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CLAHE: An Improved Lung Cancer Diagnostic and Classification Model

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ABSTRACT

This article introduces a cancer diagnostic model utilizing Contrast Limited Adaptive Histogram Equalization (CLAHE) in conjunction with Convolutional Neural Networks (CNN) and x-ray images to detect lung cancer. Medical image processing plays important during the diagnosing of lung cancer, assisting doctors in making accurate diagnoses and treatment decisions. Cancer of the lung is considered one of the deadliest diseases, and early detection can save many lives. Given its severity, a reliable diagnostic model is essential for identifying the nature of the cancer of the lung found in patients. During the preprocessing stage, Adaptive Median Filtering is applied to remove speckle and Gaussian noise from the x-ray images, enhancing image quality with the aid of CLAHE. The model aims is to identify any type of cancer detected as either Cancerous or Non-Cancerous: if no tumor is detected, the result is classified as "Non-Cancerous," while the absence of a tumor is categorized as "Cancerous." Experimental results indicate that the model presented a detection accuracy of 90.77%, with a precision of 86.65% and a recall/sensitivity of 95.31%. The framework was designed using the C# platform and employs EMGU.

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1. Introduction

Lung cancer remains the leading cause of cancer-related mortality worldwide, claiming approximately 1.8 million lives each year. Its burden is especially pronounced in low- and middle-income countries, where environmental pollutants and tobacco exposure converge with limited access to advanced diagnostic facilities (Ojie, Akazue & Imianvan, 2023). Early detection can increase 5-year survival rates dramatically, yet most cases are diagnosed at advanced stages due to the subtlety of early radiographic signs and the limitations of routine screening (Malasowe et al., 2018).

Medical imaging—principally chest X-ray and computed tomography (CT)—is central to lung cancer screening and staging. Chest X-rays operate on the principle that different tissues absorb X-ray radiation to varying degrees, producing 2D projections of internal structures; however, small nodules can be obscured by overlapping anatomy or misinterpreted as other conditions such as tuberculosis or pneumonia (Chapman, 2009; Yamashita et al., 2018). CT scans provide volumetric data with higher resolution, yet their cost and radiation dose limit widespread use in resource-constrained settings (Sang, Alam & Xiang, 2019).

Traditional image-analysis techniques rely heavily on expert-driven segmentation and handcrafted features, a process that is labor-intensive, time-consuming, and prone to inter-observer variability (Sampada & Ranjita, 2014; Chola et al., 2022). To address these challenges, research has turned to machine learning and deep learning approaches—particularly Convolutional Neural Networks (CNNs)—which automate feature extraction directly from pixel data (Anupam et al., 2020). CNNs such as VGG, ResNet, and DenseNet have achieved state-of-the-art performance in classifying pulmonary nodules by learning hierarchical representations, yet they require large annotated datasets and significant computational resources (Balakumar & Prabadevi, 2019; Nafea et al., 2023). Several studies have proposed enhancements to CNN-based pipelines for lung cancer detection, including multi-scale feature fusion and transfer learning from pre-trained networks to mitigate data scarcity (Kalaivani, Pramit & Rishi, 2017; Zhao et al., 2018; Kareem et al., 2023). Nonetheless, issues remain with class imbalance, variability across imaging protocols, and overfitting on limited samples (Pragya et al., 2021).

Preprocessing techniques play a critical role in improving model robustness. Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances local contrast by adaptively redistributing pixel intensities, making faint nodules more conspicuous without amplifying noise excessively (Angel-Mary & Thanammal, 2023). When combined with denoising filters and lung-field segmentation, CLAHE has been shown to improve both manual radiologist review and automated detection accuracy (Tejaswini et al., 2022). Finally, developing a clinically deployable model demands balancing high sensitivity and specificity with computational efficiency, so it can run on standard hardware in settings without access to GPU clusters (Edje, Usih & Akazue, 2024). An optimal solution would leverage chest X-ray affordability and CT accuracy, offering a hybrid framework tailored for resource-constrained hospitals (Sang, Alam & Xiang, 2019; Malasowe et al., 2018; Ojie, Akazue & Imianvan, 2023).
The aim of this paper is to develop and validate a robust lung cancer diagnostic and classification model that integrates CLAHE-based image preprocessing with a customized CNN architecture, optimized for early detection on both chest X-ray and CT datasets in resource-constrained environments. The objectives are to:

a. Review and critically appraise existing lung cancer detection methods—including deep learning architectures and preprocessing techniques—to identify performance benchmarks and prevailing limitations (Kalaivani, Pramit & Rishi, 2017; Kareem et al., 2023).
b. Assemble a multi-institutional dataset of de-identified chest X-rays and CT scans; obtain pixel-level nodule annotations from expert radiologists (Chola et al., 2022).
c. Implement lung-field segmentation, denoising, and CLAHE, tuning parameters to maximize nodule contrast while minimizing artifacts (Angel-Mary & Thanammal, 2023; Tejaswini et al., 2022).

