Shri Vile Parle Kelavani Mandal's

DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING

(Autonomous College Affiliated to the University of Mumbai)

Unified Vision-Language Model for Lung Cancer Diagnosis

Submitted in partial fulfillment of the requirement
of the degree of

Bachelor of Technology in

Computer Science and Engineering (IoT and Cyber Security with Block Chain Technology)

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A.Y. 2024 – 2025

DECLARATION

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all the principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be a cause for disciplinary action by the Institute and can also evoke penal action from the sources, which have thus not been properly cited or from whom proper permission has not been taken, when needed.

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Certificate

This is to certify that the project entitled "Unified Vision-Language Model for Lung Cancer Diagnosis" is a genuine work of "Akhil Padmanabhan"(60019210040), "Utkarsh Saxena" (60019210093), "Manasvi Deshmukh" (60019210088) and "Suhanee Shimpi" (60019210094) submitted in the partial fulfillment of the requirement for the award of the Bachelor of Technology in Computer Science and Engineering (IoT and Cyber Security with Block Chain Technology).

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Acknowledgement

We take this opportunity to express our deep sense of gratitude to our project guide, Prof. Swapnil Gharat for his continuous guidance and encouragement throughout the duration of our project work. It is because of his experience and wonderful knowledge we were able to fulfil the requirement for the completion of this project within the stipulated time. We would also like to thank Dr. Narendra Shekokar, Vice Principal and Head of the Department Computer Science and Engineering (IoT and Cyber Security with Block Chain Technology) for his encouragement, whole-hearted cooperation and support.

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Abstract

The cause of one of the deadliest cancers worldwide, lung cancer results in a huge mortality rate due to the late detection and delay in treatment. Early and precise detection of lung cancer will improve outcomes and survival in patients, but the current traditional workflows depend on manual examination of CT scans, which are laborious, vulnerable to human mistakes, and prone to variation. This research endeavours to address these difficulties by proposing a unified model that will automate lung cancer diagnosis while creating detailed diagnostic reports.

This paper focuses on designing, training and testing the custom CNN architecture towards attaining high-accuracy in classifying the lung cancer cases. It outlines future work that merges CNN with LLM to enable vision-language fusion to derive image-derived features together with optional textual prompts for comprehensive report generations.

The proposed framework solves important limitations in lung cancer diagnostics by leveraging artificial intelligence to automate and integrate medical processes. It offers a feasible option for health providers. Experimental results confirm the operational characteristics of the convolutional neural network, establishing the groundwork for a hybrid diagnostic approach expected to enhance precision, decrease variability, and improve efficiency. The CNN hierarchy is adjusted to the diagnostic task, combining convolutional and pooling layers for higher classification efficiency. The framework also integrates a pre-trained large language model (LLM) for report automation.

Keywords: Generative AI, Medical Imaging, Large Language Models, X-ray, CT scan, MRI scan, Computer Vision.

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List of Notations and Operations

Accuracy	The proportion of correctly classified samples out of the total samples.
Precision	The proportion of true positives among all positive predictions.
Recall	The proportion of true positives among all actual positives.
F1 Score	Harmonic mean of precision and recall.
AUC	Area Under the Curve: Measures the ability of the classifier to distinguish between classes.
Confusion Matrix	A matrix representing true vs. predicted classifications to evaluate performance.
CNN	Convolutional Neural Network: A deep learning model used to classify CT scan images into Normal, Benign, or Malignant.
LLM	Large Language Model: Used to generate natural-language diagnostic reports from CNN outputs.
GPT-2	Generative Pre-trained Transformer 2: A transformer-based model fine-tuned for medical report generation.
Softmax	Activation function applied in the final layer of the CNN to convert logits into probabilities.
ReLU	Rectified Linear Unit: A non-linear activation function used in CNN layers.
OpenCV	Open Source Computer Vision Library used for image preprocessing like color conversion, blurring, and thresholding.
Otsu Thresholding	A method to automatically choose a threshold value for converting grayscale images into binary.

Erosion / Dilation	Morphological operations applied to reduce noise and emphasize features in binary images.
Grayscale Conversion	Converts RGB images to single-channel grayscale to reduce complexity.
Gaussian Blur	A preprocessing technique used to smooth images and reduce noise.
Normalization	Scaling pixel intensity values (usually between 0 and 1) to standardize input.

Abbreviations

AI	Artificial Intelligence
AUC	Area Under the Curve
CNN	Convolutional Neural Network
CT	Computed Tomography
DL	Deep Learning
EHR	Electronic Health Record
F1 Score	Harmonic mean of precision and recall
GPT-2	Generative Pretrained Transformer 2
LLM	Large Language Model
NLP	Natural Language Processing
OpenCV	Open Source Computer Vision Library
ROC	Receiver Operating Characteristic
TPU	Tensor Processing Unit
ReLU	Rectified Linear Unit
Softmax	A function to convert scores into probabilities

Contents

CHAPTER 1

Introduction

This chapter discusses the important issue of lung cancer diagnosis and the need of artificial intelligence in changing existing diagnostic methods. Still, manual interpretation—which might cause possible inaccuracy, delays, and human mistakes—images scan technology relies so much on in diagnosis process Particularly convolutional neural networks (CNNs) and big language models (LLMs), deep learning combined with these technologies presents a potential change from traditional diagnosis to automated and accurate medical imaging analysis. The suggested integrated artificial intelligence system presented in this chapter combining image classification and automatic diagnostic report generation lays the groundwork for a whole and efficient answer for lung cancer detection.

1.1 Motivation / Objective

Still one of the most lethal cancers worldwide, lung cancer causes more than 1.8 million deaths annually. Late diagnosis and postponed treatment are two of the main causes of the high death rate. Diagnostic inconsistencies arise from the time-consuming, human-biased, and impractical manual evaluation of CT scan pictures in resource-limited environments.

The rise of artificial intelligence offers a great chance to help to remedy these constraints. Fast, scalable, and reproducible diagnosis is provided by artificial intelligence (AI) systems leveraging CNNs for image-based classification and LLMs for automated report generation. Transforming traditional diagnostic workflows into smart systems able of motivating this project is one vision driving it.

