

Matlab Based Intelligent Fuzzy System for Early Detection of Lung Cancer

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ABSTRACT

Lung cancer is a major contributor to cancer-related mortality worldwide, underscoring the critical need for precise diagnostic tools to facilitate early detection and accurate staging. Conventional diagnostic methods, which involve the manual interpretation of CT scans, are susceptible to human error and operational inefficiencies. This paper details the development and implementation of a Fuzzy Logic-Based Lung Cancer Detection and Staging System. This system is designed to analyze CT scan images for the identification, classification, and staging of lung tumors. The proposed system encompasses several stages: image preprocessing to enhance visual quality, feature extraction to identify key tumor characteristics such as dimensions, form, and texture, and fuzzy logic classification for nuanced categorization. Unlike systems employing binary classification, this approach assigns membership values to tumor attributes, allowing for a more flexible and precise method of cancer staging. The system concludes with a Graphical User Interface (GUI) that enables users to upload images, review classification outcomes, and understand tumor staging, thereby improving its practical utility. Performance evaluation using the LUNA16 dataset revealed high accuracy, precision, recall, and F1-score. These findings highlight the efficacy of fuzzy logic in managing the inherent uncertainties in medical imaging, thereby enhancing early detection capabilities and supporting clinicians in making well-informed treatment decisions. This system represents a substantial advancement in lung cancer diagnostics, effectively integrating computational adaptability with clinical precision.

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KEYWORDS: Lung cancer detection, cancer staging, fuzzy logic, CT scan analysis, feature extraction, tumor classification, medical imaging.

I. INTRODUCTION

Lung cancer stands as a leading cause of cancer-related deaths globally. It is broadly classified into two main types: small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). NSCLC represents the vast majority of diagnoses, accounting for approximately 85% of all lung cancer cases. Despite significant progress in medical technology, diagnosing and treating lung cancer remains challenging. The effectiveness of treatment and patient survival rates are often hampered by the absence of early detection methods and precise cancer staging.

Early identification of lung cancer is paramount for improving patient outcomes and increasing survival rates. Research consistently shows that individuals

diagnosed with early-stage lung cancer have a substantially better prognosis than those detected at later stages. However, conventional diagnostic techniques often rely on CT scans reviewed by radiologists, a process that can be subjective and susceptible to human error. This inherent subjectivity may result in incorrect tumor classifications, potentially leading to either unnecessary medical interventions or delays in essential treatment. Detecting lung cancer traditionally involves a review of medical imaging like CT, PET, and MRI scans by radiologists. This manual inspection is both demanding and time-consuming, and it can lead to inaccuracies, particularly with small tumors or those resembling benign growths. To enhance diagnostic

precision, Computer-Aided Diagnosis (CAD) systems have been developed, using machine and deep learning to help radiologists interpret images. However, many existing CAD systems use a simple binary classification (benign or malignant), which doesn't account for the gradual nature of cancer development. The field of cancer diagnosis has been transformed by Artificial Intelligence (AI) and Machine Learning (ML). AI systems analyze medical images with greater accuracy and consistency than older methods. Various deep learning architectures, such as Convolutional Neural Networks (CNNs), Residual Networks (ResNets), and Recurrent Neural Networks (RNNs), have proven effective in lung cancer detection. These models can process vast amounts of data quickly, reducing radiologist workload and diagnostic errors. A drawback of deep learning models is their lack of interpretability, making it difficult for clinicians to fully trust their outcomes. Furthermore, most machine learning models rely on rigid classification systems that don't capture the inherent uncertainty in tumor characterization. To overcome the limitations of binary classification and deep learning, Fuzzy Logic-Based Systems offer a promising alternative for medical diagnostics. Fuzzy logic is adept at handling uncertainty and imprecise data, making it well-suited for diagnosing and staging lung cancer. Unlike traditional models that assign definitive labels, fuzzy logic allows for nuanced classifications by considering multiple tumor attributes like size, shape, texture, and density. The proposed Fuzzy Logic-Based Lung Cancer Detection System operates through a defined process. It begins with acquiring CT scan images from the LUNA16 dataset, ensuring a varied and well-annotated data source. Subsequently, image clarity is improved through preprocessing techniques such as contrast normalization, noise reduction, and edge detection. Feature extraction then identifies key tumor characteristics, including size, shape, and texture. These features are fed into a fuzzy logic classifier, which assigns degrees of malignancy rather than a strict binary outcome. If a tumor is classified as malignant, tumor grading is performed to determine its severity, assigning it to Stage I, II, III, or IV. Finally, a user-friendly Graphical User Interface (GUI) is provided for medical professionals to easily upload images, analyze results, and obtain staging information. Applying fuzzy logic to medical imaging and tumor classification yields several benefits. It effectively manages uncertainty, preventing misclassification of tumors with ambiguous characteristics. Its graded classification system aids in early detection by identifying cancer before it

