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Fuzzy Logic-Based Lung Cancer and Cancer Stage Detection Using Tumor Grading

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***Abstract*— Lung cancer remains one of the leading causes of cancer-related deaths globally, necessitating accurate diagnostic tools for early detection and precise staging. Traditional diagnostic approaches rely on manual interpretation of CT scans, which are prone to human error and inefficiencies. This paper presents the implementation of a Fuzzy Logic-Based Lung Cancer Detection and Staging System, which processes CT scan images to identify, classify, and stage lung tumors. The proposed system integrates image preprocessing, feature extraction, fuzzy logic classification, and tumor grading to improve diagnostic accuracy and enhance clinical decision-making. The system follows a structured approach, beginning with image acquisition and preprocessing to enhance image quality. Feature extraction techniques identify tumor characteristics such as size, shape, and texture, which are then processed using fuzzy logic for nuanced classification. Unlike binary classification models, this system assigns membership values to tumor attributes, enabling a more adaptive and precise cancer staging approach. The final stage involves a Graphical User Interface (GUI) that allows users to upload images, view classification results, and interpret tumor staging for better usability. Using the LUNA16 dataset, the system was evaluated for performance, achieving high accuracy, precision, recall, and F1-score. The results demonstrate the effectiveness of fuzzy logic in handling uncertainty in medical imaging, improving early detection, and assisting clinicians in making informed treatment decisions. This system represents a significant advancement in lung cancer diagnostics, bridging the gap between computational adaptability and clinical accuracy.**

Keywords*— *Lung cancer detection, cancer staging, fuzzy logic, CT scan analysis, feature extraction, tumor classification, medical imaging.

I. Introduction

Lung cancer is one of the most prevalent and fatal types of cancer worldwide, contributing significantly to cancer-related mortality. The disease is primarily categorized into small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). Among these, NSCLC accounts for nearly 85% of cases, making it the most commonly diagnosed form. Despite advancements in medical technology, lung cancer continues to pose significant diagnostic and therapeutic challenges. The lack of early detection mechanisms and precise cancer staging methods significantly impacts patient survival rates.

Early detection of lung cancer plays a crucial role in improving patient prognosis and enhancing survival rates. Studies indicate that early-stage lung cancer patients have significantly higher survival rates than those diagnosed at an advanced stage. However, traditional diagnostic methods rely heavily on CT scans interpreted by radiologists, which can be subjective and prone to human error. This subjectivity can lead to misclassification of tumors, causing either unnecessary treatments or delays in intervention.

Traditional lung cancer diagnosis relies on several medical imaging techniques such as Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI). Radiologists manually inspect these scans for abnormalities, making the process labor-intensive and time-consuming. Moreover, false positives and false negatives remain a significant challenge, especially when tumors are small or exhibit characteristics similar to benign lesions. To improve diagnostic accuracy, Computer-Aided Diagnosis (CAD) systems have been introduced. These systems leverage machine learning and deep learning algorithms to analyze medical images, assisting radiologists in decision-making. However, conventional CAD systems often employ binary classification techniques, which classify tumors as either benign or malignant, failing to consider the gradual nature of cancer progression.

The integration of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized cancer diagnosis. AI-based systems analyze medical images with higher accuracy and consistency compared to traditional methods. Several deep learning architectures, including Convolutional Neural Networks (CNNs), Residual Networks (ResNet), and Recurrent Neural Networks (RNNs), have been successfully applied to lung cancer detection. These models can process large volumes of data efficiently, reducing the workload on radiologists and minimizing diagnostic errors. However, despite their effectiveness, deep learning models lack interpretability, making it challenging for clinicians to trust their predictions. Additionally, most machine learning models operate on a rigid classification system, which does not account for uncertainty in tumor characterization.

To address the limitations of binary classification and deep learning models, Fuzzy Logic-Based Systems have emerged as a promising approach for medical diagnostics. Fuzzy logic is a computational technique that deals with uncertainties and imprecise information, making it highly suitable for lung cancer detection and staging. Unlike traditional classification models, which assign absolute labels, fuzzy logic allows for graded classifications by considering multiple tumor characteristics such as size, shape, texture, and density.