- Reducing the diagnostic burden on radiologists by automating CT image classification.
- Enhancing diagnostic accuracy for lung cancer cases by minimizing human error.
- Accelerating the generation of comprehensive diagnostic reports using LLMs.
- Facilitating vision-language integration to improve contextual understanding and report generation.
- Improving accessibility of reliable diagnostics in resource-limited healthcare environments.

Objectives:

- To develop a CNN-based classifier that categorizes lung CT images into normal, benign, and malignant.
- To automate the generation of diagnostic reports based on CNN results using GPT-based LLMs.
- To integrate vision-language fusion for contextual and coherent report generation.
- To ensure scalability and efficiency for deployment in real-time clinical environments.
- To reduce variability, improve diagnostic consistency, and enhance clinical decision-making.

1.2 Proposed Solution

The suggested answer is a single AI-driven diagnostic framework combining large language model-based report generation and deep learning-based image classification. By combining visual data with descriptive medical study, this hybrid approach seeks to simplify lung cancer diagnosis.

- **CT Image Classification:** Lung CT images are used to train a custom Convolutional Neural Network (CNN) to categorize them into three groups: normal, benign, or malignant. Gray-scale conversion, noise reduction, normalization, and morphological operations are preprocessing processes built into the architecture.
- **Automated Report Generation:** Diagnostic reports generated from the classification result of the CNN are produced using a GPT-based LLM. Clinical findings including nodule size, presence, and malignancy are in these reports.
- **Vision-Language Fusion:** The system produces contextual, human-readable reports using features from CNNs coupled with LLM capabilities. This combination helps doctors by making decisions easier and better understandable.
- **Scalable and Deployable System:**The whole system is meant to operate in real-time clinical environments. For large-scale processing of medical scans, it facilitates GPU acceleration, cloud deployment, and data storage using secure services.
- **Evaluation:** To verify the model's efficacy in clinical settings, it is assessed using performance indicators including accuracy, precision, recall, and AUC-ROC.

Benefits of the Proposed Solution:

- **Efficiency:** Reduces the time required for lung cancer diagnosis by automating image classification and report writing.
- **Accuracy:** Enhances the reliability and consistency of diagnoses, reducing variability.
- **Accessibility:** Enables advanced diagnostics in resource-constrained environments through scalable deployment.

- **Interpretability:** Generates clear and comprehensible diagnostic reports for both clinicians and patients.

1.3 Scope of the Project

This project covers the creation of an AI-based lung cancer diagnosis system. It aims to produce descriptive reports with LLMs while classifying CT scans with CNNs. Vision-language fusion is highlighted in the project to increase diagnostic insight and efficiency. Within scope are clinical integration, real-world implementation, and feedback systems for iterative improvement. Still outside the current focus are physical testing on patients or integration with hospital-grade EHR systems.

CHAPTER 2

Literature Survey

This chapter offers an overview of the state of the art in lung cancer diagnosis using deep learning and artificial intelligence. With rising medical imaging data and the need for quick, accurate, and consistent interpretation, several studies have investigated convolutional neural networks (CNNs) and combined vision-language models for image analysis and diagnostic reporting. Though CNNs have shown great efficacy in classifying lung cancer from CT scans [7], limitations remain in dataset variety, scalability, and compatibility with textual diagnostics. The unified vision-language model suggested in this study is based on a survey that highlights major strengths, approaches, and research gaps in current systems [4, 5].

2.1 Literature Related to Existing Systems/Methodology/Technology

Several research studies have applied CNN-based deep learning techniques for the detection and classification of lung cancer using CT images.

- **Real-Time Detection of Lung Cancer Using CNN**: A system using accelerated preprocessing methods for CT scans' real-time prediction. It guarantees low latency and great sensitivity but has no assessment over various clinical data sets and imaging artifacts [8].

- **Early Lung Cancer Intelligent Prediction System Using CNN**: To increase sensitivity, probabilistic scoring and data augmentation techniques were introduced. Though it attained great recall, it lacks integration with clinical metadata and does not support 3D volumetric data [9].

- **Enhancing Lung Cancer Diagnosis with Data Fusion and Mobile Edge Computing**: Patient metadata was fused with image-based CNN predictions and deployed on edge devices. While the solution improves accessibility to diagnostics, validation in full-scale clinical trials is lacking [12].

- **LCDctCNN**: A custom CNN compared with ResNet and Xception models, achieving superior accuracy and interpretability. However, it was trained on limited datasets, which limits generalization [7].

- **Deep Machine Learning for Medical Diagnosis**: A hybrid model combining CNN-based feature engineering with modular architecture. Despite high sensitivity, it remains prone to overfitting and lacks extensive validation on rare cancer types [?].

Each of these models has contributed significantly toward advancing automated diagnostics, yet they face shared issues: dataset limitations, static image handling, lack of interpretability, and insufficient integration of textual insights for comprehensive reporting.

2.2 Observations / Research Gaps

However, several gaps still constrain the promising developments of AI-based diagnostic systems for practical deployment in lung cancer:

- **Dataset Limitations:** Most models rely on datasets like LIDC-IDRI or LUNA16, images captured under controlled conditions and not representative of real-world variability in equipment and patient demographics [13].
- **Lack of Longitudinal Analysis:** CNNs operate on static images and fail to consider temporal disease progression, such as changes in nodule size over time [9].
- **Black Box Interpretability:** Despite their accuracy, CNNs offer little transparency, reducing clinician trust in AI-generated decisions [5].
- **Fragmented Vision-Language Approaches:** Existing systems typically handle image classification and report generation separately, lacking tightly coupled semantic integration [4].
- **Limited Multimodal Integration:** Most frameworks fail to combine patient metadata or other imaging modalities like PET or MRI, which could enhance diagnostic accuracy [12].
- **Scalability and Efficiency Constraints:** Deep learning models demand high-end hardware, limiting deployment in low-resource clinical environments [6].
- **Lack of Adaptive Learning:** Changing clinical standards or imaging protocols often require complete retraining of models due to limited support for continual learning [**?**].

Addressing these gaps will require the development of:

- Multimodal learning architectures capable of synthesizing vision and language.
- Lightweight, scalable models that perform efficiently on limited hardware.
- Improved interpretability frameworks to increase clinician trust.
- Diverse, real-world datasets with multimodal annotations.

The proposed system aims to address these challenges by integrating CNN-based CT scan classification with GPT-based diagnostic report generation, forming a seamless vision-language AI framework tailored for lung cancer diagnosis.