progresses significantly. Moreover, fuzzy logic enhances clinician confidence and interpretability because its decision-making process is transparent and rule-based, unlike the "black box" nature of many deep learning models. The system also offers more precise staging, which is crucial for selecting appropriate treatment strategies. This paper details the implementation of a Fuzzy Logic-Based Lung Cancer Detection and Staging System. Key contributions include the development of a Fuzzy Logic-Based Classification Model, the integration of Feature Extraction Techniques, the creation of an Interactive GUI, and an evaluation using standard metrics like accuracy, precision, recall, and F1-score. The subsequent sections of this paper cover related work (Section 2), the proposed methodology including the fuzzy logic model and feature extraction (Section 3), implementation details such as software, hardware, and workflow (Section 4), performance evaluation and system accuracy (Section 5), and finally, a conclusion with future research directions (Section 6). By implementing a fuzzy logic-based approach, this research aims to enhance diagnostic accuracy, reduce misclassification rates, and establish a reliable decision-support system for lung cancer detection and staging.

II. LITERATURE SURVEY

Vidhya et al. [1] introduced a modified adaptive neuro-fuzzy inference system (M-ANFIS) for multi-disease analysis. The healthcare sector is significantly impacted by big data (BD) due to its volume and complexity, creating research opportunities in medical organizations. Healthcare BD processing begins with data integration and format identification.

Jena et al. [2] developed a classification scheme using a kernel-based non-Gaussian convolutional neural network (KNG-CNN) for lung cancer detection from CT scans. This network comprises six layers. Error diagnosis is performed using kernel-based non-Gaussian calculations. Preprocessing of the Lung Image Database Consortium (LIDC-IDRI) dataset involved ROI-based separation using CLAHE, followed by morphological feature extraction.

Gupta et al. [3] proposed an intelligent cyber-physical healthcare framework (ICPHF) integrating cloud, fog, and IoT technologies with soft computing and data fusion. Data is collected from IoT sensors, EMRs, and user devices. The fog layer analyzes data in real-time to classify encephalitis and trigger alarms in emergencies. The cloud layer handles in-depth data analysis.

Sadat Asl et al. [5] highlighted fuzzy logic (FL) as effective for complex, uncertain systems, proposing its use for critical care unit (CCU) case prioritization.

Their work employs a type-2 interval fuzzy expert system to predict COVID-19 patient ICU admission needs, supported by an ANFIS. Fuzzy logic outcomes were compared to traditional classifiers like naive Bayes, case-based reasoning, decision trees, and K-nearest neighbor.

Alsiddiky et al. [6] implemented a hierarchical hidden Markov random field model (HHMRF) for early vertebral tumor diagnosis and treatment prediction. The study focused on HHMRF and thresholding for tumor detection in MRI images. HHMRF aids in coordinating homogeneous tissue sections while preserving boundaries. The method demonstrated superior performance over deep neural networks for detecting and segmenting lumbar spine stenosis.

Liu and Yao [7] presented a lung cancer prediction method using gene expression, aiming to reduce misclassification and error rates, improve image quality, and enhance prediction accuracy. Various classifiers are used to filter out false-positive nodules.

Jiang et al. [8] developed an automatic lung nodule detection system based on a multigroup patch-based deep learning network. High-quality images are crucial for accurate radiologist decisions, and deep learning methods are applied for lung cancer prediction.