The proposed Fuzzy Logic-Based Lung Cancer Detection System follows a structured pipeline. The first step involves image acquisition, where CT scan images are collected from the LUNA16 dataset, ensuring a diverse and well-annotated data source. Next, preprocessing techniques such as contrast normalization, noise reduction, and edge detection are applied to improve image clarity. Following this, feature extraction is performed to capture key characteristics such as tumor size, shape, and texture. These extracted features are then processed through fuzzy logic classification, which assigns degrees of malignancy rather than a strict binary classification. If a tumor is classified as malignant, tumor grading is carried out to determine the severity of cancer progression, categorizing it into Stage I, II, III, or IV. Finally, a Graphical User Interface (GUI) is provided to ensure ease of use for medical practitioners, allowing them to upload images, analyze results, and retrieve staging information efficiently.

The application of fuzzy logic in medical imaging and tumor classification offers several advantages. First, it effectively handles uncertainty, ensuring that tumors exhibiting borderline characteristics are not misclassified. Second, it improves early-stage cancer detection by incorporating a graded classification system, which enables early diagnosis before the tumor progresses to an advanced stage. Additionally, fuzzy logic enhances clinician trust and interpretability, as its decision-making process is transparent and rule-based, unlike deep learning models that function as a black box. Furthermore, the system provides more accurate staging, which is essential for determining appropriate treatment plans.

This paper presents a detailed implementation of a Fuzzy Logic-Based Lung Cancer Detection and Staging System. The key contributions include the development of a Fuzzy Logic-Based Classification Model, integration of Feature Extraction Techniques, implementation of an Interactive GUI, and evaluation using standard performance metrics such as accuracy, precision, recall, and F1-score. The rest of this paper is structured as follows: Section 2 (Related Work) discusses existing methods for lung cancer detection and their limitations. Section 3 (Proposed Methodology) describes the fuzzy logic model and feature extraction techniques. Section 4 (Implementation) details software tools, hardware requirements, and system workflow. Section 5 (Results and Discussion) presents performance evaluation and system accuracy. Finally, Section 6 (Conclusion and Future Scope) summarizes the findings and highlights future research directions.

By implementing a fuzzy logic-based approach, this study aims to improve diagnostic accuracy, reduce misclassification rates, and provide a robust decision-support system for lung cancer detection and staging.

II. LITERATURE SURVEY

Vidhya, K et al. [1] proposed multi-disease analysis by utilizing modified adaptive neuro-fuzzy inference system (M-ANFIS). The medical sector has been profoundly impacted by BD due to the volume, difficulty, and highBD analytical methodologies, platforms, and tools is realized across many domains, the impact on medical organizations for possible applications in healthcare reveals lucrative research opportunities. The healthcare BD starts in the initial processing stage. In this phase, the healthcare BD dataset is integrated and its data formats are identified.

Jena, S. R et al. [2] elaborated a classification scheme, kernel-based non-Gaussian convolutional neural network (KNG-CNN), which is used to create a classification technique for detecting lung cancer using CT scans. KNGCNN has a total of six layers: one completely connected, two convolutional, and three mixing. When a false positive or error occurs, it is diagnosed using a kernel based non-Gaussian calculation. Before performing feature extraction, pictures from the Preprocessing the Lung Image Database Consortium (LIDC-IDRI) dataset involve an ROI-based separation performed using the efficient CLAHE method. Segmentation is followed by the extraction of mor phological characteristics.

Gupta, A et al. [3] delivered an intelligent cyber-physical healthcare framework [ICPHF] in accordance with the interconnected cloud, fog, and things using a combination of soft computing and data fusion. IoT-based sensors, EMRs, and user devices all contribute to the data collection process in the proposed system. The fog layer, made up of many nodes, analyzes data on the most specific symptoms of encephalitis to classify potential instances of encephalitis in actual time and trigger an alarm if a life-threatening medical emergency occurs. For further in-depth data analysis, a multi-stage processing strategy is used as well by the cloud layer.