CHAPTER 3

Proposed Methodology / Approach

This chapter describes how the suggested AI-based diagnostic framework was developed. It incorporates a Large Language Model (LLM) for automated diagnostic reporting and a custom Convolutional Neural Network (CNN) for image classification. The system is intended to produce thorough, organized medical reports and automatically identify lung cancer from CT scan images. This cohesive framework fills the diagnostic gap in existing clinical workflows by fusing natural language processing and computer vision.

3.1 Problem Definition

The limitations of manual CT scan analysis in the diagnosis of lung cancer include subjectivity, time, and the possibility of error. Rapidly interpreting ever-increasing amounts of imaging data is becoming an increasingly difficult task for radiologists. The workload is further increased by producing consistent and contextually aware diagnostic reports.

To resolve these challenges, we propose a system that:

- Classifies lung CT images into normal, benign, or malignant categories using a CNN.
- Automatically generates textual diagnostic reports using an LLM.
- Combines visual and language models for end-to-end diagnosis.

3.2 Objectives

- Design a CNN architecture for accurate classification of CT scans.
- Integrate preprocessing steps to clean and standardize medical images.
- Generate reports using a fine-tuned LLM based on the classification outcome.
- Fuse vision and language outputs into a single automated framework.
- Ensure the system is scalable, fast, and adaptable to other imaging modalities.

3.3 Proposed System Workflow

The development process follows the Waterfall Model, covering each stage in sequential steps: requirement analysis, system design, implementation, testing, deployment, and maintenance.