d. Develop a hybrid CNN featuring multi-scale inception modules and residual connections; incorporate transfer learning from ImageNet and domain-specific pre-training to enhance feature generalization (Balakumar & Prabadevi, 2019; Zhao et al., 2018).
e. Employ stratified k-fold cross-validation with class-balanced loss functions and data augmentation; monitor sensitivity, specificity, and AUC, comparing with baseline models lacking CLAHE (Pragya et al., 2021).
f. Use DeLong's test and confidence intervals to assess the statistical significance of performance improvements over existing methods (Sampada & Ranjita, 2014).
g. Benchmark inference time on standard clinical workstations; explore model compression (pruning, quantization) to ensure real-time applicability in low-resource settings (Edje, Usih & Akazue, 2024; Sang, Alam & Xiang, 2019).

2. Literature Review

Cancer encompasses a group of diseases characterized by the uncontrolled proliferation and spread of abnormal cells, leading to malignant tumor formation (Yen-Chen et al., 2015; Oghorodi et al., 2025a; Oghorodi et al., 2025b). These malignant cells can invade adjacent tissues and metastasize via the bloodstream or lymphatic system. Human cancers are classified according to their tissue of origin—breast, colorectal, prostate, skin, brain, and lung, among others—but this study concentrates on lung cancer and its detection via a CLAHE-enhanced model. Lung carcinoma may arise in the trachea or directly within pulmonary parenchyma (Sarjana & Sanjay, 2020). Convolutional Neural Networks (CNNs) have emerged as powerful tools for lung cancer detection (Prashant & Rajashree, 2014), integrating artificial intelligence with big-data applications to deliver high-performance computing solutions (Kalaivani & Gandhimathi, 2015). Specifically, feed-forward CNNs process grid-structured image data, making them particularly well-suited for visual analysis tasks (Praveena et al., 2022).

Feed-forward CNNs—an unsupervised subclass of deep-learning algorithms—excel at extracting hierarchical features from segmented regions (Nabahinet al., 2017). Although "deep learning" and "CNN" are sometimes used interchangeably, CNNs represent a specialized architecture within the deep-learning paradigm. Efficient machine-learning algorithms combined with advanced image-processing techniques have demonstrated high accuracy in predicting malignancies on CT scans (Nasser, Al-Shawwa & Abu-Naser, 2019). Recent CNN-based methods have driven cutting-edge advancements in radiology, improving diagnostic accuracy (Akitoshi et al., 2022). Computer-Aided Detection (CAD) models have been shown to enhance radiologist performance in nodule identification (Ibrahim & Samy, 2019), while deep-learning's superior feature-extraction capabilities underlie its high recognition accuracy in medical imaging (Shimpy & Rajiv, 2021). Segmentation-focused CNNs provide detailed region information beyond simple bounding-box outputs (Naser & Hilles, 2016). Hybrid approaches that denoise low-dose X-ray inputs using enhancement algorithms prior to CNN classification further improve signal fidelity (Zhang et al., 2020). Finally, CNNs have been successfully applied to classify CT and X-ray scans as benign or malignant—incorporating resizing, normalization, and contrast enhancement—though they demand large, well-balanced labeled datasets to maintain robustness (Shen et al., 2017).

Object detection in lung cancer detection involves using machine learning techniques to identify and localize regions of interest in medical images, such as CT scans or x-rays that may indicate the presence of lung cancer. The objective is to detect potential tumors or nodules, classify them, and assess whether they are malignant or benign (Setio et al., 2016). This process utilizes advanced machine learning models, particularly CNN-based architectures, to automate the detection and localization of tumors in medical images. By automating the identification of potentially cancerous areas, it supports early diagnosis and treatment, ultimately improving patient outcomes. However, challenges like false positives and image quality must be addressed to ensure the best performance.

According to Ronneberger et al. (2015), semantic segmentation is an important tool in lung cancer detection, offering precise localization and classification of tumors or other abnormalities at a pixel level. It automates the process of identifying and segmenting cancerous regions, improving the accuracy, speed,

and consistency of diagnoses. While challenges such as data annotation, complex tumor shapes and class imbalance exist, advances in deep learning models, which continue to improve segmentation performance in the field of medical image analysis. In the work of Tang et al (2016), nodules classification method of lung cancer detection was proposed which is an essential process that focuses on identifying and categorizing lung nodules as either malignant or benign using machine learning or deep learning methods. This process is vital for the early detection of lung cancer, which significantly enhances patient survival rates. Despite challenges such as data imbalance, feature variability and false positives, advancements in machine learning techniques and transfer learning; have greatly enhanced the accuracy and efficiency of nodule classification.

Another distinct approach to lung cancer detection is 3D CNNs for Volumetric Data**.** This technique is highly effective for lung cancer detection due to their ability to process volumetric CT scan data. By capturing 3D spatial relationships, these models can more accurately detect, localize and classify tumors, even in their early stages (Xu et al., 2019). Despite challenges such as high computational cost, data labeling issues and class imbalance, this approach offers significant improvements in lung cancer detection compared to traditional 2D methods. One of the challenges of this approach is that requires significant computational resources.