Sadat Asl, A. A et al. [5] delivered fuzzy logic (FL) as one of the best approaches to describing complicated, uncertain systems. Here, the plan is to leverage FL’s benefits when deciding which critical care unit (CCU) cases to treat. It is a fuzzy expert system of the interval type-2 variety in this work used to predict whether or not COVID-19 patients will need to be admitted to the intensive care unit. In addition, an ANFIS is created to aid in this task of prediction. The findings of these fuzzy logic are then compared to those obtained using more conventional classification strategies such as naive Bayes, case-based reasoning, decision tree, and K-nearest neighbor

Alsiddiky, A et al. [6] incorporated using the hierarchical hidden Markov random field model (HHMRF) an efficient early diagnosis and treatment of vertebral tumor prediction. The implementation of HHMRF and threshold approaches for tumor detection in imaging of the IoM using MRI platform is the primary motivation behind this study. By applying computing, HHMRF facilitates the coordination of the last section of homogenous tissue sections in a vertebral tumor while retaining the boundaries between distinct tissue constituents. The proposed method has been shown to outperform cutting-edge methods for detecting and segmenting stenosis of the lumbar spine with neural networks that are deep in experimental settings.

Using a deep learning algorithm, various techniques have been developed to interpret and learn data representations from unorganized (raw) data. Inner body details are examined, and valuable information is extracted from this data. Deep learning models, algorithms, and methods play a critical role in increasing accuracy and reducing errors in lung cancer classification. Deep learning-based automatic segmentation outperforms manual segmentation in several aspects [7]. It helps to avoid misclassification, reduces the error rate, provides high-quality images, and accurately predicts can cer. False-positive nodules are filtered out using various classifiers [8]. High-quality images correlate directly with the radiologist's ability to make fast and accurate diagnostic decisions. Furthermore, deep learning methods are also applied to predict lung cancer [9]. Training images are provided, and features are extracted automatically, with deep learning being more cost-effective than conventional CAD frameworks. Deep learning enables high-definition representation of input data, enhancing the detection and identification process, thus aiding radiologists. The pixel-level analysis of images con tributes to cancer detection, as cancerous and non-cancerous areas are identified based on pixel data Consequently, deep learning assists medical professionals in providing accurate disease diagnoses and improving healthcare services

The CNN architecture includes multiple layers, with one of the core components being Convolutional Layers (CLs). By using various convolution filters, the CL layers extract distinct information from cancer cell images [10]. The initial step in this methodology is image preprocessing, which employs techniques to enhance medical image quality. Enhanced images then undergo segmentation, a critical phase for identifying relevant areas within lung images. Post-identification, the segmented regions are subjected to feature extraction, focusing on significant patterns indicative of lung cancer. The classification phase is anchored in a sophisticated architecture, the Deep Convolutional Neural Network (DCNN), which dynamically learns hierarchical features via several convolutional layers, each comprising filters, activation functions, and pooling operations. Additional dense layers, known as fully connected layers, process high-level features learned by the convolutional layers. The final output presents classification results, differentiating various lung cancer types. The DCNN effectively classifies lung cancer with high accuracy, as its convolutional layers are instrumental in learning com plex patterns automatically.

Hexuan Li, Hu, and associates [11]. Its network model is created by fusing DenseNet with the hybrid attention mechanism module. The parallel deep learning algorithm that utilized a hybrid attention mechanism attained an accuracy of 94.61% when it came to the photo recognition of lung cancer. These findings are based on the overall results of the testing.

Wang, Xi, Chen, and colleagues [12] suggested a semi-supervised learning method in this pa per to solve the full slide cancer picture classification with minimal annotation effort. The author tested the method on a TCGA open lung disease WSIs dataset before creating the most extensive fine-grained lung cancer WSI dataset, SUCC, for thorough analysis

Jue Jiang et al. [13], In this study, the authors suggest using two different neural network models to differentiate lung tumors from CT scans by merging many residual channels with varying degrees of quality. The findings demonstrate that the classification technique has improved across several datasets. For classifying lung nodules, the MV-KBC model exhibited an accuracy of 91.60% and an AUC of 95.70%.

Sarfaraz Hussein and colleagues [14] With Computer-Aided Diagnosis (CAD) techniques, risk characterization of cancers from radiological images may be more precise and quicker. To characterize tumors, this work develops both supervised and unsupervised learning techniques. This paper proposed a new 3D CNN architecture based on Graph Organizational culture model Sparse for the supervised learning approach. Multithread learning and evaluating CT scans for lung nodule characterization.

N. Mohanapriya and colleagues [15] Lung cancer is a potentially fatal disease affecting people of both genders today. In CT imaging, DCNN categorizes benign and malignant lung cancers. The LIDC database was used to test the recommended designs. When the findings of the DCNN classifier were compared to those of other classifiers, such as the Artificial Neural Network Simulation, it became clear that the DCNN classifier performed significantly better.