3.3 Proposed System Workflow

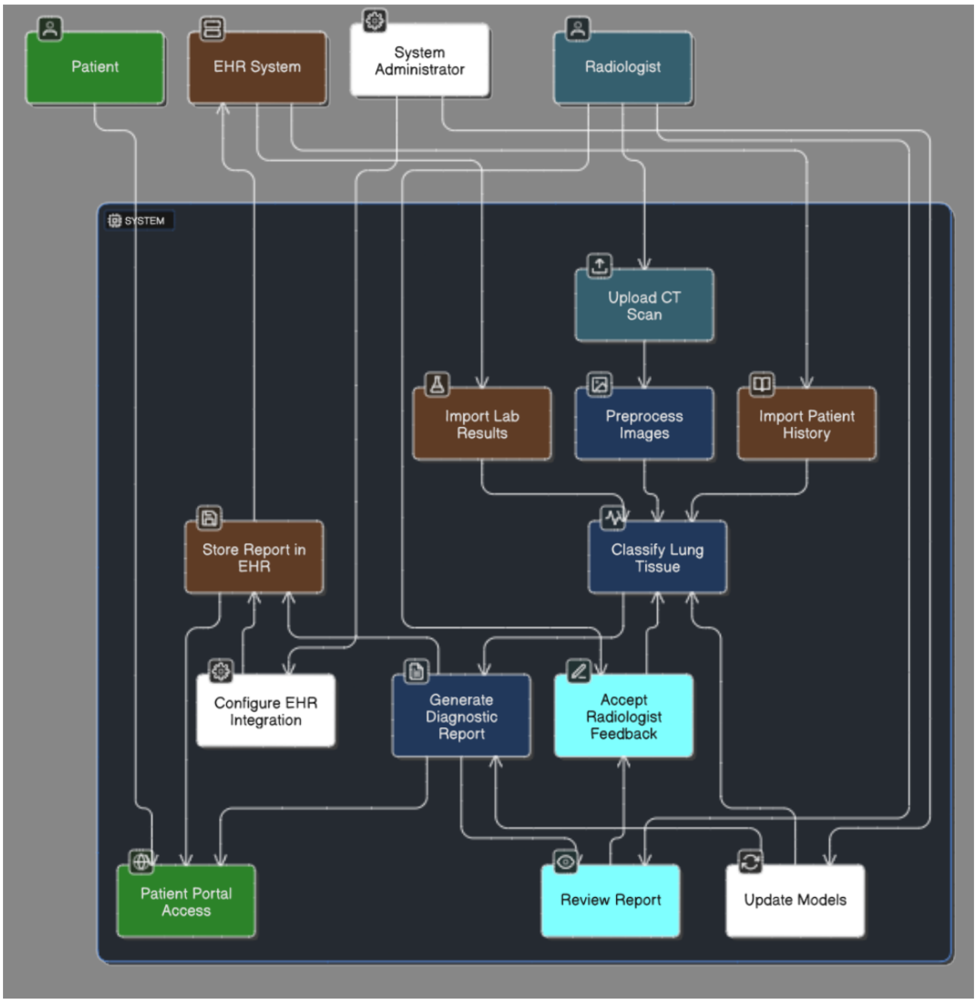

Figure 3.1: Use Case Diagram of the Proposed System

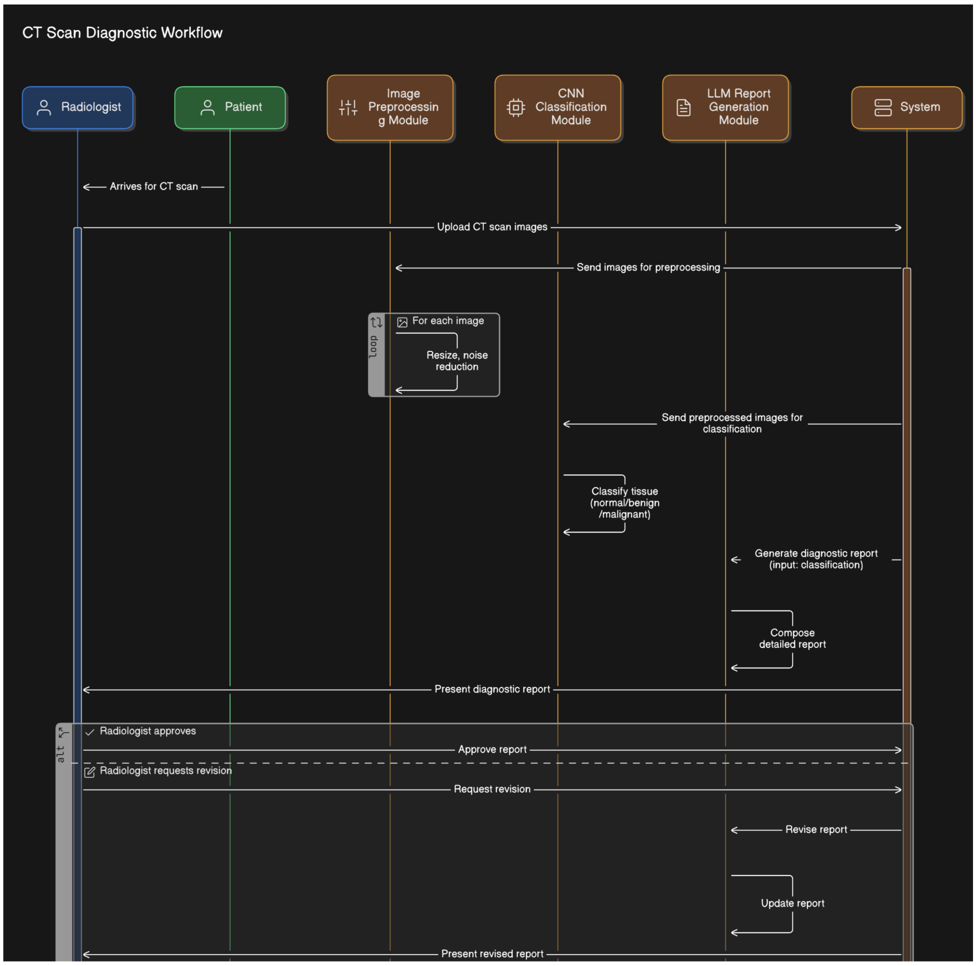

Figure 3.2: Sequence Diagram of User Interaction (Replace with actual)

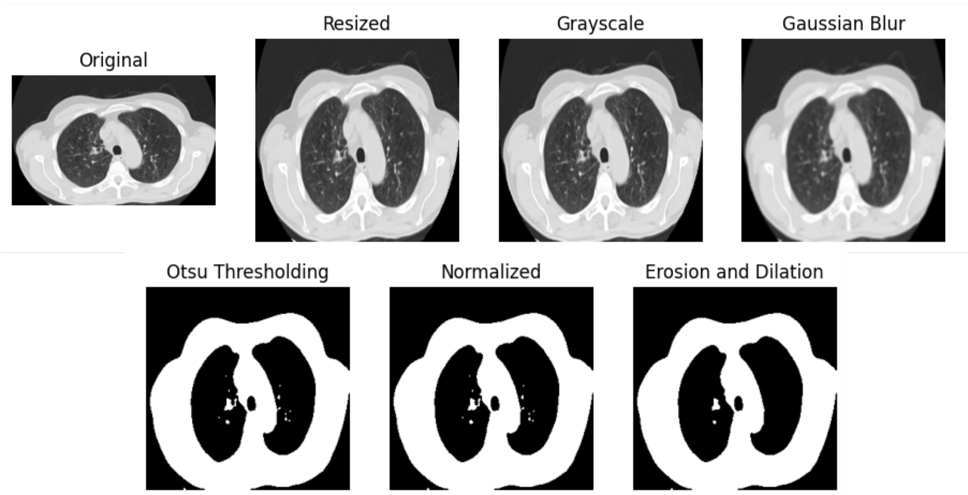

Figure 3.3: Image Preprocessing Steps (Replace with actual)

3.4 Image Preprocessing Steps

- **RGB Conversion:** Images converted from BGR to RGB using `cv2.cvtColor()`.
- **Resizing:** All images resized to 256×256 pixels for CNN compatibility.
- **Grayscale Conversion:** Reduces image complexity for faster processing.
- **Gaussian Blur:** Removes noise and smoothens the image.
- **Otsu Thresholding:** Segments foreground (potential nodules) from the background.
- **Normalization:** Scales pixel values to [0, 1].
- **Morphological Operations:**
  - *Erosion:* Eliminates small noise.
  - *Dilation:* Highlights key regions of interest.

3.5 CNN-Based Image Classification

The custom CNN includes multiple convolution and pooling layers optimized for extracting hierarchical features from CT scan images. The model outputs probabilities for three classes:

- Class 0 – Normal
- Class 1 – Benign
- Class 2 – Malignant

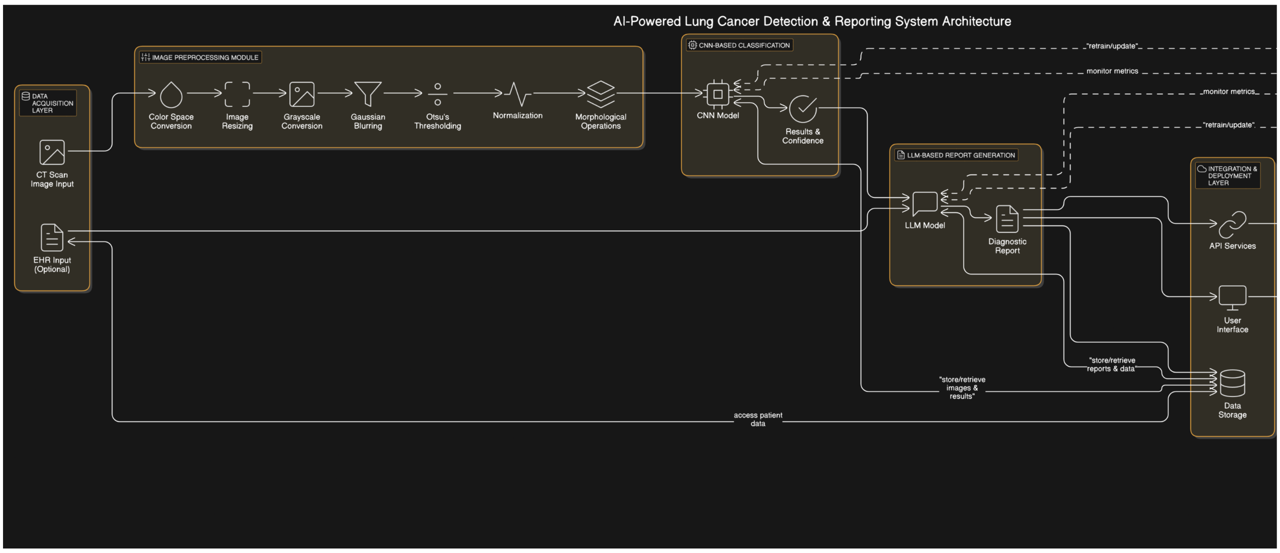

Figure 3.4: System Architecture of the Proposed CNN-LLM Framework (Replace with actual)