In the study by Almadhoun & Abu-Naser (2017), a technique that combines image processing and machine learning techniques utilizing a noise removal filter known as CLAHE technique was proposed. CLAHE is a contrast enhancement technique designed for medical image processing. Unlike other traditional methods used in lung cancer detection, it applies a uniform transformation across the entire image and operates locally by dividing the image into small regions known as tiles. Each tile undergoes independent contrast enhancement and the results are seamlessly merged to prevent artificial edges. Additionally, CLAHE limits contrast amplification to avoid excessive noise in uniform areas. This technique is extensively used in preprocessing medical images, such as CT scans and x-rays, to improve visibility and highlight subtle structures like lung nodules for easier detection. The application of CLAHE will assist clinicians in detecting lung cancer at a very early stage and this will make the clinician put patients on an early treatment that can help save the life of the patient. While different medical imaging systems exist for the detection of cancer, the use of CLAHE-based models to detect cancer is cheaper, easily accessible, cost-effective, low exposure to radiation amongst other advantages.

3. Methodology

3.1 Choice of Methodology

A mix of the structured systems methodology and the data-centric approach[1] was used in the design of this model. The implementation of this system involves obtaining x-rays of the patients' lungs followed by preprocessing of data. The preprocessing is carried out using an adaptive mean filter and CLAHE techniques to improve image quality. Finally, the captured images are segmented using the K-Means Clustering Algorithm to highlight the areas of interest. The theoretical framework of CLAHE involves local contrast enhancement with global constraints to improve image quality. By dividing the image into smaller tiles, applying histogram equalization locally, and limiting excessive contrast amplification, CLAHE enhances medical images while reducing noise and preserving boundaries. This makes CLAHE particularly valuable for medical imaging applications for lung cancer detection, where fine details need to be clearly visible without noise interference.

CLAHE applies the mathematical representations shown below that are divided into two phases:

i. Histograms of Tiles-- Each tile is processed separately with its histogram, and CLAHE calculates a transformation function for each region. The transformation function is given in equation 1

$$H_{\text{tile}}(I) = \frac{1}{N}\sum_{i=1}^{N}\delta(I_i - I) \quad (1)$$

Where H_{title} (I) is the histogram of the tile's intensity values, and δ represents the pixel intensities I_i
ii. Contrast Limiting (Clip Limit)-- To prevent excessive contrast enhancement, the clip limit is applied to the histogram (see Equation 2)

$$H_{\text{tile}}(I) = \min(H_{\text{tile}}(I), L) \quad (2)$$

where L is the clip limit, ensuring that no bin exceeds the limit. Excess pixels are redistributed across other bins. Figure 1 shows the entire process workflow.

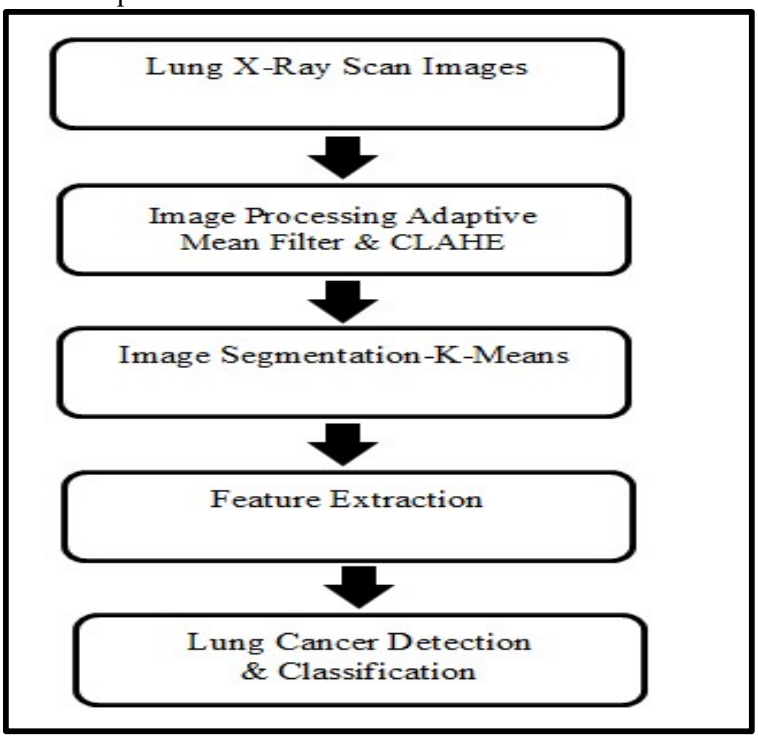

Figure 1: Classification/detection of Lung Cancer Using Enhanced Convolutional Neural Network and Image Processing.