The better contrast of PET scans and the superior spatial resolution of CT images are used in this work by Ju, Wei, and colleagues [16] to merge the two modalities successfully. The random variable and graph cut methods are combined to address this separation challenge. A random walk activation method on PET and CT images provides object seeds for graph cut segmentation.

Rekka Mastouri, in addition to their collaborators [18] This method focuses on a few aspects of the information mining algorithms used to make patient-specific projections about the progression of lung tumors. Ideas for information extraction can aid the characterization of lung tumors.

Hongyang Jiang et al. [19], Neural network technique is used in this method because the characteristics are picked at random and neural networks improve the study's validity. The proposed strategy falls short when dealing with low-quality imagery because the algorithm cannot identify tumor cells.

A.R. Talebpour and colleagues [20] The suggested methodology uses CAD frameworks to handle complex tasks. Because of its intricate structure, the program's performance deteriorates. After preprocessing, the suggested approach will do a manual investigation.

III. METHODOLOGY

The block diagram of the fuzzy logic-based lung cancer and cancer stage detection using tumor grading is shown in Fig.1.

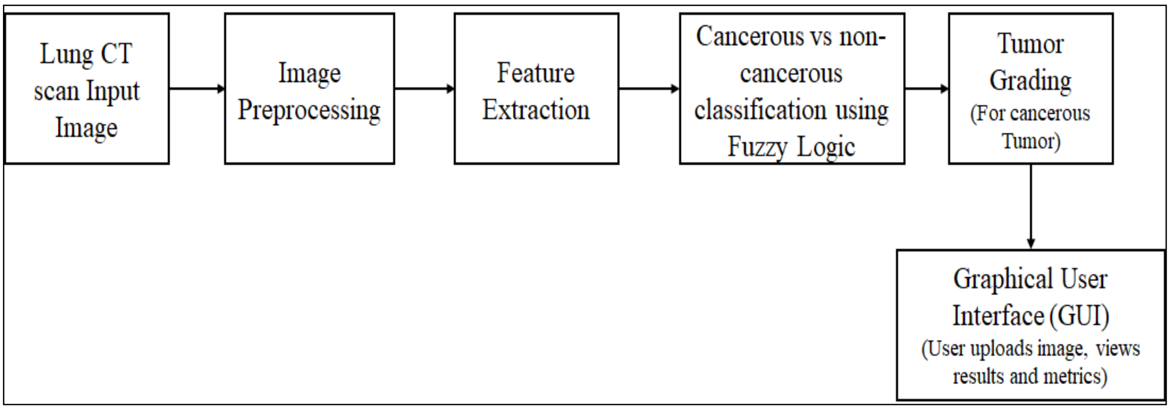

Fig. 1. Block diagram of fuzzy logic-based lung cancer and cancer stage detection using tumor grading

The block diagram for the Lung Cancer Detection and Staging System outlines a sequential workflow comprising several stages that facilitate the detection, classification, and staging of lung tumors. The main components in this process include Input CT Images, Tumor Detection, Feature Extraction, Classification using Fuzzy Logic, Tumor Grading for cancerous cases, and a Graphical User Interface (GUI) for user interaction.

A. *Lung CT Scan Input Image*

The system begins by acquiring lung CT scan images, which serve as the primary data source for tumor detection. These images are typically sourced from established medical imaging databases like the LUNA16 dataset, ensuring they are high-resolution and annotated for training and validation. Each scan contains detailed representations of lung structures and potential nodules, enabling the system to identify any abnormal tissue growth that could indicate cancer. This initial input provides the foundational basis for accurate detection.

B. *Image Preprocessing*

In the preprocessing phase, the input images are enhanced to improve clarity and quality, which is crucial for accurately identifying tumor characteristics. Preprocessing techniques include:

- Noise Reduction: Filters, such as Gaussian or median filters, are applied to reduce noise that may be present in raw CT images. This step ensures a cleaner image, removing extraneous artifacts that could interfere with nodule detection.
- Contrast Enhancement: Techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) improve the visibility of nodule regions by enhancing the contrast, making subtle structures within lung tissue more distinguishable.
- Normalization and Resizing: Ensuring consistency in image dimensions and intensity values across the dataset aids in standardizing model input, which simplifies data processing and ensures that variations in image sizes do not impact model performance.