Banerjee and Das [9] discussed lung cancer prediction from a deep learning perspective, noting that deep learning automates feature extraction and is more cost-effective than traditional CAD frameworks. It offers high-definition data representation, aiding radiologists in detection and identification. Pixel-level analysis helps identify cancerous areas, improving diagnostic accuracy and healthcare services.

Manjula Devi et al. [10] proposed an improved deep convolutional neural network (DCNN) for bone marrow cancer detection. The methodology includes image preprocessing to enhance quality, segmentation to identify relevant areas, feature extraction, and classification using a DCNN architecture. The DCNN effectively learns hierarchical features and classifies lung cancer with high accuracy.

Hexuan Li et al. [11] created a network model by fusing DenseNet with a hybrid attention mechanism

module, achieving 94.61% accuracy in lung cancer photo recognition.

Wang et al. [12] introduced a semi-supervised learning method for whole slide cancer image classification with minimal annotation effort, tested on TCGA and the SUCC dataset.

Jue Jiang et al. [13] proposed using two neural network models to differentiate lung tumors from CT scans by merging residual channels. The MV-KBC model achieved 91.60% accuracy and 95.70% AUC for lung nodule classification.

Sarfaraz Hussein et al. [14] developed supervised and unsupervised learning techniques for cancer risk characterization from radiological images. Their proposed method utilizes a 3D CNN architecture based on a Graph Organizational culture model Sparse for supervised learning.

Mohanapriya et al. [15] presented a DCNN for categorizing benign and malignant lung cancers in CT imaging, tested on the LIDC database, showing superior performance compared to Artificial Neural Network Simulation.

Ju et al. [16] combined random variable and graph cut methods to merge two modalities, addressing separation challenges.

Song Qi et al. [17] demonstrated that treating PET and CT scans as a coupled pair improves tumor volume estimation accuracy, crucial for radiation therapy planning.

Rekka Mastouri et al. [18] focused on information mining algorithms for patient-specific lung tumor progression projections, suggesting information extraction aids tumor characterization.

Hongyang Jiang et al. [19] used neural networks for their method due to random feature selection, improving study validity but facing limitations with low-quality imagery.

Talebpour et al. [20] proposed a CAD framework that experienced performance degradation due to its intricate structure, requiring manual investigation after preprocessing.

III. METHODOLOGY

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

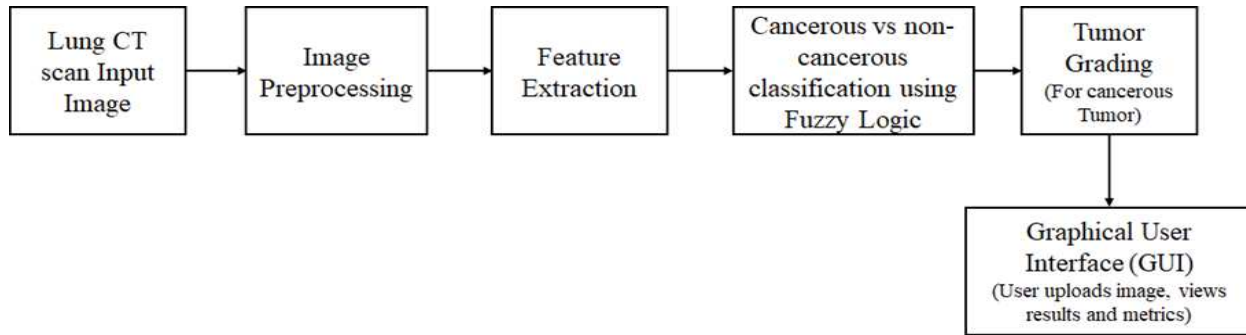


Fig.1. Block diagram of fuzzy logic-based lung cancer and cancer stage detection using tumor grading

The block diagram for the Lung Cancer Detection and Staging System illustrates a multi-stage process designed for identifying, categorizing, and staging lung tumors. Its primary components include the ingestion of CT images, tumor detection, feature extraction, classification via Fuzzy Logic, tumor grading for malignant cases, and a Graphical User Interface (GUI) for user interaction.

