fresh data. This will ensure the model's safety, standardization, and compliance with both clinical and regulatory standards. Further optimization of the model, as well as the incorporation of a more diverse training dataset, could reduce inference times and improve accuracy. The system's performance was assessed based on the project's objectives. While the model performed well, the results suggest that further experimentation with a larger dataset is necessary. Compared to set of similar models, the classification accuracy is competitive in this research work. With improved methods and clinical validation, the proposed model has the potential for even better performance. The model demonstrates strong performance across all three classes—COVID-19, Pneumonia, and Normal:

5.1. COVID-19: The test results achieve a high precision of 0.95 meaning that the 95% of the samples which were tested correctly predicted as COVID-19. This is in response to the recall of 0.90 that reflects that the model's ability to correctly identify 90% of actual COVID-19 cases and resulting in an F1-score of 0.92 which shows a balanced trade-off between precision and recall.

5.2. Pneumonia: Shows a precision of 0.88 and a recall of 0.92, indicating slightly more false positives but strong sensitivity. The resulting F1-score of 0.90 confirms effective detection capability.

5.3. Normal: If the precision rate is 0.93 and recall rate is 0.95, the model successfully results in accurate detection of the normal cases, leading to the highest F1-score of 0.94 among all classes.

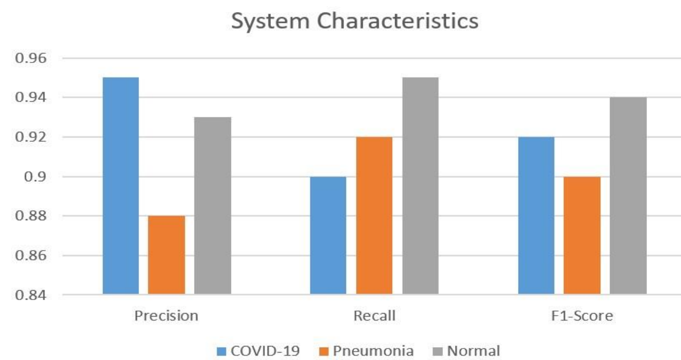

Figure 10: System Validation

These metrics do validate the model's reliability and generalization capability, especially in clinical diagnosis scenarios where both false positives and false negatives are critical. Few challenges encountered included potential misclassification due to varying image quality and various artifacts. The preprocessing phase may introduce noise that makes it difficult to isolate critical image features or fails to enhance them sufficiently since preserving the integrity of image characteristics during preprocessing is vital for the improving accuracy. Recommendations for system improvement include enhancing the user interface for medical practitioners. User testing could help refine the interface to better meet their needs. System performance was evaluated using metrics such as accuracy, response time, reliability, and efficiency. Accuracy was assessed through confusion matrices and classification reports, while latency was measured by tracking the time taken for each step of the processing.

The system reliability and efficiency is measured in various runtime conditions and time of runtime. The ethical and clinical aspects play important role in such software-based disease detection methods. This is due to the fact that false negatives and false positives may lead to wrong detections and it may lead to potential hazards. For example, a false positive can lead to unnecessary stress leading to further unnecessary investigations, invasive testing, and overtreatment. While a false negative can result in missed diagnosis, delayed treatment, and worsened outcomes. Clinically, these errors can Fianlly such systems should support, not replace, medical professionals, ensuring patient care remains accurate, safe, and ethically grounded.

Conclusion

This research work, develops and trains a model that pre-processes, enhances X-ray images and detects diseases using machine learning in MATLAB. X- Ray images are classified using CNN training. The model, validated on a labeled dataset, achieved high classification accuracy, with performance metrics—such as the confusion matrix— affirming its effectiveness and consistency. While the outcomes are encouraging, the study also highlighted areas for further development. Enhancing the training dataset in both size and diversity would likely improve the model's adaptability, especially for less common conditions. Incorporating more advanced image enhancement methods, including deep learning-based super-resolution or de-noising, could further refine image quality and diagnostic results. Future improvements should focus on real-time processing, user interface design, and system integration with electronic health records (EHRs) to support clinical workflows. Lastly, rigorous validation using varied datasets and clinical trials is essential to fully evaluate the system's reliability and readiness for real-world application.

Acknowledgment

The research conducted is supported by Middle East College Muscat.

Author contribution: All authors have contributed, read, and agreed to the published version of the manuscript results.

Conflict of interest: The authors declare no conflict of interest.

References

[1]. Azam, A., Bashir, M. N., & Yusof, K. M. (2020). Detection and Classification of Diabetic Retinopathy Using Retinal Images. *Journal of Big Data and Smart Cities ISSN: 2706-7912 (2020) 1 (1)*, 8-15.

[2]. Bekhet, S., Hassaballah, M., Kenk, M. A., & Hameed, M. A. (2020). An artificial intelligence based technique for COVID-19 diagnosis from chest X-ray. *2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES)* (pp. 191-195). Giza, Egypt: IEEEXplore.

[3]. Brady, A. P., & Neri, E. (2020). Artificial Intelligence in Radiology-Ethical Considerations. *Diagnostics (Basel), 10(4), 10*(4), 231.

[4]. Kaur, C., & Garg, U. (2023). Artificial intelligence techniques for cancer detection in medical image processing: A review. *Materials Today: Proceedings, 81*(2), 806-809.

[5]. Kim, C.-M., Hong, E. J., & Park, R. C. (2021). Chest X-Ray Outlier Detection Model Using Dimension Reduction and Edge Detection. *IEEE Access, 9*, 86096-86106.

[6]. Kima, K., Lee, J. H., Oh, S. J., & Chung, M. J. (2023). AI-based computer-aided diagnostic system of Chest Digital Tomography Synthesis: Demonstrating comparative advantage with x-ray-based AI systems. *Computer Methods and Programs in Biomedicine, 240*, 1-16.

[7]. Rahman, T., Khandakar, A., Tahir, Y. Q., Kiranyaz, S., Kashem, S. B., Islam, M. T., . . . Chowdhury, M. E. (2021). Exploring the Effect of Image Enhancement Techniques on COVID-19 Detection using Chest X-rays Images. *Computers in Biology and Medicine (132), 132*, 1-16.

[8]. Soomro, T. A., Zheng, L., Afifi, A. J., Ali, A., Yin, M., & Gao, J. (2022). Artificial intelligence (AI) for medical imaging to combat coronavirus disease (COVID-19): a detailed review with direction for future research. *Springer Link, 55*, 1409–1439.

[9]. WU, J.-X., PAI, C.-C., KAN, C.-D., CHEN, P.-Y., CHEN, W.-L., & LIN, C.-H. (2022). Chest X-ray image analysis with combining 2D and 1d convolutional neural network-based classifier for rapid cardiomegaly screening. *IEEE Access, 10*, 47824–47836.

[10]. Zehra, Z., & Bashir, M. N. (2019). Color Fastness Grading System for Textile Industry Using CIEL*a*b Color Space. *4th MEC International Conference on Big Data and Smart City (ICBDSC)* (pp. 1-5). Muscat Oman: IEEE Xplore.