C. *Tumor Detection and Feature Extraction*

Following preprocessing, the system proceeds with Tumor Detection, identifying and isolating regions of interest (ROIs) where potential nodules are located. This is followed by Feature Extraction, where the system derives critical features from these nodules, including:

- Size: Larger nodules are often more suspicious, though size alone is not a definitive indicator, hence the need for additional features.
- Shape: Malignant nodules often have irregular shapes or undefined boundaries, setting them apart from benign structures.
- Texture: The internal consistency or texture of a nodule can reveal patterns suggestive of ma lignancy. Heterogeneous textures, for instance, may indicate more aggressive tumor growth. These features are essential inputs for the classification model, aiding in informed and accurate decision-making for nodule classification.

D. *Cancerous vs. Non-Cancerous Classification Using Fuzzy Logic*

Using the extracted features, the system applies Fuzzy Logic to classify nodules as either cancerous or non-cancerous. Fuzzy logic is beneficial here as it handles uncertainty and variability, accommodating the ambiguous nature of medical imaging data. Unlike binary classification, fuzzy logic assigns degrees of membership to features, allowing the model to make nuanced classifications. For example, if a nodule displays characteristics associated with both benign and malignant nodules, fuzzy logic evaluates these probabilities, providing a classification that reflects the level of risk.

E. *Tumor Grading (for Cancerous Tumors)*

If a nodule is classified as cancerous, the system proceeds to the Tumor Grading stage to determine the tumor's severity level. This grading is essential for guiding treatment plans, evaluating the extent of tumor progression. Based on extracted features, the system assigns a grade according to medical stan dards, such as those outlined in the TNM classification (Tumor size, Node involvement, Metastasis). This provides insights into cancer progression, allowing clinicians to select appropriate treatments such as surgery, chemotherapy, or radiotherapy.

F. Graphical User Interface (GUI)

The Graphical User Interface (GUI) is designed to facilitate user interaction with the system, making it accessible for clinical use. The GUI allows users to upload CT images, run analyses, and view classification results in real-time. Users can see whether a detected nodule is cancerous or non-cancerous and, if cancerous, access detailed tumor grading information. The GUI also provides additional metrics, such as confidence scores, offering insights into the reliability of the results. By consolidating all stages of the system in one interface, the GUI enables clinicians to navigate the diagnostic process intuitively, making the system easier to integrate into clinical workflows.

G. Evaluation Metrics

In the context of lung cancer detection and classification, several evaluation metrics are used to assess the system's performance in terms of accuracy, reliability, and robustness. These metrics are essential to gauge how well the model performs in detecting, classifying, and staging lung cancer.

- Accuracy: Accuracy is the ratio of correctly predicted instances (both cancerous and non-cancerous) to the total number of cases evaluated.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

This metric provides an overall measure of correctness, but may be insufficient alone if there is a class imbalance (e.g., more non-cancerous than cancerous cases).

- Precision: Precision, or Positive Predictive Value, is the proportion of true positive predictions Using Tumor Grading (correctly identified cancerous nodules) out of all positive predictions.

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

(2)

Precision is crucial for reducing false positives, indicating the model's ability to accurately identify cancerous cases.

- Recall (Sensitivity): Recall, or Sensitivity, is the proportion of actual positive cases (cancerous nodules) that the model correctly identifies.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

High recall reflects the model's ability to detect most true cancer cases, reducing the risk of missed diagnoses.

- F1 Score: The F1 score is the harmonic mean of precision and recall, providing a balanced measure when there is an uneven class distribution.

$$F1\ score = \frac{PXR}{P+R} \quad (4)$$

The F1 score is particularly valuable when balancing both precision and recall is important, as in medical diagnostics.

IV. RESULTS AND DISCUSSION

The effectiveness of the proposed Fuzzy Logic-Based Lung Cancer and Cancer Stage Detection System is evaluated in this section through experimental analysis and performance metrics. The system's results are assessed based on its ability to detect, classify, and stage lung tumors using fuzzy logic, providing a more adaptive and precise diagnostic approach. The evaluation is carried out using CT scan images from the LUNA16 dataset, where image preprocessing, feature extraction, and fuzzy logic-based classification contribute to an improved detection framework. Key performance indicators such as accuracy, precision, recall, and F1-score are used to measure the reliability of the system. Additionally, tumor grading results are discussed to validate the effectiveness of fuzzy logic in handling uncertainties and providing nuanced classifications. Comparative analysis with traditional and deep learning-based approaches is also presented to highlight the advantages of the proposed system. The results obtained demonstrate the system's capability to enhance early-stage lung cancer detection and assist clinicians in making more informed treatment decisions.