Table 3.1: Lung Cancer Detection CNN Model Summary

Layer Type	**Output Shape**	**Parameters**
Conv2D (x1)	(224, 224, 32)	896
BatchNorm (x1)	(224, 224, 32)	128
BatchNorm (x2)	(122, 112, 32)	9,248
Conv2D (x1)	(112, 112, 32)	9,248
BatchNorm (x3)	(112, 112, 64)	256
Dropout (x1)	(112, 112, 64)	1,385
Conv2D (x3)	(56, 56, 128)	51,380,736
BatchNorm (x3)	(112, 56, 64)	512
Dense (x1)	(36, 56, 128)	512
Flatten (x1)	(100352)	0
Dense (Output)	(512, 3)	512
Dropout	(100032)	51,380,736
Dense (Output)	(003)	1,539
Total Parameters: 51.67 Million		
Trainable Parameters: 51.67 Million		
Memory Usage: Max 197 MB		

3.6 Automated Report Generation using LLM

Post-classification, the result is passed to a GPT-based LLM, which generates a structured diagnostic report. The report includes:

- Class prediction and confidence score
- Possible nodule observations
- Suggested clinical actions (optional)

3.7 Performance Evaluation

The system is evaluated using:

- Accuracy, Precision, Recall, F1-score

- AUC-ROC for class separation
- Model latency and inference time

CHAPTER 4

Project Management

Structured project planning, adherence to software engineering principles, and a solid grasp of machine learning and AI integration are the reasons behind the successful development of this lung cancer diagnosis system. The different stages of project management that go into developing a single vision-language system that can classify images and generate diagnostic reports are highlighted in this chapter.

The chapter describes lifecycle planning, feasibility studies, and comprehensive hardware and software specifications. These elements serve as the foundation for project execution and guarantee the system's repeatability, scalability, and dependability. This project is an excellent illustration of how to integrate theoretical concepts with useful, real-world healthcare applications.

4.1 Project Management

The Waterfall model was used to implement the traditional Software Development Life Cycle (SDLC) for project management in this work. Every stage of the lifecycle was carried out with meticulous recording and assessment.

- **Requirement Analysis:** Defining data formats, comprehending the diagnostic procedure, and stating the necessity of classification and report production.
- **System Design:** An architectural blueprint for combining GPT-based LLMs for language generation with CNNs for vision.
- **Implementation:** Text and classification modules are integrated, models are constructed, and images are preprocessed.
- **Testing:** Accuracy, precision, recall, and AUC-ROC are used to evaluate performance.
- **Deployment:** Demonstration of a working prototype with support for real-time diagnosis.
- **Maintenance:** Adding new datasets and medical guidelines to LLM prompts and model weights.

4.2 Feasibility Study

To ensure successful execution, the project's viability was evaluated from technical, operational, and financial perspectives prior to implementation.

4.2.1 Technical Feasibility

- For CNN training, the system makes use of Python and deep learning libraries like TensorFlow and Keras.
- To handle CT scan images, preprocessing libraries such as scikit-image and OpenCV were utilized.

- Hugging Face transformers were used to integrate GPT-based LLMs, such as GPT-2 or GPT-J.
- Every development tool utilized operated on standard hardware configurations and was open-source.

4.2.2 Operational Feasibility

- Made to function in offline testing environments or real-time clinical setups.
- The system reduces radiologists' workload by providing an easy-to-understand diagnostic report;
- The output is visualized, interpretable, and requires little technical knowledge.

4.2.3 Economic Feasibility

- Since the system makes use of publicly accessible datasets (like LIDC-IDRI), there are no expenses associated with data acquisition.
- Every framework and tool is open-source.
- Requires little infrastructure—it operates on workstations or laptops with GPU support.
- By increasing diagnostic throughput and reducing radiologist effort, it lowers long-term diagnostic costs.

4.3 Project Resources

4.3.1 Hardware Requirements

- **Processor:** Intel Core i7 / AMD Ryzen 7 or higher
- **RAM:** Minimum 16 GB
- **Storage:** SSD with at least 512 GB capacity
- **Graphics Card:** NVIDIA GPU (e.g., GTX 1660 or higher) recommended for CNN training

4.3.2 Software Requirements

- **OS:** Windows 10 / Ubuntu 20.04
- **Languages:** Python 3.10
- **Libraries:** TensorFlow/Keras, OpenCV, scikit-learn, transformers (Hugging Face), Matplotlib
- **Tools:** JupyterLab, Google Colab (GPU-based), Visual Studio Code

4.3.3 Operating Requirements

- A system with internet access to pull model weights and pre-trained LLMs.
- Proper file system and permission settings for handling large DICOM image files (converted to PNG/JPEG).
- Regular updates of model checkpoints to include new clinical guidelines or image data.

CHAPTER 5

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5.1 Literature Related to Existing Systems/Methodology/Technology

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Addressing these gaps will require the development of:

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- Improved interpretability frameworks to increase clinician trust.
- Diverse, real-world datasets with multimodal annotations.

The proposed system aims to address these challenges by integrating CNN-based CT scan classification with GPT-based diagnostic report generation, forming a seamless vision-language AI framework tailored for lung cancer diagnosis

CHAPTER 6

Implementation

This chapter describes how the suggested system that uses CT scan classification and diagnostic report generation to automatically diagnose lung cancer is put into practice. The implementation includes the large language model for textual reporting, preprocessing methods, deep learning models for classification, and datasets used. A breakdown of modular architecture and system development tools is also included.

6.1 Description of Dataset

The lung CT image dataset used is derived from the publicly available **IQ-OTH/NCCD** database. This dataset contains images categorized into three main classes:

- **Normal:** Healthy lung tissues without abnormalities.
- **Benign:** Non-cancerous nodules or lesions.
- **Malignant:** Cancerous nodules indicating lung cancer.

Each image is stored in PNG format and varies in resolution and clarity. The dataset was manually cleaned, balanced across classes, and annotated for supervised learning. A total of approximately 1100 CT scan images were used.