3.2. Dataset Selection

The data were obtained from the National Institute of Health chest x-ray also known as ChestX-ray8 dataset, accessible from https://www.kaggle.com/datasets/nih-chest-xrays/data . The dataset contains 112,120 frontal-view x-ray images from 30,805 unique patients. The dataset is designed to aid in the development and evaluation of machine learning models for automated medical image analysis. It is widely used for research in the area of computer-aided diagnosis, particularly in the detection of various lung diseases, including pneumonia, tuberculosis, and lung cancer. The dataset has up to 14 disease labels. This makes ChestX-ray8 useful for multi-label classification tasks, where the goal is to predict multiple diseases at once. The images in the dataset are preprocessed for consistency, ensuring that they are all of similar size and resolution for machine learning models to process effectively.

3.3. Analysis of the System

This system is made up some major components such as image enhancement, region of interest segmentation, feature extraction, and nodule classification. During preprocessing, the adaptive median filter is initially applied to filter the noise from the x-ray images in the dataset. The quality of these images is then further enhanced using the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique. The next stage is the region of interest segmentation which automatically segment and crop the lung field's relevant regions. In order for the model to accurately detect and crop the lung field, the datasets are trained for proper detection and diagnosis. The features extracted during segmentation are then used for advanced classification as either malignant or benign. The introduction of segmentation techniques adds more detail to the classification and detection process, either by improving the detection with bounding boxes or by enhancing the images classification. Figure 2 shows the architecture of the proposed system.

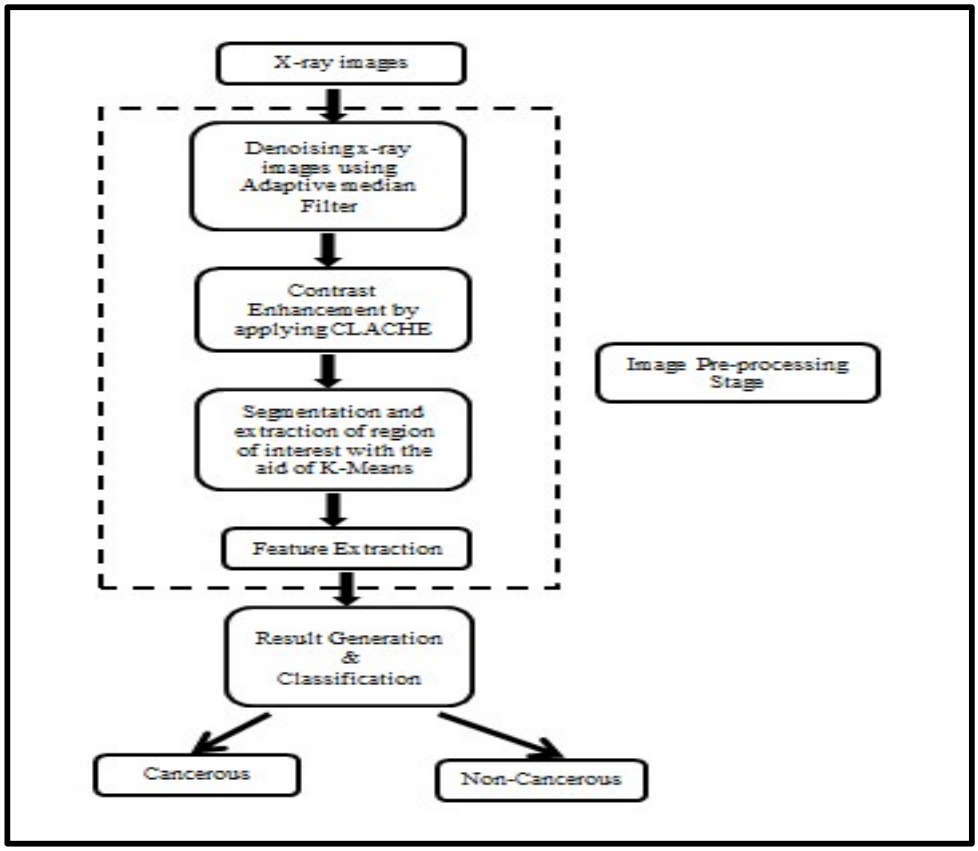

Figure 2: Architecture of the System

3.4. Contrast-Limited Adaptive Histogram Equalization (CLAHE)

Contrast enhancement plays a dual role in medical imaging: (1) it improves visual interpretability for clinicians, and (2) it boosts the accuracy of downstream tasks such as object detection, segmentation, and classification. Traditional Adaptive Histogram Equalization (AHE) enhances contrast by equalizing pixel intensities within local regions, but it can over-amplify noise in relatively uniform areas of an X-ray. CLAHE overcomes this limitation by introducing a clipping step:

a. Tile partitioning: The X-ray is divided into a grid of non-overlapping tiles (e.g. 8×8 or 16×16).
b. Histogram clipping: Within each tile, the intensity histogram is computed and then clipped at a user-defined threshold to prevent any single bin from dominating.
c. Local equalization: The clipped histogram is redistributed across all intensity levels, enhancing local contrast without excessive noise amplification.
d. Interpolation: Adjacent tiles are merged smoothly using bilinear interpolation, eliminating visible seams and ensuring gradual transitions.