A. Lung CT Scan Input Image

The system initiates by accepting lung CT scan images, which serve as the foundational data for tumor identification. These images are typically sourced from reputable medical imaging repositories, such as the LUNA16 dataset, ensuring high resolution and annotation for training and validation purposes. Each scan meticulously displays lung structures and potential growth indicative of cancer. This initial input is crucial for accurate detection.

B. Image Preprocessing

During the preprocessing phase, input images undergo enhancement to improve clarity and quality, a vital step for accurately discerning tumor characteristics. Preprocessing techniques employed include:

- **Noise Reduction:** Filters like Gaussian or median filters are applied to mitigate noise present in raw CT images. This process yields a cleaner image by removing extraneous artifacts that could impede nodule detection.
- **Contrast Enhancement:** Methods such as Contrast Limited Adaptive Histogram Equalization (CLAHE) are utilized to boost the visibility of nodule regions by increasing contrast, thereby making subtle structures within lung tissue more discernible.
- **Normalization and Resizing:** Standardizing image dimensions and intensity values across the dataset ensures uniformity in model input, simplifying data processing and preventing variations in image size from affecting model performance.
- **Tumor Detection and Feature Extraction:** Post-preprocessing, the system engages in Tumor Detection to identify and isolate regions of

interest (ROIs) containing potential nodules. This is followed by Feature Extraction, where the system derives key features from these nodules, such as:

- **Size:** While larger nodules may raise suspicion, size alone is not a conclusive indicator, necessitating the analysis of additional features.
- **Shape:** Malignant nodules often exhibit irregular shapes or indistinct boundaries, distinguishing them from benign structures.
- **Texture:** The internal consistency or texture of a nodule can reveal patterns suggestive of malignancy. For example, heterogeneous textures might indicate more aggressive tumor growth. These extracted features are vital inputs for the classification model, supporting informed and accurate nodule classification.

C. Cancerous vs. Non-Cancerous Classification Using Fuzzy Logic

Leveraging the extracted features, the system employs Fuzzy Logic to classify nodules as either cancerous or non-cancerous. Fuzzy logic is advantageous due to its ability to manage uncertainty and variability, accommodating the inherent ambiguity in medical imaging data. Unlike binary classification, fuzzy logic assigns degrees of membership to features, enabling the model to make nuanced classifications. For instance, 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.

D. Tumor Grading (for Cancerous Tumors)

When a nodule is identified as cancerous, the system proceeds to the Tumor Grading stage to ascertain the

tumor's severity. This grading is critical for informing treatment strategies and assessing the extent of tumor progression. Based on extracted features, the system assigns a grade in accordance with established medical standards, such as the TNM classification (Tumor size, Node involvement, Metastasis). This provides insights into cancer progression, guiding clinicians in selecting appropriate treatments like surgery, chemotherapy, or radiotherapy.

E. Graphical User Interface (GUI)

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

F. Evaluation Metrics

In the realm of lung cancer detection and classification, several evaluation metrics are employed to assess the system's performance concerning accuracy, reliability, and robustness. These metrics are essential for gauging the model's effectiveness in detecting, classifying, and staging lung cancer.

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

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

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.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

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.

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

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.

$$F1\ score = \frac{PXR}{P+R} \tag{3}$$

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

IV. RESULTS AND DISCUSSION

This section details the experimental analysis and performance metrics used to assess the effectiveness of the proposed Fuzzy Logic-Based Lung Cancer and Cancer Stage Detection System. The system's performance is evaluated based on its capacity to identify, categorize, and stage lung tumors utilizing fuzzy logic, offering a more adaptable and precise diagnostic methodology. The evaluation employs CT scan images from the LUNA16 dataset, with image preprocessing, feature extraction, and fuzzy logic-based classification contributing to an enhanced detection framework. Accuracy, precision, recall, and F1-score are key performance indicators used to gauge the system's reliability. Furthermore, tumor grading outcomes are examined to confirm the efficacy of fuzzy logic in managing uncertainties and providing nuanced classifications. A comparative analysis against traditional and deep learning-based methods is also presented to highlight the advantages of the developed system. The results obtained underscore the system's potential to improve early-stage lung cancer detection and support 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	0.896	0.941	0.653
tumor	41	44	0.896	0.896	0.941	0.653