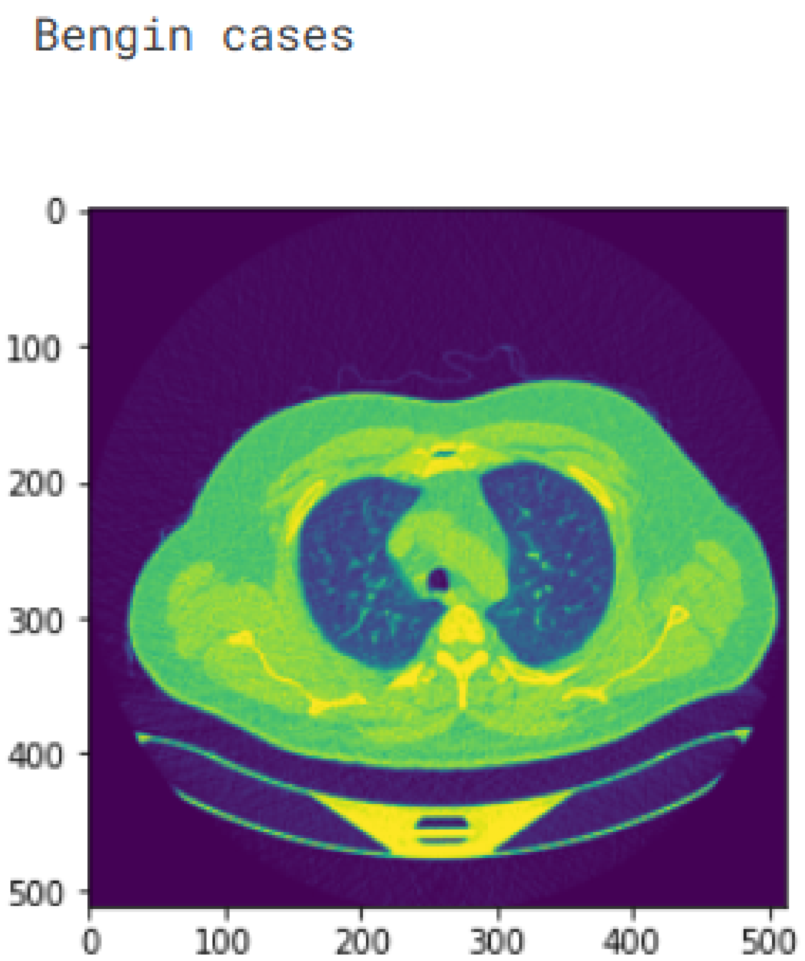

Figure 6.1: Dataset image showcasing a Benign case

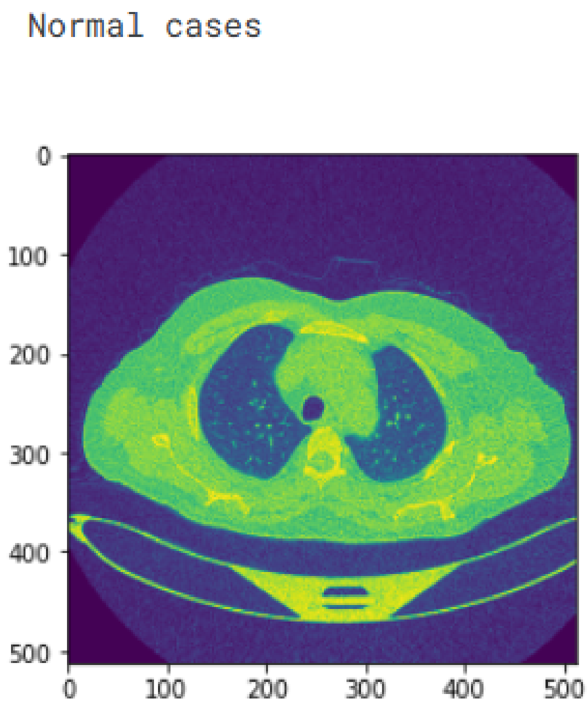

Figure 6.2: Dataset image showcasing a Normal case

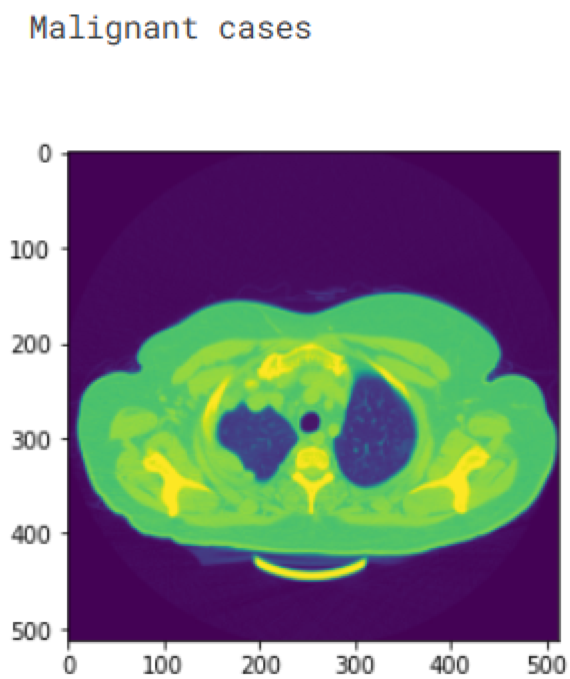

Figure 6.3: Dataset image showcasing a Malignant case

6.2 Preprocessing

Preprocessing ensures that the CT scan images are normalized and optimized for deep learning input. The following steps were applied:

- **Grayscale Conversion:** Converts RGB images to single-channel grayscale to reduce complexity.
- **Resizing:** All images resized to 256×256 pixels using bilinear interpolation.
- **Gaussian Blur:** Applied to smooth image and reduce noise.
- **Otsu Thresholding:** Segments lung nodules from the background for clearer learning.
- **Morphological Operations:** Erosion and dilation to enhance nodule edges.
- **Normalization:** Scales pixel values to [0, 1] for CNN compatibility.

All preprocessing was implemented using OpenCV and 'scikit-image' in Python.

6.3 Model Architecture and Algorithms

The system consists of two major components:

1. CNN-Based Image Classification

Objective: Classify CT scan images into normal, benign, or malignant categories.

Model Details:

- 3 Convolutional Layers (with ReLU activation)
- 2 MaxPooling Layers (stride = 2)
- Flatten + Dense Layers with Dropout
- Output Layer with Softmax activation (3 classes)

Technologies: TensorFlow, Keras, NumPy, Matplotlib

2. LLM-Based Report Generator

Objective: Generate diagnostic reports based on the CNN's prediction.