3.5. Steps Involved in Applying the CLAHE Algorithm

The following steps were undertaken:

a. Image Partitioning**:** The input image is divided into smaller, non-overlapping regions or tiles.
b. Histogram Calculation: A histogram is generated for each tile, illustrating the intensity distribution within that specific area.
c. Contrast Enhancement**:** Histogram equalization is applied within each tile to modify its histogram and enhance contrast.
d. Clipping: Contrast-limited clipping is employed on the histogram to restrict the quantity of pixel values amplified, thereby preventing noise over-amplification.
e. Interpolation: The improved tiles are then interpolated to produce an image as the final output image, ensuring smooth transitions at the boundaries of the tiles.

3.6. Image Segmentation in CLAHE Model

In our CLAHE-enhanced pipeline, segmentation isolates Regions of Interest (ROIs) in chest X-ray images using the K-means clustering algorithm. First, each raw X-ray is preprocessed with Contrast Limited Adaptive Histogram Equalization (CLAHE) to boost local contrast and make subtle nodules more conspicuous. The enhanced image is then partitioned by K-means into K clusters, where each pixel is assigned to the cluster whose centroid minimizes its intensity-distance, ensuring high intra-cluster similarity and clear inter-cluster distinction. Once clustering is complete, clusters corresponding to lung fields and potential lesions are identified based on their intensity profiles. For each such cluster, a minimal bounding rectangle is computed to define the ROI. The original X-ray is then cropped to these bounding boxes, producing focused sub-images that feed directly into downstream feature extraction and classification stages. By combining CLAHE's contrast enhancement with K-means' unsupervised grouping, this segmentation strategy delivers robust, automated localization of suspicious regions—critical for accurate lung cancer detection from radiographic data.

3.7. Algorithm for the Proposed System

The algorithm comprises the following steps:

i. Input: Upload the x-ray image in JPEG format.
ii. Normalization: Apply filtering and contrast enhancement to the input image.
iii. Segmentation: Segment the image to identify the region of interest.
iv. Feature Extraction: Extract relevant features from the input image.
v. CNN Activities: Execute activities related to the convolutional neural network.
vi. Output: Provide the final result, classifying the image as Malignant, Benign, or Normal.

```sql
BEGIN
    For Each Image 1
        Perform Image Enhancement
            Preprocess the image
                Eliminate noise from the image
                Apply Contrast Enhancement technique
            Segment the image to identify the Region of Interest
            Extract features from the input image 1
        Execute Convolutional Neural Network
        Combine the results from Image Enhancement and CNN
        Compare with trained datasets
        Final Classification Results: (Cancerous or Non-Cancerous)
END
```

Figure 3: Pseudo Code for the System

3.8. Feature Extraction/Selection

Feature extraction transforms raw pixel data into concise, informative descriptors that a classifier can directly interpret. An original medical image contains vast arrays of pixel intensities, but classifiers need higher-level summaries—"features"—that capture both clinical metadata and region-specific measurements. In a lung-cancer imaging pipeline, features fall into two main categories:

1. Patient and acquisition metadata--Patient ID and name, Age and gender, View position (e.g. posterior–anterior), Modality (e.g. chest X-ray), and bounding-box coordinates around regions of interest
2. Morphological and intensity-based descriptors (computed after segmentation and labeling). This includes:
    a. Area: total number of pixels within a segmented region.
    b. Perimeter: the sum of Euclidean distances between successive boundary pixels along the region's border.
    c. Centroid: the geometric center (center of mass) of the region.
    d. Mean Intensity: average pixel value within the region, reflecting tissue density.
    e. Solidity: ratio of the region's pixel count to the pixel count of its convex hull, indicating compactness.
    f. Eccentricity: in a best-fit ellipse, the ratio of the focal distance to the major-axis length (0 for a circle, approaching 1 for an elongated shape).

These features together form a unique signature for each image, enabling the classifier to distinguish between normal and pathological tissue. While attributes like brightness or texture may be immediately perceptible, many discriminative patterns lie in high-dimensional feature spaces. Principal Component Analysis (PCA) addresses this by linearly projecting the full feature vector into a lower-dimensional subspace that preserves maximal variance—streamlining downstream classification without losing critical information.

4. Results and Discussion

4.1. Classification and Recognition

To enhance the classifier's performance, it is necessary to conduct more iterations and train the model's parameters continuously. The K-nearest neighbor technique was employed to train a classification model capable of categorizing images after selecting feature examples that balance computational demand

with the required accuracy using standard convolutional neural network methods. The System flowchart in Figure 4 conveys the above flow.