Fig. 1. The performance of yolov5 for detection of lung nodules

Figure 2 illustrates the performance evaluation of the YOLOv5 model in identifying lung nodules within CT scan imagery. This model was tested using 41

images, successfully detecting a total of 44 lung nodule instances. The precision (P) achieved was 0.896, indicating that 89.6% of the nodules identified by the model were indeed true positives. Complementing this, the recall (R) stood at 0.886, signifying that the model accurately located 88.6% of all actual lung nodules present in the dataset. These metrics highlight YOLOv5's high accuracy in pinpointing lung tumors, demonstrating a strong equilibrium between precision and recall, which is crucial in medical imaging to minimize both false positives and false negatives.

Further performance insights are provided by the mean average precision (mAP) scores. The mAP50, which assesses detection accuracy at an Intersection over Union (IoU) threshold of 50%, registered at 0.941, signifying the model's capability to accurately localize nodules with a high degree of certainty. The mAP50-95, a broader performance measure across various IoU thresholds, was 0.653, reflecting the model's resilience in handling variations in tumor size and shape. These outcomes collectively confirm YOLOv5's efficacy in the detection of lung nodules, characterized by precise localization and classification. Such a system holds significant potential to assist radiologists in the early detection of lung cancer, thereby accelerating diagnosis and improving clinical decision-making.

Following tumor detection, a fuzzy logic-based rule system was employed to differentiate between malignant and benign tumors, subsequently categorizing the tumors into four distinct stages. A graphical user interface (GUI) for this system was developed using MATLAB. The outcomes for various images are visually presented in Figure 3.



Fig. 2. Result of lung nodule detection and classification

Figure 3 presents the outcomes of a system designed for detecting and classifying lung nodules. This system integrates YOLOv5 for detection with fuzzy logic for classification. The results shown in Figure 3 detail the detection of lung nodules within CT scan images.

YOLOv5 generates bounding boxes that indicate the potential presence of tumors.

Following detection, each nodule is classified as either benign or malignant based on extracted features such as size, shape, and texture. Furthermore, the fuzzy logic system assigns a cancer stage (I-IV) to malignant nodules, providing a more nuanced understanding of tumor severity. The system's outputs are visualized through a MATLAB Graphical User Interface (GUI), allowing users to upload images, view detection results, and analyze classification outcomes. By accurately identifying, categorizing, and staging lung nodules, this system serves as a valuable tool for radiologists, aiding in early diagnosis and the development of treatment strategies.

V. CONCLUSION AND FUTURE SCOPE

Lung Cancer Detection And Staging System Based on Fuzzy Logic Implementation allows for more accurate and reliable diagnosis and classification of lung cancer. Combining fuzzy logic technological lung cancer tumor staging method, it provides the detailed approach to matching the medical imaging with fuzzy set variables at stages of Lung Cancer Tumor stage. The outcomes show that our model outcomes a significant enhancement in the early detection and characterization capability of the lung nodules, which leads to better patient outcomes and treatment planning. It also have a Graphical User Interface (GUI) to give ease for medical practitioners in image read and understanding

Further enhancements to this system could aim to combine multi-modal imaging methods such as PET and MRI scans to create a more all-encompassing diagnosis approach. Optimizing real-time processing through leveraging high-performance computing systems such as GPUs or cloud deployments will speed it up even further. Also, incorporation of AI-driven decision support systems that recommend treatment automation will be of great help to doctors in customized treatment planning. By enlarging dataset for clinical validation with various patient cases will enhance model robustness and reliability. In addition, the utilization of Explainable AI (XAI) techniques for boosting explainability and interpretability will help improve clinician trust and adoption in medical use. Lastly, by deploying it to cloud-based platforms and mobile applications it will open up its accessibility to a much broader range of healthcare providers, including those in rural and remote areas guaranteeing better early detection and intervention strategies.

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