The performance of yolov5 algorithm for detection of lung tumor is presented in Fig.2.

Class	Images	Instances	P	R	mAP50	mAP50-95:
all	41	44	0.896	0.886	0.941	0.653
tumor	41	44	0.896	0.886	0.941	0.653

Fig. 2. The performance of yolov5 for detection of lung nodules

Figure 2 shows the performance analysis of the YOLOv5 model for lung nodule detection in CT scan images. The model was validated against 41 images, detecting a total of 44 lung nodule instances. The precision (P) recorded was 0.896, meaning that 89.6% of the detected nodules were true positives. In the same vein, recall (R) was 0.886, which implies the model accurately picked up 88.6% of all real lung nodules from the data. Such indicators show the high precision of YOLOv5 in identifying lung tumors with high accuracy while having a robust balance between precision and recall, as this is important for medical imaging in avoiding both false positives and false negatives.

Additional performance measurement appears in the mean average precision (mAP) scores. The mAP50, a measure of detection precision at an IoU threshold of 50%, was 0.941, which meant that the model localized nodules with high confidence correctly. The mAP50-95, which is a measure of performance over a spectrum of IoU thresholds, was 0.653, reflecting the robustness of the model in coping with differences in tumor size and shape. These findings affirm that YOLOv5 is very efficient for lung nodule detection, with precise localization and tumor classification. Such a system can help radiologists immensely in early detection of lung cancer, saving time in diagnosis and enhancing clinical decision-making.

The fuzzy based ruled applied to the detected tumor to classify the malignant and benign tumor and then the tumor is grading into four stages. The GUI is created in the MATLAB. The results of different images are presented in Fig.3.

Fig. 3. Result of lung nodule detection and classification

Figure 3 demonstrates results for detection and classification of lung nodules employing the introduced system that couples YOLOv5 with detection and fuzzy logic-based classification. Figure 3 indicates the results for detection of detected lung nodules and CT scan images based on which YOLOv5-produced bounding boxes illustrate presence indications for the likelihood of a tumor. Every nodule detected is subsequently categorized as either benign or malignant based on feature-extracted dimensions like size, shape, and texture. The fuzzy logic grading system also infers a cancer stage (I-IV) for malignant findings, offering finer insight into the severity of tumors. The outputs are also depicted in the form of a Graphical User Interface (GUI) in MATLAB that enables users to upload images, observe detection outputs, and study classification results. The capability of the system to identify, categorize, and stage lung nodules accurately enables it to become a helpful assistant for radiologists in making an early diagnosis as well as designing treatment strategies.

V. Conclusion and Future Scope

The implementation of a Fuzzy Logic-Based Lung Cancer Detection and Staging System successfully enhances the accuracy and reliability of lung cancer diagnosis and classification. By leveraging fuzzy logic and feature extraction techniques, the system provides a nuanced approach to cancer staging, accommodating the inherent uncertainties present in medical imaging. The results demonstrate that the proposed model significantly improves early detection and classification of lung tumors, enabling better treatment planning and patient outcomes. The incorporation of a Graphical User Interface (GUI) ensures ease of use for medical practitioners, allowing for seamless image analysis and interpretation.

Future advancements in this system can focus on integrating multi-modal imaging techniques such as PET and MRI scans to provide a more comprehensive diagnostic approach. Optimizing real-time processing by deploying the system on high-performance computing platforms like GPUs or cloud environments can enhance speed and efficiency. Additionally, incorporating automated treatment recommendations through AI-driven decision support systems can aid clinicians in personalized treatment planning. Expanding the dataset for clinical validation with diverse patient cases will improve the robustness and reliability of the model. Furthermore, enhancing explainability and interpretability using Explainable AI (XAI) techniques will help increase clinician trust and system adoption in medical practice. Finally, deploying the system on cloud-based platforms and mobile applications will make it accessible to a wider range of healthcare providers, including those in remote and rural areas, ensuring better early detection and intervention strategies.

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