Model Used: GPT-2 via Hugging Face Transformers (fine-tuned on medical reports)

Input: Classification label + metadata **Output:** Text report with predicted label, clinical suggestion, and scan interpretation.

3. Report Generation Pipeline

- Input class label is mapped to a prompt template.
- Prompt is sent to the GPT-2 model for completion.
- Generated report is formatted into structured output (PDF or TXT).

6.4 Tools Used for Implementation

- **Python 3.10:** Core programming environment.
- **TensorFlow/Keras:** Model building and training for CNN.
- **OpenCV:** Image preprocessing (grayscale, blur, erosion, etc.)
- **Scikit-learn:** Evaluation metrics (accuracy, precision, recall, AUC).
- **Hugging Face Transformers:** GPT-2 model for diagnostic text generation.
- **Matplotlib/Seaborn:** Visualization of model performance and image samples.
- **Google Colab (GPU):** Model training and testing on GPU.
- **Jupyter Notebook:** Development and interactive debugging.
- **Git + GitHub:** Version control and code collaboration.
- **LaTeX (Overleaf):** Report writing and diagram rendering.

6.5 Advantages of Modular Architecture

- **Scalability:** Easy to extend with more image classes or modalities.
- **Interoperability:** CNN and LLM modules can be updated independently.
- **Interpretability:** Classification outputs and textual explanations complement each other.
- **Efficiency:** Modular design ensures lower inference time.

CHAPTER 7

Results and Discussions

The experimental findings and performance assessment of the suggested AI-based lung cancer diagnosis system are presented in this chapter. The outcomes confirm that the LLM-powered report generation module and the image classification model are both effective. Classification results are evaluated using key performance metrics like accuracy, precision, recall, F1 score, and AUC. Text reports and visual outputs show the system's dependability and interpretability.

7.1 Classification Performance

The CNN classifier was evaluated on the preprocessed CT scan images from the IQ-OTH/NCCD dataset. The final model achieved the following results:

- **Accuracy:** 94.09%
- **Precision:** 94.7%
- **Recall:** 94.1%
- **F1 Score:** 94.1%
- **AUC (ROC):** 97.74%

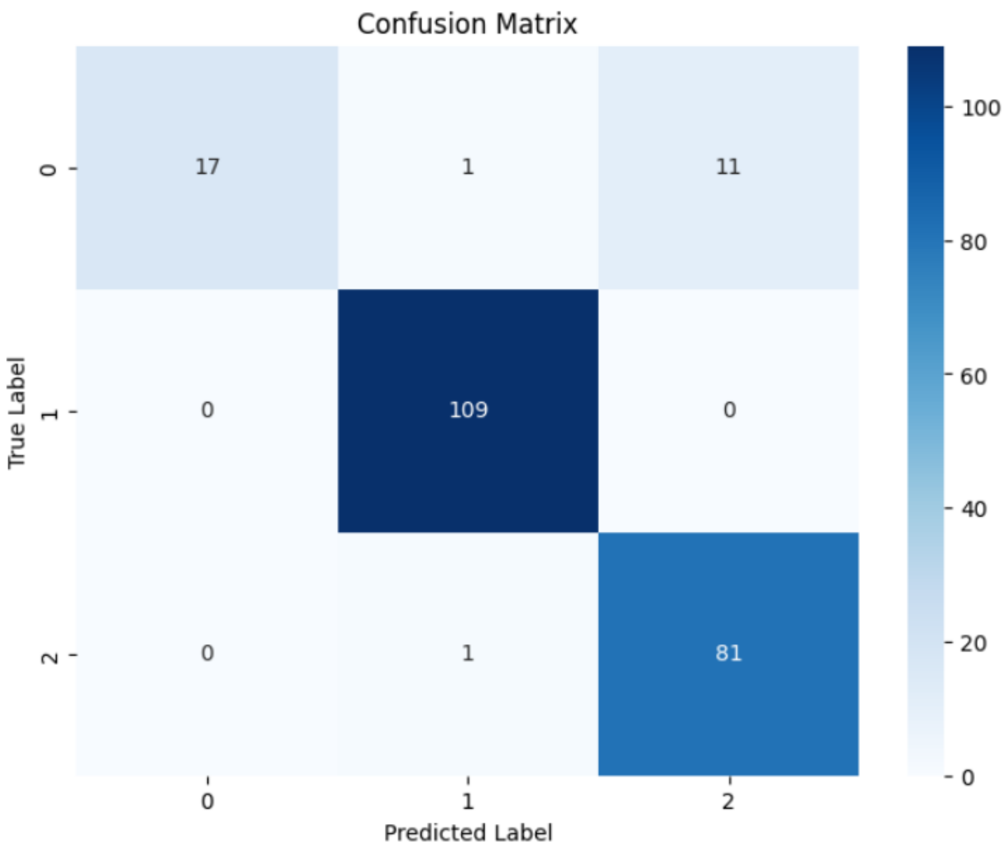

Figure 7.1: Confusion Matrix for CNN-Based Classification (Replace with actual)

Figure 7.1 shows the confusion matrix, indicating accurate separation among Normal, Benign, and Malignant cases.

7.2 Training Evaluation

The training history of the model, including accuracy and loss curves, shows a stable convergence and minimal overfitting.

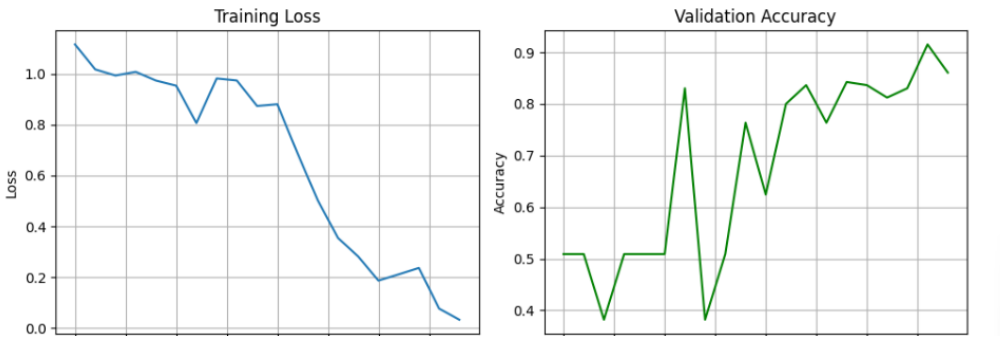

Figure 7.2: Training Accuracy and Loss Curves (Replace with actual)

The curves in Figure 7.3 demonstrate that the model effectively learned lung-specific features from CT scans.