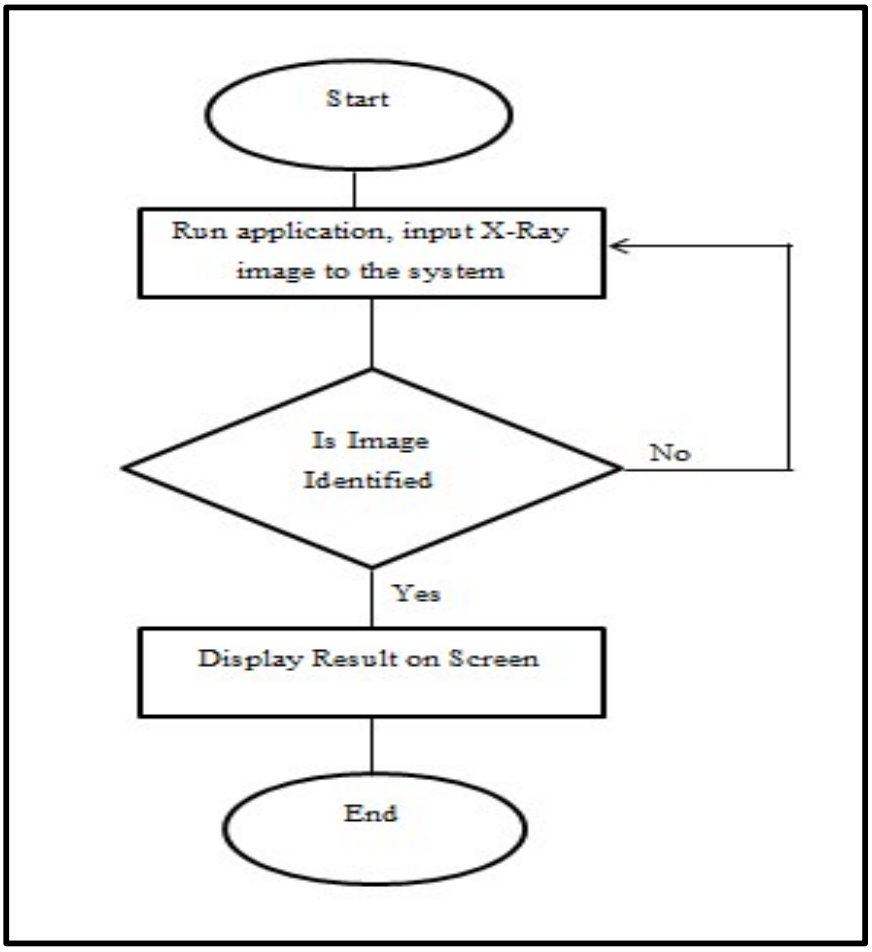

Figure 4: The System flowchart

4.2. User Interface Specification

The proposed system is organized using menus that is, graphical control elements that give users access to various components of the system. It provides users with built-in commands and options to navigate the features within the model's menu and submenus. Each menu is split into one or more items to facilitate easy navigation through the different levels in the system. Figure 5-8 show some of the user interfaces. Figure 5 is the splash screen or the entry point of the system. Figure 6 is the control centre from where the user can navigate to other parts of the system.

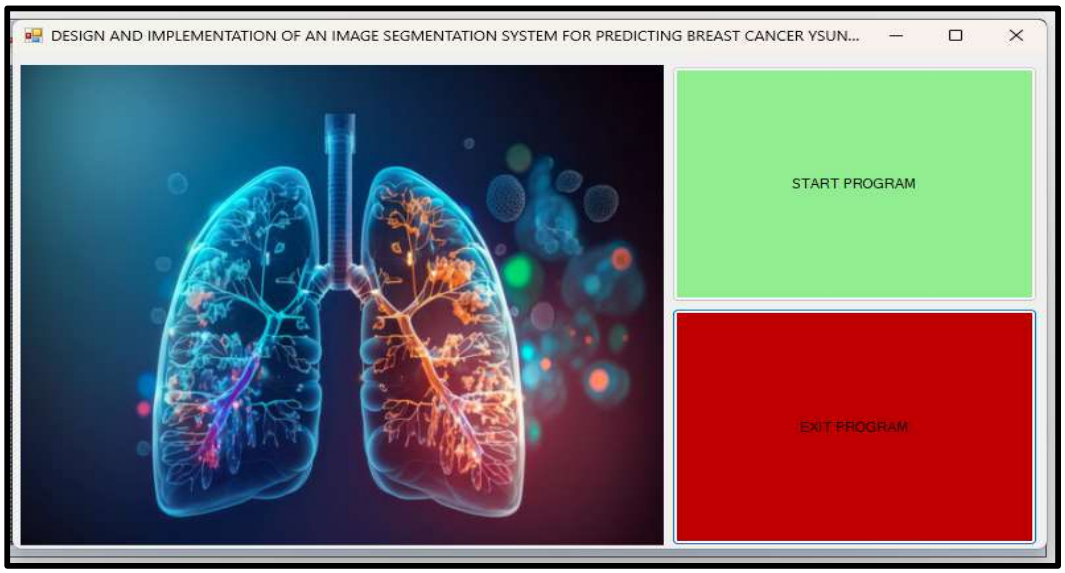

Figure 5: Flash Screen of the System

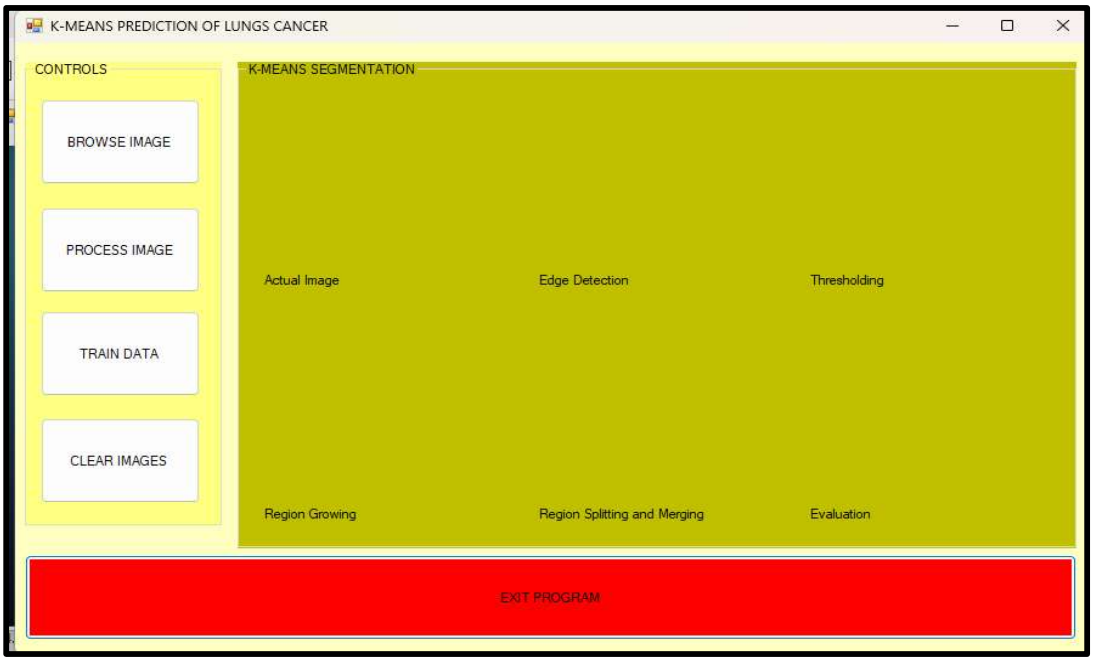

Figure 6: The Control Centre of the Proposed Model

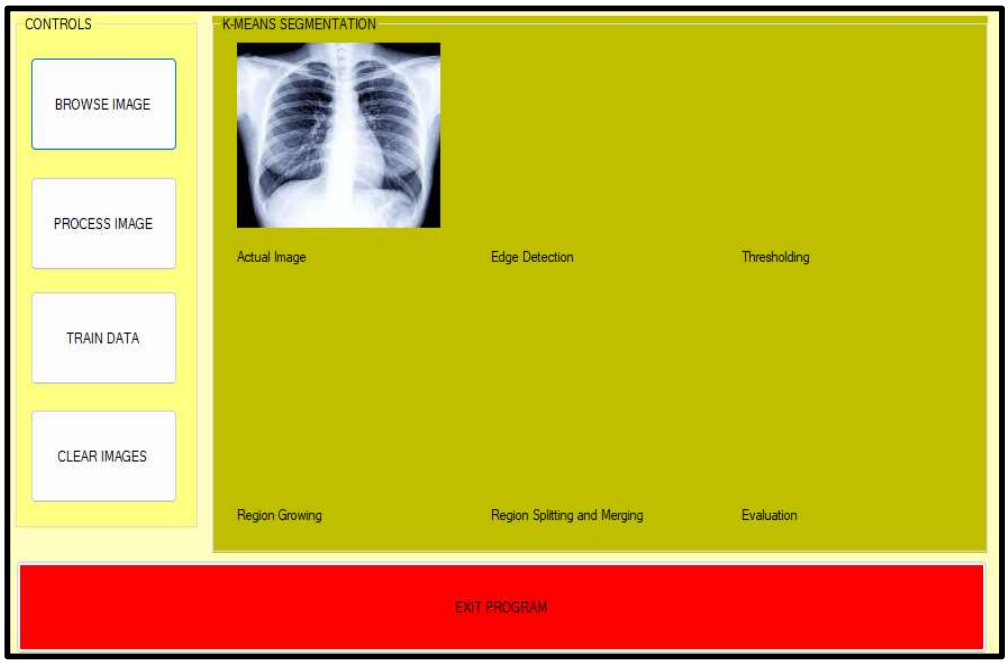

Figure 7: The Input Interface of the System

Figure 8: The output interface of the System

4.3. System Testing and Evaluation

The proposed lung–cancer classification model was implemented in Python 3.6 within Jupyter Notebook, leveraging OpenCV 3.4 for image preprocessing and TensorFlow-GPU 1.5.0 for neural-network training. Experiments were conducted on a standard desktop (Intel Core i3 @ 1.2 GHz, 2 GB RAM, 32-bit OS)