Evaluation Metrics

- **Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:**

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall (Sensitivity):**

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1 Score:**

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **AUC (Area Under Curve):** AUC is computed as the integral of the ROC curve:

$$AUC = \int_0^1 TPR(FPR)\, dFPR$$

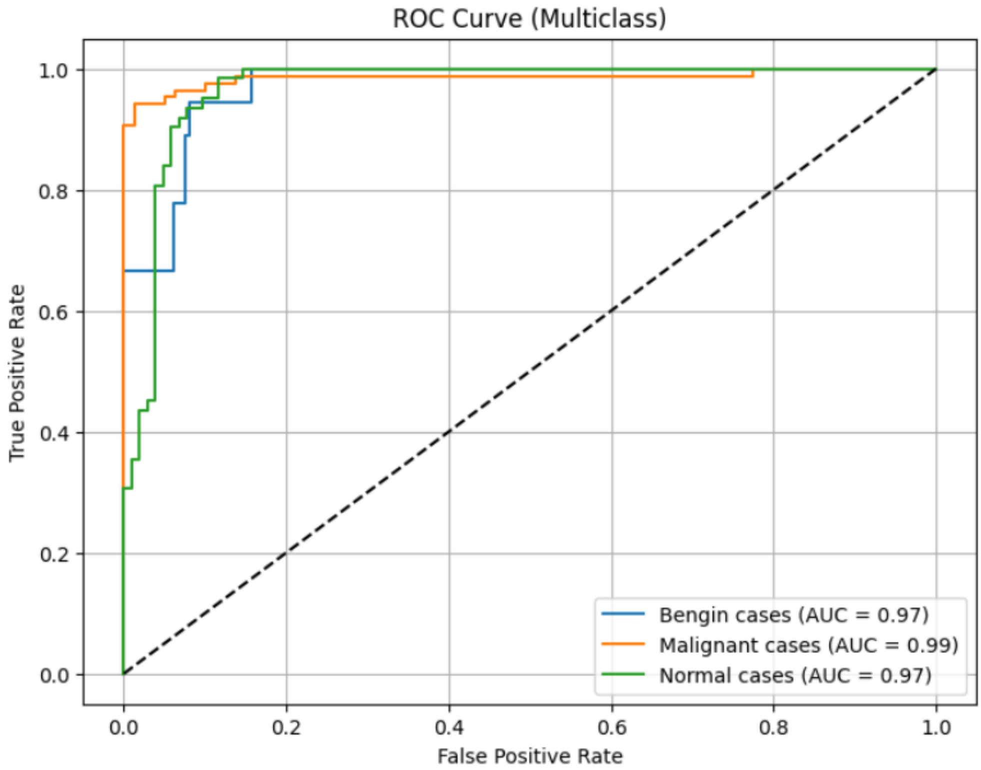

Figure 7.3: AUC - ROC Curve

7.3 LLM-Based Report Generation

The LLM (GPT-2) successfully produced structured diagnostic reports from predicted labels. Below is a sample output:

> *"Diagnosis: The CT scan shows signs consistent with a malignant lung lesion. The lesion is irregular in shape and located in the upper right lobe. Immediate follow-up with a biopsy and oncological consultation is advised."*

This output indicates that the report generation module complements the classifier by providing interpretable and actionable information.

7.4 Discussion

The system performs well in both quantitative metrics and qualitative interpretability, according to the results. Strong model confidence is indicated by the high AUC score, and the LLM-generated reports show good agreement with the predicted classes. Due to visual ambiguity, minor misclassifications were noted in cases that were on the border between benign and malignant.

The system's modularity enables the CNN or LLM to be independently fine-tuned, and the pipeline can be expanded to other organ-specific cancer diagnosis tasks with little retraining.

CHAPTER 8

Conclusions & Future Scope

The main conclusions and ramifications of the suggested AI-based lung cancer diagnostic system are presented in this chapter, emphasizing how the combination of sophisticated image classification and natural language generation methods results in more precise and expandable medical treatments. Future directions for improving system performance are also outlined, such as extending the usefulness of diagnostic recommendations and speeding up model inference times. The modular framework under discussion guarantees ongoing development, opening the door for more extensive uses in medical diagnostics aided by AI.

8.1 Conclusions

The suggested system's combination of Convolutional Neural Networks (CNNs) and Large Language Models (LLMs) represents a major breakthrough in automated lung cancer diagnosis. The system improves lung cancer detection accuracy and interpretability by using CNNs to accurately classify CT scan images and LLMs to produce comprehensive, readable diagnostic reports.

The project offers a framework that is scalable, modular, and flexible enough to accommodate future improvements by skillfully fusing explainable outputs with data-driven machine learning. The system exhibits strong predictive performance across the Normal, Benign, and Malignant classes, achieving a high AUC score of 97.74%. This solution is useful in actual medical workflows since the reports that are produced provide clinicians with contextually relevant insights.

8.2 Future Scope

Future enhancements of the system will focus on several key areas:

- **Model Optimization:** Improving the CNN architecture to lower computational overhead and increase classification accuracy, enabling deployment in settings with limited resources, like rural healthcare facilities.
- **LLM Fine-Tuning:** To produce more precise, current diagnostic narratives, the LLM is modified and adjusted using updated biomedical corpora and domain-specific clinical guidelines.
- **Integration with Electronic Health Records (EHRs):** Creating safe interfaces that enable the direct export of diagnostic results into EHR systems for improved longitudinal care and patient monitoring.
- **Explainability and Transparency:** By using explainable AI methods like Grad-CAM and SHAP to show which CT scan regions affected the model's choice, clinical adoption and trust are increased.
- **Regulatory Compliance and Clinical Trials:** aligning the system with FDA

and CE standards for medical software certification and working with hospitals to carry out prospective clinical validation studies.

The system intends to develop into a strong clinical-grade tool for early lung cancer detection by tackling these issues, assisting oncologists with diagnosis and treatment planning, and eventually enhancing patient outcomes.

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