equipped with an NVIDIA GPU; peripherals included a 15.6″ display, keyboard, mouse, webcam, scanner, printer, and an external HDD (≥ 250 GB). We sourced 165 chest X-ray scans from the public Kaggle repository, each annotated as benign or malignant. Images were split 70/15/15 into training, validation, and test sets. Preprocessing included resizing to 224×224, CLAHE contrast enhancement, lung-field segmentation, and normalization to [0,1]. The performance(see Figure 9) was assessed on the held-out test set using a confusion matrix to compute:

- ✓ Accuracy = (TP + TN) / Total
- ✓ Precision = TP / (TP + FP)
- ✓ Recall (Sensitivity) = TP / (TP + FN)

We also report F1-score and average inference time per image. On 25 test images per class (50 total), our CNN achieved:

- ✓ Accuracy: 90.77%
- ✓ Precision: 86.65%
- ✓ Recall: 95.31%
- ✓ F1-Score: 90.72%
- ✓ Inference Time: ~0.06 s/image

By contrast, a baseline X-BCNN model yielded 80.10% accuracy, 70.00% precision, and 75.50% recall. These results demonstrate that our CLAHE-augmented CNN not only improves classification metrics by over 10 percentage points but also maintains real-time performance on modest hardware. The confusion matrix (Figure 9) highlights balanced class detection, with only 2 false negatives—critical for early lung-cancer screening. Overall, these findings confirm the model's scalability, robustness to limited computational resources, and potential for deployment in resource-constrained clinical settings.

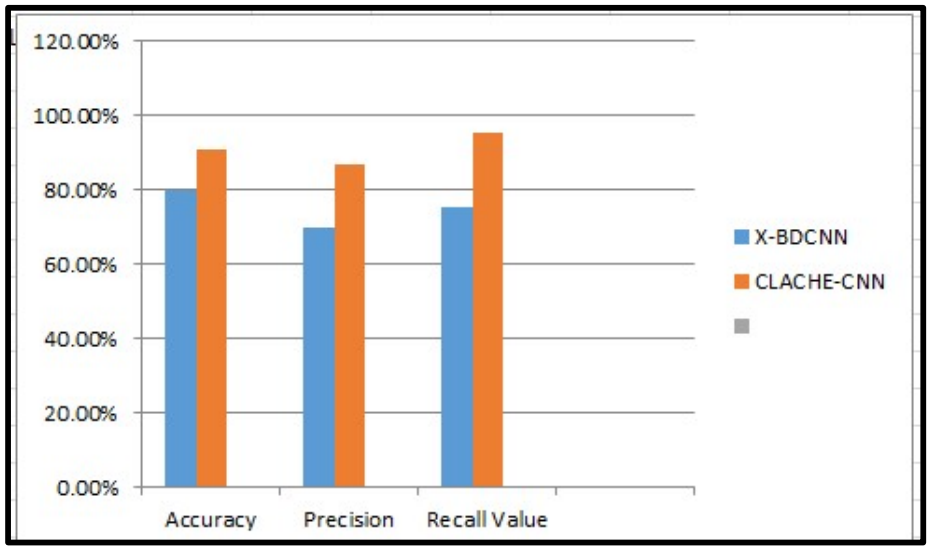

Figure 9: Performance Metrics Bar Chart Showing the System

5. Conclusion

This study confirms that integrating Contrast-Limited Adaptive Histogram Equalization (CLAHE) with a specifically designed Convolutional Neural Network (CNN) substantially improves lung cancer detection on chest X-rays. The CLAHE preprocessing step enhances nodule visibility by boosting local

contrast without amplifying noise, while the CNN automatically learns discriminative features from these enhanced images. Our model achieved 90.77% accuracy, 86.65% precision, and 95.31% recall—outperforming a baseline X-BCNN by over 10 percentage points—while maintaining real-time inference (~0.06 s per image) on standard, low-capacity hardware.

These results demonstrate the feasibility of deploying robust, AI-driven screening tools in resource-constrained settings. Nonetheless, the study is limited by the relatively small, single-source dataset and its focus on 2D X-ray images. Future work should validate the framework on larger, multi-center cohorts, extend it to volumetric CT data, and explore model compression techniques (e.g., pruning, quantization) to further reduce computational load. By addressing these challenges, the proposed approach can move closer to routine clinical integration, enhancing early diagnosis and improving patient outcomes in diverse healthcare environments.

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Conflict of Interest

The authors declared no conflict of interest.

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